Income tax and the careers of women

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Abstract

Under a jointly assessed system of income tax, the marginal rate faced by individuals in a couple depends on their combined income. As a result, the lower earner in a couple - typically a woman - can face the higher marginal rates imposed by a progressive tax schedule from even low levels of earnings. This paper considers how such a system of taxation affects the careers of women. I first adopt a differences-in-differences approach, exploiting the UK's abolition of joint taxation in 1990. Estimates suggest that absent the reform, employment rates for married women would have been 4-6% lower. However, income taxes also affect the incentives to invest in education, accumulate human capital and take time out from the labour market. To investigate these longer-run responses, and to unpack the mechanisms underlying them, I develop (and estimate the parameters of) a dynamic lifecycle model capturing women's education, employment, fertility and savings decisions. Simulations from this suggest that moving away from a progressive income tax schedule applied to couples' joint income can increase the employment and earnings of women in the long-run, and result in women choosing to have children later in life.

Keywords: income tax; labour supply; human capital; fertility.

JEL Codes: H24; H3; J22; J24;

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1 Introduction

Many advanced economies - including the United States - calculate married individuals' income tax liabilities through a system of joint assessment, that is one which depends on the combined income of a couple. This means the lower earner in a couple - typically a woman - can face the higher marginal rates imposed by a progressive tax schedule from even low levels of earnings. Given we know that women are relatively responsive to taxes,[1] such a system may dissuade them from working, especially full-time when returning to work after having children.

This paper examines how joint taxation affects the careers of women, in particular through the decisions they make over employment and fertility. I first adopt a differences-in-differences approach, comparing changes in the employment rates of highly educated married and single women before and after the UK's abolition of joint taxation in 1990. Higher educated women were the most likely to be affected by abolition, both because they have higher earnings than less educated women, and are more likely to have a higher earning spouse. The two groups experienced very similar pre-reform trends that diverged in the years after 1990, with married women seeing much faster employment growth that is robust to controls for observable differences between the groups. Difference-in-difference estimates suggest that absent the reform, employment rates for married women would have been 4-6% lower.

However, as Keane (2015) among others have shown, responses to permanent tax changes can be amplified by a human capital channel when wages depend on accumulated experience, with (e.g.) increases in labour supply today leading to higher wages - and so even higher labour supply - tomorrow. In addition, individuals can adjust to tax changes along margins other than labour supply, which if made at a lower frequency - like education and fertility decisions - may take time to respond. All this suggests that the long-run effects of abolishing

[1] See Blundell and Macurdy (1999) and Keane (2011) for comprehensive surveys.

joint taxation may differ substantially from those short-run responses which can be identified in a differences-in-differences framework.

To investigate these longer-run responses, and to unpack the mechanisms underlying them, I develop a dynamic lifecycle model of women's education, employment, fertility and savings decisions. I estimate the parameters of this model, replicating key lifecycle patterns of employment, wages and fertility observed in the British Household Panel Survey (BHPS) for women of secondary, high-school and university education.

Using the model, I simulate the long-run effects of the reform and find that moving to individual assessment led to modest increases in employment, education, and the proportion of women who do not have children. More striking are the reform's effects on the intensive margin and over the lifecycle. By improving the incentive to accumulate experience - which feeds into higher future wages - abolishing joint taxation results in a 6.8% (4.5ppt) rise in full-time employment across all women, more than offsetting a decline of a fifth (3.4ppt) in part-time employment, which is much less valuable in terms of human capital accumulation. The dynamic feedback between wages and human capital underpins impacts on labour supply and earnings that grow with age, and leads to big changes in the timing of fertility decisions. I find the reform leads many more women to delay the point at which they have their first child than to forgo having a child at all, with the share that have a child by age 30 falling by 8%: four times the reduction in the share of women that ever have children.

