Intertemporal substitution and household production in labour supply

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Abstract

The demands on a person's time vary over their working life, so that the years in which they might be expected to devote most time to work may also be the period when other commitments, such as bringing up children, are most pressing. Estimates of the intertemporal labour supply elasticity that do not take this possibility into account are likely to be biased. Recent research that uses US data from three time-use surveys has found evidence for a large downward bias to the labour supply elasticity. This paper uses a large UK survey to test this hypothesis. It finds convincing evidence for a similar downward bias in estimates of the UK labour supply elasticity for males. The analysis is extended by differentiating by sex, marital status, skill and business cycle. The bias appears in every case, but is less evident for married men. The labour supply elasticity for single women is, interestingly, similar to that for single men.

Key words: Labour supply, intertemporal substitution, home production, bias.

JEL classification: J20, J22, C33.

Summary

Estimates of the intertemporal labour supply elasticity obtained from standard life-cycle models may be subject to a downward bias, because the standard intertemporal optimisation approach assumes that individuals adjust only their leisure in response to changes in wages. This neglects the potentially important substitution of hours of work in the market for hours of work at home. Ignoring this extra margin of adjustment will result in smaller responses of market hours to changes in wages.

The balance between labour supply and demand has implications for inflationary pressure. Therefore, establishing the true size of the elasticity of substitution will be important to policymakers, as it will be one of the key factors in determining how labour supply may change over any forecast horizon.

Distinguishing between hours of work at home and hours of work in the market delivers a labour supply relationship augmented by hours spent in 'home production'. Recent research using cross-sectional US survey data has used this result to estimate the 'true' relationship between hours worked and wages. The results confirm that ignoring home production leads to a large downward bias in the estimated wage elasticity.

This paper applies a similar approach to the United Kingdom, using the British Household Panel Survey (BHPS), to see whether there may be similar biases in UK labour supply elasticity estimates. The BHPS has a large sample, which leads to accurate estimates of the labour supply elasticity.

The paper finds convincing evidence for a downward bias in estimates of the UK labour supply elasticity if home production is not included. When home production is incorporated, estimates of the labour supply elasticity at least double (although they remain fairly low in absolute size). The approach is extended by estimating separately by marital status, skill levels, and by testing for cyclical effects. The bias is present in every case, but is less obvious for married men. The elasticity is not affected by controlling for cyclical or time-related effects, and skills do not seem to affect it in a

predictable manner. The paper also finds that the elasticity for single women is very similar to that for single men.

1. Introduction

A great deal of research has stressed the importance of the intertemporal elasticity of labour supply for equilibrium business cycle models.(1) These models replicate the observed fluctuations in hours worked in advanced economies only by assuming that individuals are willing to substitute leisure across time in response to anticipated changes in wages. However, the empirical evidence based on individual data does not support intertemporal substitution elasticities sufficiently large to replicate the actual data.(2)

A strand of research pioneered by Becker (1991) and Gronau (1986), and adapted to macroeconomic modelling by Benhabib *et al* (1991) and Greenwood *et al* (1995), provided new insight into how individuals allocate their time. According to this theory, the response of someone's hours of work in the market to changes in wages could be larger when 'hours of work at home' are an additional margin of adjustment. This would imply that changes in wages over the life cycle motivate individuals to substitute hours of work at home for hours of work in the market, in addition to the standard substitution between consumption and leisure.

Home production occurs when individuals spend some fraction of their non-market time producing a non-marketable home-produced 'good'. While consumption of this home-produced good will earn utility, the time spent producing it will have an associated disutility. Gronau (1986) distinguishes these activities from leisure by classifying them as intermediate goods that could be 'purchased' in the market. Typical examples of home-production activities are cooking, cleaning and childcare.

Chart 1 describes the allocation of time problem in a static set-up as in Gronau (1986). The concave curve *TAoCo* describes the opportunity set facing the individual in the absence of market opportunities. Working in the market at a constant wage rate (described by the slope of the line *AoDo*), expands this set to *TAoDo*. In the

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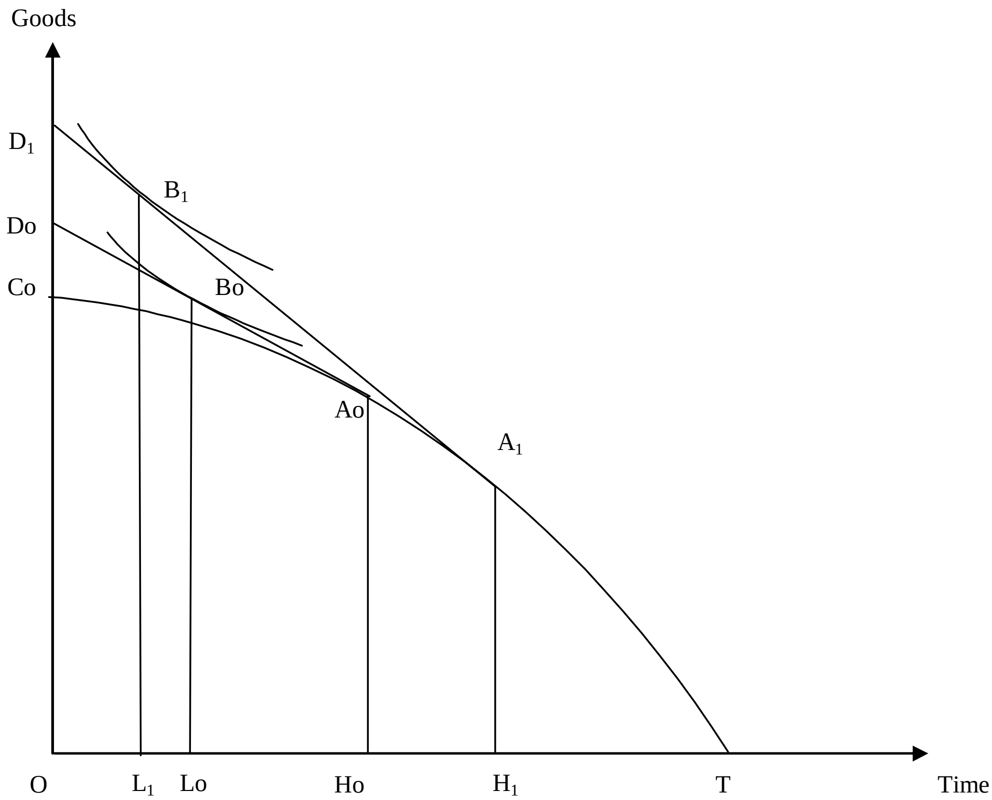
(1) See, for example, Lucas and Rapping (1969), Eichenbaum, Hansen and Singleton (1988), and Cooley (1995).
(2) See, for example, MaCurdy (1981), Pencavel (1986) and Blundell and MaCurdy (1999).

equilibrium depicted by *Bo*, the person allocates *OLo* hours to leisure, *LoHo* to market work and *HoT* to home production.

An increase in the real wage reduces the profitability of work at home ($HoT>H_1T$), but its effect on leisure and market time is indeterminate. The income effect tends to increase leisure, while the substitution effect increases market work. Most empirical studies that estimate this substitution effect in a life-cycle set-up neglect the movement from *Ao* to A_1.

Chart 1: Allocation of time in a static framework



The ideas behind this static model also hold in a life-cycle framework. An equilibrium relationship between hours of work, both in the market and at home, and real wages can be tested. In a paper in the *Journal of Monetary Economics* (2000), Rupert, Rogerson and Wright (RRW) argue that estimates of the intertemporal labour supply elasticity obtained from standard life-cycle models are subject to a downward bias. This occurs because the standard approach makes an implicit assumption that other factors influencing hours of work in the market are not highly correlated with wages over the life cycle.

If the time spent in home production varies over an individual's life cycle, it is possible that ignoring it when estimating intertemporal labour supply elasticities will result in a misspecfied model and biased estimates. RRW argue that it is indeed likely that hours spent in home production will vary in this manner, as the phase of the life cycle in which wages are high may also be the period in which individuals have the greatest demands on their time for home production. They show that, in these circumstances, ignoring home production will lead to a downward bias in estimates of the labour supply elasticity. If this bias is important, then the change in market hours that would result from a given change in wages holding hours spent in home production constant would be much larger than implied by existing estimates.

RRW estimate a labour supply relationship augmented by hours spent in home production. This allows the authors to estimate the 'true' intertemporal substitution elasticity using cross-sectional US survey data. They find that the downward bias is large and conclude that the analysis of labour supply effects of wage changes that ignore this bias will be seriously misleading.

In this paper we apply the RRW approach to the United Kingdom, using the British Household Panel Survey (BHPS) in order to see whether there may be potentially misleading biases in UK labour supply elasticity estimates. We extend this analysis by estimating separately by marital status, skill levels, and by testing for the possible effect of changing business cycle conditions on the choice of hours (time effects) across the sample period.

One of the advantages of following the RRW approach for the United Kingdom is the quality of data available. The BHPS is an annual longitudinal panel available from 1991 onwards. It contains data on the time spent (hours per week) doing housework, caring for children and working in the market. The BHPS provides us with a much bigger sample than RRW had in their study. This allows us to calculate estimates of the labour supply elasticity with fairly tight confidence intervals, and means we can conduct a range of sensitivity checks.

To summarise our results, we find strong evidence for a bias in the elasticity of intertemporal substitution when home production is not taken into account. We find that the bias is also present when estimating separately by marital status, skill levels, and when using time dummies to control for business cycle conditions. The result is also robust across a range of utility parameterisations. However, we also note that the elasticity remains low even when home production is included.(3)

The balance between labour supply and demand has implications for inflationary pressure. Therefore establishing the true size of the elasticity of substitution will be important to policymakers, as it will be one of the key factors in determining how labour supply may change over any forecast horizon.

The elasticity of substitution is a key parameter in dynamic general equilibrium models which attempt to replicate the cyclical comovements of the main macroeconomic variables, and assess the welfare effects of various fiscal and monetary policies. Furthermore, its importance builds on the assumption that labour markets are perfectly competitive in their baseline representation. Both the early Real Business Cycle model (RBC) and later the New Keynesian model (NK),(4) model labour supply by equating the marginal utility of leisure to the marginal utility of the wage earned by an extra unit of labour. Thus, a transitory increase in the current wage rate will motivate individuals to substitute leisure today for leisure tomorrow, and the willingness to do so will depend on the size of the intertemporal elasticity of labour supply.

This labour supply relationship predicts that wages are contemporaneously correlated with employment and, therefore, output. However, one of the main difficulties faced by these models is that in order to mimic the observed covariance of employment,

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(3) We regard these elasticities as low when compared to other studies for males both in the US and the UK. A comprehensive survey by Pencavel (1986) reports intertemporal labour supply elasticities between 0 and 0.5 for men. The intertemporal elasticities calculated using British data in this survey are around 0.05. Altonji (1986) finds elasticities between 0 and 0.35 using US data. Female estimates, however, are almost always higher than those for men. Blundell *et al* (1993) for example, obtain intertemporal elasticities that range from 0.5 to 1 for the UK.

(4) The main difference between the baseline RBC model and the baseline NK model is that the latter assumes monopolistic competition and sticky prices in the goods market. This assumption allows nominal variables (monetary policy) to have real effects in the short run. See Goodfriend and King (1997) for a discussion of the RBC and the New Keynesian paradigms.

output and real wages, they require values of the intertemporal elasticity that are much larger than those estimated in the literature, implying a much flatter labour supply curve than that suggested by the data. The empirical evidence summarised in Pencavel (1986) suggests that the intertemporal elasticity of substitution is less than one for males. However, in order to match the data many business cycle models require values close to two and even higher.(5)

Incorporating home production should take us in the right direction as a higher elasticity of substitution would decrease the volatility of wages, while increasing that of hours in a calibrated business cycle model. Whether this larger elasticity accounts fully for the observed correlation of wages and employment, and other variables, would involve contrasting the business cycle statistics of a calibrated general equilibrium model with those extracted from the data. Kydland (1995) carries out a similar exercise for the United States, while Millard *et al* (1999) does so for the United Kingdom, although they do not calibrate the intertemporal elasticity explicitly.

The higher labour supply elasticity in a model with home production would certainly help us, at least partially, to reconcile the data with the predictions of a perfectly competitive labour market with the data. However, the specification of the labour market can be altered in many different ways that can complement the higher elasticity obtained with home production. Other alternatives include distinguishing between an intensive and an extensive margin of labour;(6) labour market frictions (nominal or real);(7) and the interaction of the labour market with other components of the model, such as physical and human capital accumulation.(8) All of these are of course a matter for future research.

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(5) King and Rebelo (1999) note that ‘The RBC model does not need to rely on a high degree of intertemporal substitution in labor choice… However, either intertemporal or intratemporal substitution must be strong enough to produce realistic labor movements...’.
(6) See, for example, Kydland (1995), and Trigari (2003) for a model with two margins and matching.
(7) See Erceg, Henderson and Levin (2000) for a model with price and wage rigidities, and Alexopoulos (2004) for a model with real wage rigidities.
(8) For a model with price and wage rigidities and alternative physical capital accumulation set-ups see Canzoneri, Cumby and Diba (2004). For a model with skill accumulation see Chang, Gomes and Schorfheide (2002).

The rest of this paper has three broad sections. First, we set out more formally the standard life-cycle labour supply model and expand it to allow for the possibility of home production. We then discuss the construction of synthetic cohorts using the BHPS. In the rest of the paper, we replicate the RRW approach on our data, discussing summary statistics, life-cycle profiles and regression results. Finally, we extend these results by disaggregating the analysis by gender, marital status and skills.

2. The model

Rupert, Rogerson and Wright start their analysis by outlining the basic model of intertemporal labour supply. The standard model can be found in Ghez and Becker (1975), MaCurdy (1981) and Altonji (1986). The individual's problem is to maximise their lifetime utility subject to a budget constraint:

$$\max \sum_{t=1}^{T} \beta^t U(c_{mt}, h_{mt}) \qquad \textbf{(1)}$$

$$s.t. \sum_{t=1}^{T} (1+r)^{-t} c_{mt} \leq A_0 + \sum_{t=1}^{T} (1+r)^{-t} h_{mt} w_{t,} \qquad h_{mt} \leq H \qquad \textbf{(2)}$$

where c_{mt}, h_{mt} and w_t are market consumption, hours of market work, and the real wage at time t. A_0 denotes initial asset holdings, β the subjective discount factor, r is the interest rate and H the per period time endowment. The first-order conditions for an interior solution for this problem, assuming a convex utility function, are $\beta^t U_1(t) = \lambda(1+r)^t$ and $-\beta^t U_2(t) = \lambda(1+r)^{-t} w_t$, where λ is the lifetime budget constraint multiplier (assumed constant) and $U(t)$ is U evaluated at time t. Taking logs of the second condition implies:

$$\log[-U_2(t)] = \log\lambda - t\log\beta(1+r) + \log w_t \qquad \textbf{(3)}$$

Specifying a functional form for the utility function allows this equation to be turned into a standard labour supply curve. If the utility function is additively separable between consumption and market hours then equation **(3)** will not contain a term for market consumption. For example, if $U = u(c_{mt}) - v(h_{mt})$ and we specify the disutility of market hours as $v(h_{mt}) = \phi\, h_{mt}^{\gamma}$ then **(3)** becomes:

$$(\gamma - 1)\log h_{mt} = \log\frac{\lambda}{\gamma\phi} - t\log\beta(1+r) + \log w_t \qquad \textbf{(4)}$$

Equation **(4)** is a simple expression connecting market hours to the wage. Making an assumption on the distribution of the preference parameter γ allows for regression equations to be estimated when suitable data is available.