The primary contribution of this paper is to show that moving away from a progressive income tax system applied to couples' joint income can increase the employment and earnings of women in the long-run. Existing evidence on this question is mainly limited to reduced-form estimates of short-run effects, exploiting policy reforms in the United States (LaLumia, 2008), Canada (Crossley and Jeon, 2007), Sweden (Selin, 2014), Czechia (Kaliskova, 2014) and Ireland

(Doorley, 2018).[2] The difference-in-difference evidence I present is consistent with these papers, all of which find that reducing (increasing) the degree of jointness in the assessment of income tax liabilities leads to modest short-run increases (reductions) in the employment rate of women.

However, the structural approach I adopt allows me to go further by examining the long-run impacts of the reform. The lifecycle model I develop to analyse these is most closely related to that of Blundell et al. (2016), who consider the education, employment and savings - but not fertility - decisions of women. While it has long been recognised that the employment and fertility decisions of women are closely related, and that time spent out of the labour market to look after children has significant impacts on wages through the depreciation of human capital (e.g. Weiss and Gronau, 1981; Eckstein and Wolpin, 1989), almost all work modelling these decisions jointly in a lifetime framework abstracts from the role of savings.[3] In the absence of complete insurance and credit markets, savings provide an important means of (self) insurance against shocks. They also serve as a key source of dynamics by facilitating consumption smoothing through career breaks taken to have children, financed by assets accumulated earlier in working life. Ignoring savings is therefore likely to distort any assessment of behavioural responses to tax changes, by constraining the margins along which consumption can be smoothed and shocks insured against.[4]

To the best of my knowledge, mine is the first paper to assess the long-run impacts of income tax changes in a lifecycle framework accounting for education,

[2] In addition, Bick and Fuchs-Schündeln (2017) use a calibrated macro model to try quantify the disincentive effects of joint taxation in the US and Europe, finding that moving to an individually assessed system would increase the annual hours worked by women by an average of 10%. Borella et al. (2017) explore the effects of eliminating the marriage-related provisions of the US tax and Social Security code in a lifecycle framework, finding they depress the employment and savings of couples.

[3] See, for example, Eckstein and Wolpin (1989); Francesconi (2002); Keane and Wolpin (2007) and Keane and Wolpin (2010). A notable exception is Adda et al. (2016), whose focus is on the occupational choices of women and do not account for taxes or transfers, the subject of interest in this paper.

[4] Indeed, Blundell et al. (2016) show that ignoring savings limits the ability of their model to capture patterns of behaviour observed in data, and biases estimates of labour supply responses to tax changes substantially upwards.

employment, fertility and savings decisions. In doing so, I contribute to a growing branch of research which emphasises the long-run effects of the tax and transfer system on individuals choices and outcomes: for example, Blundell et al. (2016), who find that wage-subsidies for low earning individuals have employment effects that do not extend beyond the period of eligibility; and Hoynes et al. (2016), who show that access to Food Stamps in utero and during early childhood lead to a large reduction in metabolic syndrome and increase in economic self-sufficiency later in life.

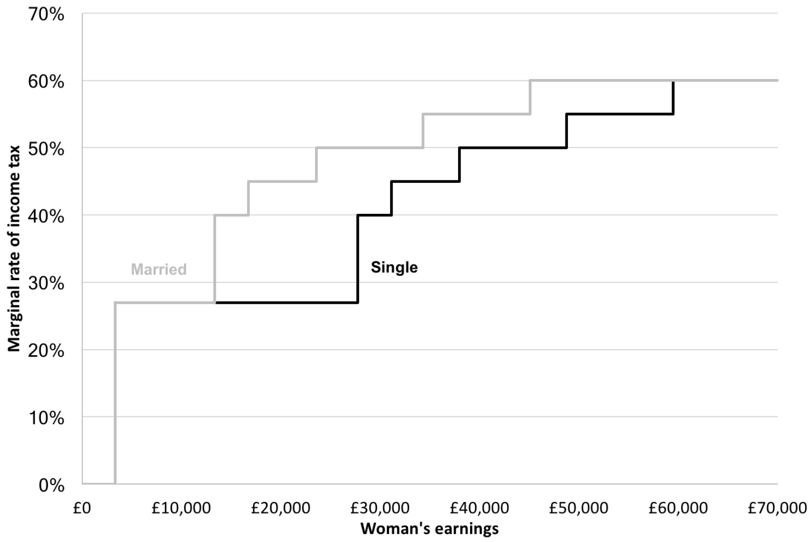
The remainder of this paper proceeds as follows. I begin by presenting the results from a reduced form analysis of the UK's 1990 abolition of joint income taxation. Section 3 outlines the dynamic lifecycle model of education, employment, savings and fertility decisions, with the model solution, parameters and counterfactual simulations discussed in Section 4. The Appendix to this paper provides a detailed description of the data used and the computational approach used to solve and simulate the model.