Rupert, Rogerson and Wright then generalise the standard model to include the possibility of home production. Total hours are now split between three possibilities: market hours h_{mt}, non-market work hours or home production h_{nt}, and leisure $(H\text{-}h_{mt}\text{-}h_{nt})$. Hours of home work are combined with home capital k_{nt} to produce a non-tradable home consumption good c_{nt} according to a home production function $g_t(h_{nt},k_{nt})$. The home production function depends upon t, thus allowing for the possibility that home productivity varies over time.

The individual's maximisation problem with home production can now be specified as:

$$\max\sum_{t=1}^{T}\beta^t U(c_{mt}, c_{nt}, h_{mt}, h_{nt}) \qquad \textbf{(5)}$$

$$s.t.\sum_{t=1}^{T}(1+r)^{-t}(c_{mt} + i_{nt}) \le A_o + \sum_{t=1}^{T}(1+r)^{-t} w_t h_{mt} \qquad \textbf{(6)}$$

$$c_{nt} \le g_t(h_{nt}, k_{nt})$$

$$k_{nt+1} = (1-\delta)k_{nt} + i_{nt}$$

$$H \ge h_{mt} + h_{nt}$$

where i_{nt} is the individuals' investment in home capital and δ is its depreciation rate. The individual therefore now seeks to maximise life-utility by choosing between consumption of market and non-market goods, and by choosing how to allocate their time between market hours, home hours and leisure.

First-order conditions can be obtained for this problem as for the standard case. For market hours, h_{mt}, this is $-\beta^t U_3(t) = \lambda(1+r)^{-t} w_t$. Taking logs yields:

$$\log[-U_3(t)] = \log\lambda - t\log\beta(1+r) + \log w_t \quad \textbf{(7)}$$

which is the analogous equation to **(3)**.

As before, specifying a functional form for the utility function will then allow a relationship between market and non-market hours to be specified. For example, if $U(c_{mt}, c_{nt}, h_{mt}, h_{nt}) = u(c_{mt}, c_{nt}) - v(h_{mt}, h_{nt})$ and $v(h_{mt}, h_{nt}) = \phi(h_{mt} + h_{nt})^{\gamma}$ then we have:

$$(\gamma - 1)\log(h_{mt} + h_{nt}) = \log\frac{\lambda}{\gamma\phi} - t\log\beta(1+r) + \log w_t \quad \textbf{(8)}$$

Comparing equation **(8)** with **(4)** shows the only difference from including home production in this specification is that the left-hand side hours variable is the sum of market and non-market hours. The labour supply curve is now a relationship between home and market work and the wage.

A form of the utility function that is useful in providing intuition is for the case where $v(h_{mt}, h_{nt}) = \phi\exp[-\gamma(H - h_{mt} - h_{nt})]$. In this instance equation **(8)** becomes:

$$\gamma(H - h_{mt} - h_{nt}) = \log\frac{\lambda}{\gamma\phi} - t\log\beta(1+r) + \log w_t \quad \textbf{(9)}$$

which can be expressed as:

$$h_{mt} = \alpha_0 + \alpha_1 t + \alpha_2 \log w_t - h_{nt} \quad \textbf{(10)}$$

In the model without home production, the analogous utility function $v(h_{mt}) = \phi\exp[-\gamma(H - h_{mt})]$ leads to:

$$h_{mt} = \alpha_0 + \alpha_1 t + \alpha_2 \log w_t \quad \textbf{(11)}$$

Equations **(10)** and **(11)** clearly illustrate the effect of misspecifying the model by not including home production. In this case the non home production model can be thought of as having an omitted variable h_{nt}. In a regression of market hours on wages, the coefficient on the wage will therefore be biased if h_{nt} is correlated with the wage. If the hours spent engaged in home production are positively correlated with wages over the life cycle, then the bias will be downwards.

3. The synthetic cohort approach

In this paper, we follow RRW in estimating labour supply functions augmented with home production by utilising a 'synthetic cohort' approach. This involves constructing a representative life-cycle profile from a data set by aggregating across individuals, turning one or several cross-sections into a representative agent profile by taking the mean of the relevant variables (hours worked and wage variables for example) by age. We can then follow this representative individual as they age over the sample frame of the survey and analyse their behaviour.

Following RRW, we index individuals by (a,i) where a is the individual's age and i is an index of heterogeneous preferences and opportunities. Two assumptions are made on the distribution of agents in the underlying population from which the sample is drawn. First, it is assumed that the mean of $\log\phi$ is constant across time and equals $\bar{\phi}$. Second, a balanced growth assumption is made, so that life-cycle wage profiles shift up at a rate x across successive cohorts for a given type i. Assuming the preference specifications are consistent with balanced growth, this implies that consumption will by $1+x$ higher for successively younger cohorts, and the multiplier for cohort a will be decreasing at rate x: $\lambda_{ai}= \lambda_{0i}(1+x)^{-a}$,where λ_{0i} does not depend on a. This means that for a given cohort a the mean of $\log(\lambda_a)$ is equal to $\bar{\lambda} - xa$.

For any individual of age a and type i the analogous equation to **(8)** will be:

$$(\gamma-1)\log(h_{mai}+h_{nai}) = \log\frac{\lambda_{ai}}{\gamma\phi_{ai}} - a\log\beta(1+r) + \log w_{ai} \quad \textbf{(12)}$$

A synthetic cohort is generated from **(12)** by adding across individuals of the same age but differing i's. Adding over these individuals and then dividing by the number in the cohort yields:

$$(\gamma-1)\hat{h}_a = \hat{\lambda}_a - \log\gamma - \hat{\varphi}_a - a\log\beta(1+r) + \hat{w}_a \quad \textbf{(13)}$$

where $\hat{h}_a, \hat{w}_a, \hat{\varphi}_a$, and $\hat{\lambda}_a$ are the sample averages of the variables in **(12)**. For a large sample, λ_a would approach $\overline{\lambda} - xa$, $\hat{\varphi}_a$ would approach $\hat{\varphi}$, and hence the following equation would hold exactly:

$$\hat{h}_a = \alpha_0 + \alpha_1 a + \alpha_2 \hat{w}_a \qquad \textbf{(14)}$$

where α_0 is a constant, $\alpha_1 = [\log \beta(1+r) - x]/(\gamma - 1)$, and $\alpha_2 = 1/(\gamma - 1)$

However **(14)** will not hold exactly in estimation as the samples the synthetic cohorts are drawn from may not be large enough. The estimating equation will therefore look like:

$$\hat{h}_a = \alpha_0 + \alpha_1 a + \alpha_2 \hat{w}_a + \varepsilon_a \qquad \textbf{(15)}$$

where:

$$\varepsilon_a = \varepsilon_{\phi a} + \varepsilon_{\lambda a}$$

$$\varepsilon_{\phi a} = \hat{\phi}_a - \overline{\phi}$$

$$\varepsilon_{\lambda a} = \overline{\lambda}_a - (\overline{\lambda} - xa)$$

The disturbance term, ε_a, reflects the variation in preferences ($\varepsilon_{\phi a}$) and the multiplier ($\varepsilon_{\lambda a}$) that arise from not having an infinite sample.

Equation **(14)** can now be used for estimation given an appropriate data source. However, the usual homoskedastic assumption required for OLS to be efficient will not be met. This is because the sample size for the construction of each age group is likely to vary. Equation **(14)** should therefore be estimated using a GLS estimator. Following RRW we use GLS estimators weighted by cohort size and by the inverse of the variance of the within-cohort observations on total or market hours depending on the regression ran.

We can specify estimating equations similar to **(14)** for other utility functions. As well as the case where $v(h_{mt}, h_{nt}) = \phi(h_{mt} + h_{nt})^{\gamma}$, we also estimate equations where $v(h_{mt}, h_{nt}) = -\phi(H - h_{mt} - h_{nt})^{\gamma}$ and where $v(h_{mt}, h_{nt}) = \phi \exp[-\gamma(H - h_{mt} - h_{nt})]$. In the first case the estimating equation is similar to **(14)** but with the average of the log of leisure on the left-hand side, so that α_2 measures the intertemporal elasticity of leisure with respect to wages. In the second case the left-hand side variable is the (unlogged) level of market and home hours. In this case α_2 is not an elasticity, but one can compute it at the sample mean.

The data source for our estimation is the British Household Panel Survey (BHPS). This gives us eleven years of cross-sectional data from which to construct synthetic cohorts. The BHPS offers certain advantages over the RRW sample. In particular, unlike RRW, we do not have to combine information from different data sets, as the BHPS offers data on hours and wages, including hours of work at home. Moreover, we use BHPS data for ten consecutive years, each of which contains approximately 2,000 data points. This allows us to construct one synthetic cohort per year and to control for the possibility of year (or business cycle) effects on labour supply decisions.

An alternative approach would be to utilise the individual level panel data. For example, MaCurdy (1981) uses a first-difference estimator to estimate the labour supply elasticity, while Altonji (1986) shows how one can use consumption data to estimate **(3)**.[9] Mulligan (1995) discusses the relative merits of both methods and ends up arguing in favour of the synthetic cohorts approach, in essence because (in panel micro studies) it is difficult to distinguish whether the variation in wages is due to anticipated changes, unanticipated changes or measurement error in wages. This is important because the intertemporal elasticity should be pinned down by *wage changes that are expected to occur over the life cycle*. Panel studies, nonetheless, allow one to model individual-specific characteristics and error terms that are aggregated by age group in synthetic cohort approaches. In principle, we could apply both panel and synthetic cohort techniques, but we choose to follow the RRW approach so that our results are strictly comparable with theirs.

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(9) We plan to follow this approach to exploit the cross-section properties of the BHPS in a separate paper.

4. Data and summary statistics

The BHPS contains information on the number of hours individuals devote to housework, their hours of market work, and several measures of pay. The market hours variable measures the number of hours normally worked per week[(10)] and the variable referring to home-related work measures the number of weekly hours spent doing housework. The BHPS also allows us to use two measures of pay in this study: net and gross usual pay per month.[(11)] Usual gross pay is used as a cross-check to the results with the net variable as well as with the results found by RRW.[(12)]

The BHPS is an annual survey of each adult member of a nationally representative sample of more than 5,000 households (approximately 10,000 individual interviews) covering the period between 1992 and 2002.[(13)] This means that the sample is much larger than that in RRW. The sample size for males between 22 and 65 years of age is 16,677 in the BHPS, while it is 2,265 in RRW. This implies that the average number of observation per cohort in the BHPS is 400, compared with only 28 in RRW. This represents a considerable advantage in terms of the validity of the life-cycle profiles constructed from cross-sectional data. RRW are also forced to pool hours data from three time use surveys, and use wage data from the CPS. But, on the other hand, the RRW home hours variable is more comprehensive than the one we construct from the BHPS, as it includes hours of house/yard work, childcare, and shopping; the BHPS provides reliable data on housework only.[(14)]

As do RRW, we restrict the study to those who report positive hours of market work. For older workers, this may cause some sample selection problems. We address this issue by considering two subsamples, individuals between the ages of 22 and 45 and

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[(10)] Excluding overtime pay.
[(11)] There are also variables for net and gross actual pay. We focus on usual pay as this is the closest to our theoretical measure of wages.
[(12)] These variables are expressed as pay per hour by dividing weekly earnings over usual weekly hours worked.
[(13)] Note that the bulk of interviews are conducted between September and October of each year, with a small percentage of them carried out at the beginning of the following year. For this reason, one should identify wave 1 (the first wave) with 1991 and wave 11 (the most recent) with 2001.
[(14)] The BHPS also provides data on hours spent caring. These data are not included because the number of responses is very small. Moreover the responses are recorded in brackets (eg from 0 to 4 hours, etc) and are therefore difficult to add to the hours worked at home.

individuals between 22 and 55. We restrict the study to individuals younger than 55 because the proportions reporting positive hours fall sharply for older cohorts.[15] This is consistent with the sharp drop in employment rates among those aged over 55, in part due to early retirement. Another potential source of sample selection bias is the inclusion of women in the sample. It is well known that females sometimes choose not to participate in the labour market, which implies a choice of zero hours of work. Excluding this group could lead to a biased sample. We consider the role of gender by estimating elasticities for men and women separately. We also consider the effects of marital status and education on the labour supply decision.

Tables A, B and C present summary statistics of the data we use for males, females and both genders, for the two age categories and for the wider 22-62 age group. This allows us to explore the sensitivity of the data to the choice of age cut-off. For comparison we also show the corresponding data from RRW.[16]

Table A	**22-45**		**22-55**		**22-62**	
Men UK	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	33.6	6.6	37.5	9.2	39.1	10.5
Home hours	5.0	4.7	5.0	4.7	4.9	4.7
Market hours	39.7	6.4	39.7	6.5	39.6	6.6
Total hours	44.6	7.7	44.7	7.8	44.5	7.9
Hourly wage (£)	6.0	2.4	6.1	2.4	6.0	2.4
Men US (RRW)						
Age	33.3	6.8			39.6	11.1
Home hours	20.0	2.4			20.8	3.0
Market hours	43.7	2.2			43.3	3.0
Total hours	63.7	2.4			64.1	3.2
Hourly wage (US$)	5.0	0.7			5.2	0.7

For males (Table A), the hours spent in market work are roughly eight times as large as those spent in home production. This contrasts to RRW, where market hours are found to be just over twice as large as those spent in home production. The difference can partly be explained by our narrower definition of home production: RRW define non-market hours as housework, childcare and shopping time; the BHPS only allows us to focus on the housework dimension of home production. The other important

(15) 71% of males and 66% of females between 22-55 report positive market hours. These fractions fall below 50% for both groups after the age of 55.
(16) This is purely illustrative, as variable definitions, etc, vary across our data sources.

difference is that men work approximately four hours per week longer in the United States than in the United Kingdom.

We study women as a control group, although we are aware that their labour supply behaviour can be radically different from that of males, especially when inferring it from synthetic cohorts. For women (Table B), the time spent in home production is significantly higher than for men; and hours spent in the market are less than twice those spent in home production. There are no figures to compare with RRW here, as they concentrate on males. We find the variation in female home and market hours is significantly higher than for males. This is not surprising, given that there are more calls on female time throughout their working life that may take them in and out of the labour market.

Table B	**22-45**		**22-55**		**22-62**	
Women	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	33.6	6.8	38.1	9.5	39.5	10.5
Home hours	12.8	9.5	13.6	9.5	13.8	9.5
Market hours	31.9	9.5	31.6	9.4	31.3	9.5
Total hours	44.8	10.1	45.2	10.4	45.0	10.5
Wage (£)	5.1	2.1	5.0	2.1	5.0	2.1

For the combined group (Table C), we find that home hours are under a third of those spent in the market.

Table C	**22-45**		**22-55**		**22-62**	
Men and Women	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	33.6	6.7	37.8	9.3	39.3	10.5
Home hours	8.7	8.4	9.1	8.6	9.2	8.6
Market hours	36.0	8.9	35.8	9.0	35.6	9.1
Total hours	44.7	8.9	44.9	9.2	44.8	9.3
Wage (£)	5.6	2.3	5.6	2.3	5.5	2.3

5. Life-cycle profiles

Having constructed synthetic cohorts using the BHPS, we can plot the life-cycle profiles of our representative individuals. This allows us to look for the familiar ‘hump’ shapes we would expect to see, as earnings and hours rise over the early years of an individual’s working life to a peak in middle age.

Chart 1 in the appendix shows the life-cycle profile of total (market and home) hours and market hours, and real hourly pay for males between the ages of 22-62. The solid lines are fitted polynomials that attempt to smooth the life-cycle profiles. The market hours line does indeed show a familiar hump shape, with hours initially rising before falling back towards retirement. Total hours, the sum of market and home hours, also shows a hump-shaped pattern. Furthermore, total hours peak roughly at the same stage of the life cycle as real wages.

For there to be a downward bias in estimated labour supply elasticities, home hours would need to be positively correlated with real wages over the life cycle. For males between 22-55, the profile of home hours does indeed move in the same direction as the real wage (Chart 2). But for ages above 55, home hours begin to rise again at a time when market hours and the real wage are falling. As noted earlier, this is consistent with sample selection issues for individuals over 55 owing to the presence of retirement in the data.

The profiles for female hours of work are more complicated. In contrast to males, female market hours tend to decline until around the mid-30s (Charts 3 and 4). This presumably reflects the importance of these years for child-bearing, as home hours climb steadily. After the mid-30s, the profiles for market and non-market hours do, however, start to move together until the years over 55. The life-cycle wage profile for the representative female is also quite different from that of males. In particular, real hourly wages peak much earlier, and fall steadily after women reach their early thirties. The rising real wage and falling market hours over the early part of the female life cycle imply that it is likely that any labour supply elasticities estimated on the data may be negative. But it is interesting to note that *total* female hours do exhibit a broad hump shape. This suggests an estimate of the labour supply elasticity that takes account of both market and non-market hours may be more positive. The aggregate female life cycle constructed from the synthetic cohort tends to suggest further decomposition, such as by marital status, might be worthwhile.

The RRW’s finding that there is a downward bias in standard estimates of the labour supply elasticity depends upon there being a positive correlation between the market wage and hours spent in home production. We can check for these positive correlations directly as well as graphically. We focus here on the age groups 22-55, as this is our preferred sample.

For males, Table D confirms a very strong positive correlation between wages and hours spent at home. The strength of the correlation reflects the large sample size we can draw on using the BHPS. When we break the sample up by constructing synthetic cohorts from each wave of the BHPS we find the correlations generally fall compared with those in Table D (although they remain positive) and show some volatility from wave to wave.

Table D
Male, 22-55

	Log(hm)	Log(hh)	Log(th)	Log(w)
Log(hm)	1.000			
Log(hh)	0.503	1.000		
Log(th)	0.795	0.903	1.000	
Log(w)	0.542	0.910	0.876	1.000

Table E confirms the negative correlation between female market hours and the real wages. For females, there is also a positive correlation between the wage and the time spent in the home, and almost no correlation between total hours and wages. This suggests that the estimated elasticity for females will indeed be more positive when we include home hours, but it is still likely to be quite low.

Table E
Female, 22-55

	Log(hm)	Log(hh)	Log(th)	Log(w)
Log(hm)	1.000			
Log(hh)	-0.901	1.000		
Log(th)	-0.374	0.720	1.000	
Log(w)	-0.593	0.475	0.092	1.000

6. Econometric results

(i) Basic estimates

The next step is to use our synthetic cohort data to estimate regressions similar to **(15)** and for the other two specifications of the utility function. The left-hand side variable in the regressions is therefore one of three alternatives: (i) the log of total hours, (ii) the log of 'leisure', calculated as (112-*h*), and (iii) the level of total hours. In this final case, the elasticity of substitution varies with the level of hours. In the results we report, it is evaluated at the mean level of hours. We estimate regressions using two types of GLS estimators rather than OLS for the reasons set out earlier. We also use both a before-tax wage (BTW) and a measure of after-tax wages (ATW).

Table F shows our results for males. For each type of GLS estimator and wage data we show the elasticity of substitution when we use just market hours as the relevant dependent variable (NHP) and when we use market and non-market hours as the dependent variable (HP). The coefficients vary slightly across the form of GLS, utility function and measure of pay used, but we consistently find that the elasticity of substitution increases materially when total hours are the dependent variable rather than market hours alone.(17) Further, all our results are significant at the 5% level. The elasticity of substitution roughly doubles when we include total hours.

Table G shows our results for females. As suggested by our life-cycle profiles, the female labour supply elasticity is significant and consistently negative when the dependent variable is market hours. There is again some variation across utility specifications. As discussed in the context of the life-cycle plots, this result is not surprising as there is a period over the early part of the 'representative' female's working life where market hours are falling despite rising real wages.(18) When we

(17) We obtain almost the exact same results in terms of size and significance of the estimates when we use OLS.
(18) The negative elasticities are at odds with other studies that use cross-sectional data. Blundell *et al* (1993) for example, obtain intertemporal elasticities that range from 0.5 to 1 for the UK. We believe our results differ for two reasons. First, we transform cross-sectional data into a time series and, hence, only capture a time-series relationship between hours and wages. Second, we leave aside the participation decision and demographic controls such as the number of young children, and husbands'

include both home hours and market hours as the dependent variable, we find that the female labour supply elasticity rises. This result is intuitive given the more humped shape of the life-cycle total hours profile. However, the elasticity remains negative or insignificantly different from zero in most cases.

Table F: Estimates of the intertemporal elasticity between hours and wages: Males

	22-55				22-45			
	NHP		HP		NHP		HP	
	BTW	ATW	BTW	ATW	BTW	ATW	BTW	ATW
Dependent Variable: log(h)								
Cohort Weighted	0.041	0.046	0.141	0.163	0.045**	0.051**	0.115	0.133
Equation R^2	0.293	0.284	0.780	0.772	0.324	0.316	0.812	0.807
Variance Weighted	0.041	0.047*	0.146	0.168	0.047**	0.053**	0.126	0.144
Equation R^2	0.290	0.282	0.797	0.789	0.317	0.309	0.824	0.819
Dependent Variable: log(112-h)								
Cohort Weighted	0.012**	0.014**	0.080	0.093	0.016**	0.018**	0.058	0.067
Equation R^2	0.185	0.182	0.730	0.725	0.166	0.165	0.767	0.765
Variance Weighted	0.013**	0.014**	0.083	0.096	0.016**	0.019**	0.066	0.076
Equation R^2	0.197	0.194	0.761	0.756	0.178	0.176	0.790	0.788
Dependent Variable: h								
Cohort Weighted	0.952**	1.108**	5.546	6.414	1.104**	1.260**	4.262	4.913
Equation R^2	0.200	0.197	0.759	0.754	0.194	0.192	0.794	0.791
Variance Weighted	0.981**	1.111**	5.75	6.644	1.156**	1.309**	4.707	5.418
Equation R^2	0.208	0.204	0.785	0.779	0.201	0.197	0.813	0.810
Mean hours	39.71	39.71	44.67	44.67	39.66	39.66	44.61	44.61
Elasticity evaluated at mean hours								
Cohort Weighted	0.024	0.028	0.124	0.144	0.028	0.032	0.096	0.110
Variance Weighted	0.025	0.028	0.129	0.149	0.029	0.033	0.106	0.121

No asterisk denotes significance at 5% level; *denotes significance at 10%; ** denotes insignificant at 10% or lower.

incomes. We are aware that positive estimates could be obtained with other estimation techniques that exploit this information.

Table G: Estimates of the intertemporal elasticity between hours and wages: Females

	22-55				22-45			
	NHP		HP		NHP		HP	
	BTW	ATW	BTW	ATW	BTW	ATW	BTW	ATW
Dependent Variable: log(h)								
Cohort Weighted	-0.617	-0.719	0.020**	0.009**	-0.479	-0.576	-0.062**	-0.085**
Equation R^2	0.708	0.766	0.515	0.513	0.785	0.816	0.626	0.639
Variance Weighted	-0.539	-0.632	0.045**	0.035**	-0.407	-0.497	-0.028**	-0.048**
Equation R^2	0.779	0.818	0.530	0.525	0.819	0.842	0.604	0.612
Dependent Variable: log(112-h)								
Cohort Weighted	-0.186	-0.215	0.033**	0.031**	-0.138	-0.166	-0.031**	-0.041**
Equation R^2	0.751	0.798	0.699	0.697	0.824	0.848	0.827	0.831
Variance Weighted	-0.163	-0.19	0.043**	0.042**	-0.117	-0.142	-0.015**	-0.024**
Equation R^2	0.813	0.845	0.73	0.727	0.853	0.871	0.826	0.828
Dependent Variable: h								
Cohort Weighted	-15.25	-17.76	1.748**	1.496**	-11.36	-13.66	-2.050**	-2.796**
Equation R^2	0.743	0.793	0.641	0.639	0.818	0.843	0.765	0.772
Variance Weighted	-13.351	-15.66	2.552**	2.366**	-9.568	-11.71	-0.858*	-1.548**
Equation R^2	0.806	0.840	0.668	0.664	0.847	0.866	0.756	0.760
Mean hours	31.61	31.61	45.22	45.22	31.94	31.94	44.80	44.80
Elasticity evaluated at mean hours								
Cohort Weighted	-0.482	-0.562	0.039	0.033	-0.356	-0.427	-0.046	-0.062
Variance Weighted	-0.422	-0.495	0.056	0.052	-0.300	-0.367	-0.019	-0.035

No asterisk denotes significance at 5% level; *denotes significance at 10%; ** denotes insignificant at 10% or lower.

(ii) The role of marital status

RRW argue that hours of work at home have a hump-shaped pattern due to the fact that the demands at home are greatest for middle-aged people. Although this is true on average, the life-cycle profile can differ dramatically for married and single individuals. Indeed, we find that married men have a much flatter profile for home hours than singles (Chart 5). Single men exhibit a hump-shaped profile that is very similar to that of single women. Married women exhibit a very similar profile too, but they spend more hours of work at home than single women (Chart 6). The fact that men spend significantly less time at home than married women is consistent with the process of specialisation in home production described by Becker (1991). To investigate this further we examine any differences in the estimated elasticity for married and single individuals. Table H provides an illustration of the typical results we obtained.

We find clear evidence that the elasticity of intertemporal substitution is biased for married and single females, and for single males. However, for married males we are not able to reject the possibility that the elasticity is the same with and without home production.[19] The estimated elasticities are somewhat larger for single men than for those who are married. This result is consistent with the theory of the allocation of time described by Becker (1991), that the hours of married males and married females are complements in home production. The low elasticity for married men could imply that they are less willing to substitute home for market hours over their life cycle. This is consistent for example with a modified version of the home production technology depicted in Chart 1, where home hours respond less to changes in wage rates. Interestingly, there are no reasons *a priori* why the shape of the wage life-cycle profiles for married and single men should differ significantly.[20] The regressions by marital status can be thought of as a natural experiment that fixes the wage profiles, but changes the opportunity sets of married and single men.

The differences between the estimated labour supply elasticities for married and single women are even more marked. Again, we find that there is a bias in the labour supply elasticity for both married and single women. But, further, we find that the corrected elasticity for single women is almost identical to that for single men. This is not surprising if we assume that marital status is a reasonable (although imperfect) proxy for home time commitments such as looking after children. In other words, unlike married men or women, single individuals do not face dramatic changes in their productivity at home over their life cycle and hence are more willing to substitute home for market hours when their wages peak.

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[19] We do find positive but small significant estimates for married men when running OLS regressions, and when we do not use weights that correct the synthetic cohort averages for sampling variability.
[20] Although the shape of the profiles could be similar, it is a stylised fact that married men earn more and work longer hours in the market, holding everything else constant, than those who are single.

Table H: Estimates of the intertemporal elasticity between hours and wages by marital status and skill levels

	Males		Females	
	NHP	HP	NHP	HP
Marital Status				
Single	0.118	0.174	-0.129	0.184
Married	-0.014**	0.033**	-0.718	-0.193
Skills	0.050	0.143	-0.445	0.039**
High	0.086**	0.233	-1.003	0.031**
Intermediate	-0.065**	0.051**	-0.364	-0.117**
Low	0.118	0.174	-0.129	0.184

For the sake of brevity, estimates reported here are for the 22-55 age group using variance-weighted GLS, the dependent variable is log*(h)*. Estimates for other formulations are similar.
No asterisk denotes significance at 5% level; * denotes significance at 10%; ** denotes insignificant at 10% or lower.

(iii) The role of skills

Decomposing the synthetic cohorts by educational attainment as a proxy for 'skills' is also instructive. By contrast with the gender decomposition, where the opportunity set can be thought of as differing between marital statuses, the skills decomposition can be thought of as fixing the opportunity set and allowing for differing wages profiles.

For this purpose, synthetic cohorts were created for three different groups: a high-skill group with educational attainment higher than A Levels; a medium-skill group with A Levels or O Levels; and a low-skill group with any lower level of educational attainment (including none). We find that the downward bias is still present for males (Table H) in the high and intermediate skill categories. The differences in the size of the elasticity across the high and medium-skills levels are not readily interpretable. The low-skill group, by contrast, has a very flat pattern of wage growth and as a result the elasticity is low and insignificant. For females, we find evidence for the bias across all three skill groupings. The corrected elasticity tends to be higher for higher educated women, but they are all insignificant.

(iv) The role of time effects

A possible cause for concern in our estimates of the labour supply elasticity would arise if there were significant cyclical, or other un-modelled, effects which vary over time. This might lead to biases in our estimates of the labour supply elasticity even after we correct for the presence of home production.

Table I: Estimates of the intertemporal elasticity between hours and wages allowing for time effects and using LFS market hours

	Males		Females	
	NHP	HP	NHP	HP
Time effects				
elasticity	0.018	0.116	-0.307	-0.004**
d93	-0.007**	0.006**	0.020**	-0.008**
d94	-0.012**	-0.013**	0.029**	-0.009**
d95	-0.005**	-0.007**	0.028**	-0.010
d96	-0.006**	-0.011**	-0.004**	-0.032
d97	0.000**	0.003**	0.025**	-0.033
d98	0.004**	-0.003**	0.006**	-0.041
d99	-0.005**	-0.004**	0.021**	-0.042
d00	-0.001**	-0.007**	0.041**	-0.030
d01	-0.007**	-0.014*	0.045	-0.051
LFS market hours				
elasticity	0.154	0.260	-0.560	0.042

For the sake of brevity, estimates reported here are for the 22-55 age group using variance-weighted GLS, the dependent variable is log*(h)*. Estimates for other formulations are similar.
No asterisk denotes significance at 5% level; * denotes significance at 10%; ** denotes insignificant at 10% or lower.

One way of checking for this effect is to include a series of yearly time dummies in our equations. If we found these dummies to be significant we might conclude that there are important omitted variables. We included a series of time dummies in our estimates and, reassuringly, found them to be insignificant for males at the 10% level (Table I). We also ran regressions on separate synthetic cohorts for each wave of the BHPS as an alternative way of controlling for time effects. Again, we found evidence of the downward bias in each wave. Time dummies are significant for females in the home production model regression, because of a downward trend in female home hours.

(v) Sensitivity with the Labour Force Survey (LFS)

Although the BHPS is a fairly large data set, the most reliable source of information on hours worked in employment in the United Kingdom is the Labour Force Survey (LFS). The LFS is a much larger data set, covering approximately 59,000 households compared with 5,000 in the BHPS, and is available at a quarterly frequency since 1992.

We cannot straightforwardly use the LFS for current purposes, as it does not report data on hours worked at home. But given that the synthetic cohort data are a life-cycle summary of a 'representative' individual, we can combine the market hours data from the LFS with hours worked at home and the wages from the BHPS. Table I illustrates estimates of the labour supply elasticity when we conduct such an exercise. We find that the estimated elasticity continues to demonstrate a significant bias when we use the LFS hours data.

7. Conclusion

In their *Journal of Monetary Economics* (2000) paper, Rupert, Rogerson and Wright (RRW) argue that estimates of the intertemporal labour supply elasticity obtained from standard life-cycle models are likely to be subject to a downward bias. They find supporting evidence for this proposition using US data. In this paper we follow their approach using a large consistent data set for the United Kingdom. We find convincing evidence for a downward bias in estimates of the UK labour supply elasticity if home production is not included. When we incorporate home production our estimates often at least double, although they remain fairly low in absolute size. These estimates provide more realistic values for simulations that seek to study the effect of changes in transitory wages on hours worked. However, their absolute sizes are likely to account only partially for the large variation in hours worked relative to that of wages in the data.

We extend the approach by estimating separately by marital status, skills levels, and by testing for time effects. The bias is present in every case, but is less obvious for married men. We find no evidence for time effects, and skills do not seem to affect the elasticity in a predictable manner. But when we separate by marital status we find that labour supply elasticities are generally higher for single people than for married people. We also obtain the interesting result that the elasticity for single women is very similar to that for single men.

Appendix

Chart 1: Hours of work - Men (Age: 22-62)

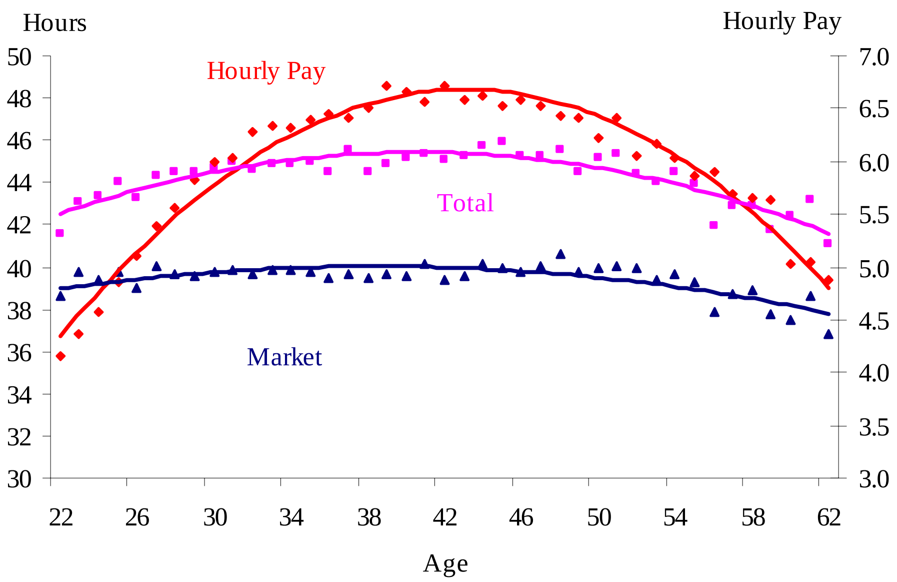


Chart 2: Hours of work at home - Men (Age: 22-62)

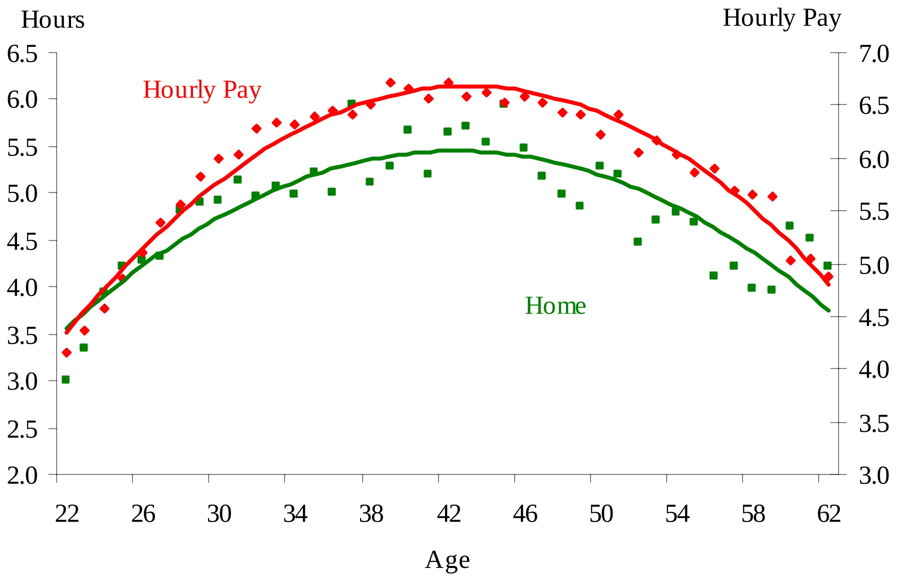


Chart 3: Hours of work - Women (Age: 22-62)

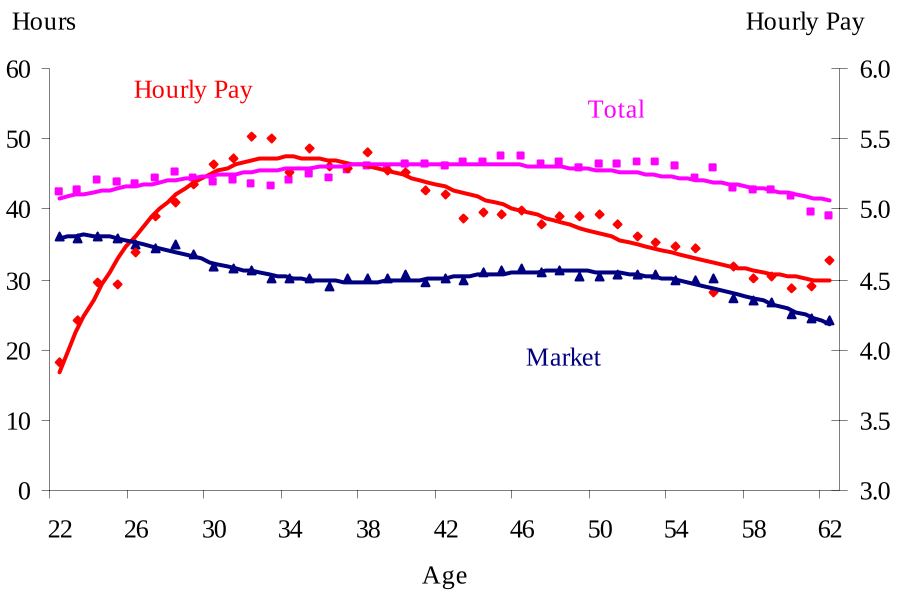


Chart 4: Hours of work at home - Women (Age: 22-62)

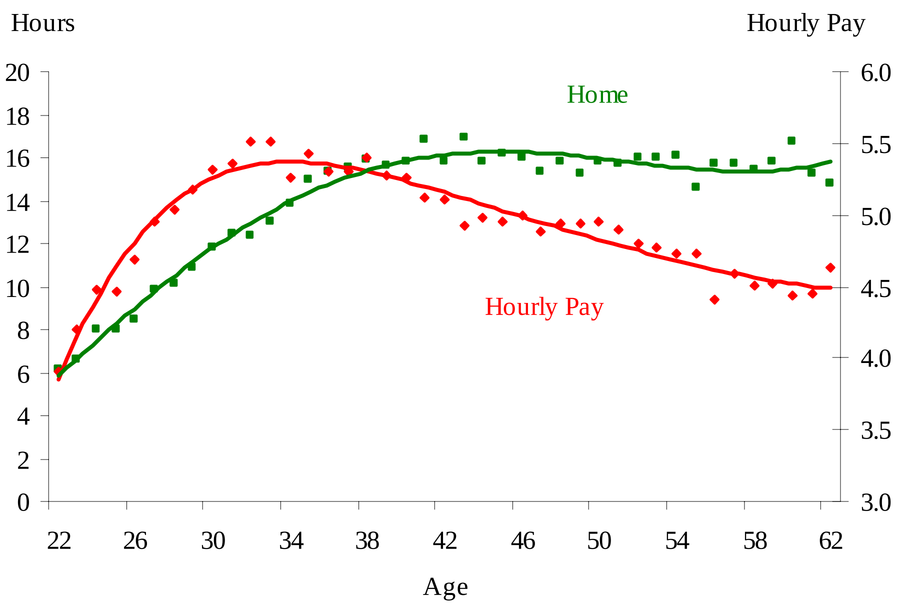


Chart 5: Hours of work at home – Men (Age: 22-62)

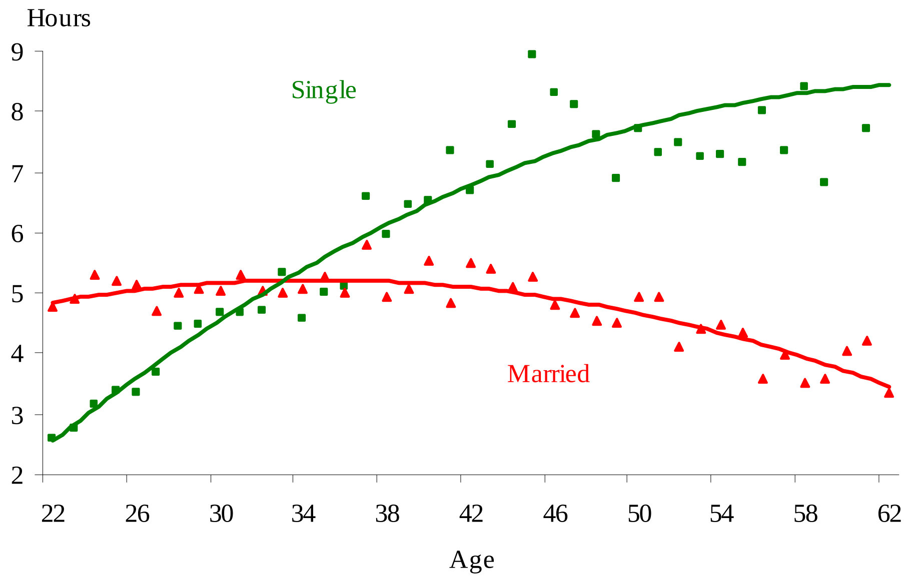
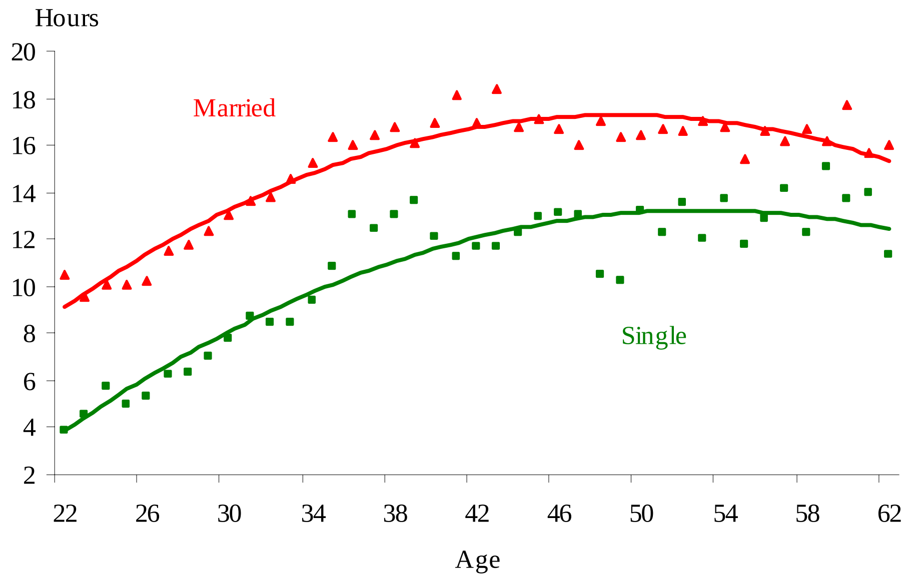


Chart 6: Hours of work at home – Women (Age: 22-62)



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