2 Reduced form analysis

Before the 1988 budget, income tax in the UK was levied at a basic rate of 27 percent and higher rates of between 40 and 60 percent.[5] Married couples were assessed on their joint income, with a wife's earnings treated as her husbands for tax purposes. Earnings above a Married Man's Allowance were subject to this progressive income tax schedule, with the couple receiving an additional tax free allowance, called Wife's Earned Income Relief, if the woman was employed. The net result of this was that women married to an income tax payer faced the higher rates of income tax from a much lower level of earnings than if single. This is shown in Figure 1 for a woman if single and if married to a partner at the 75th percentile of the male earnings distribution.

[5]Rates of income tax were higher on dividends and other forms of unearned income.

Figure 1: *Income tax schedule for single and married women, 1987*



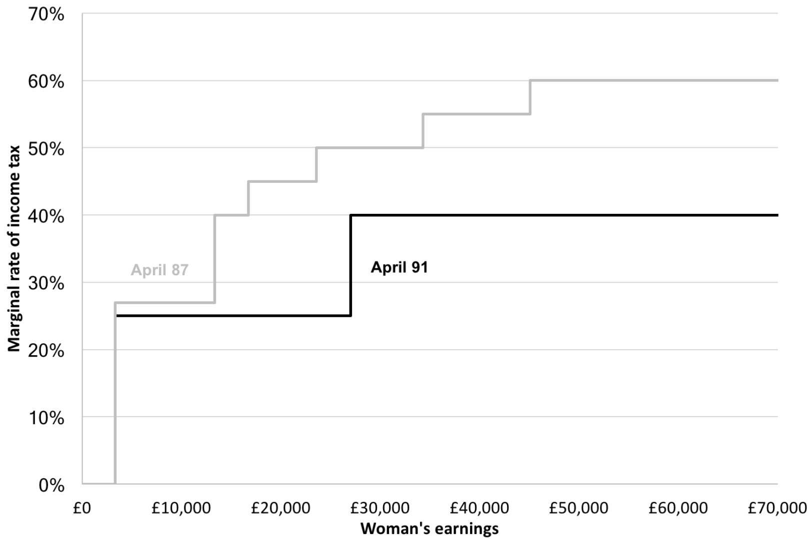
Note: Assumes married woman's partner at the 75th percentile of the 1991 male earnings distribution. All figures in April 1991 prices.
Source: author's calculations based on HM Treasury (2009).

In his 1988 Budget, then Chancellor of the Exchequer Nigel Lawson announced a major reform to income tax, consisting of both reductions in rates and changes to its structure for married couples. The higher rates of income tax of between 40 and 60 percent were replaced with a single 40 percent rate, while the basic rate was cut from 27 percent to 25 percent. More radical was the announcement that from April 1990, couples would no longer have their incomes assessed jointly for the purposes of income tax. Instead, each individual would be entitled to a personal tax free allowance, above which their income was subject to the revised (less progressive) income tax schedule.[6]

The effect of these reforms was to leave married women facing a reduced basic rate of tax for longer, significantly raising the point at which the higher rate of income tax began to apply. This is shown by Figure 2 for the same example married women as Figure 1, with a husband located at the 75th percentile of the male earnings distribution. A woman in this situation faced the higher rate at

[6]In addition, married couples were to receive a Married Couples Allowance (MCA) which was paid in the first instance to the man, with any unused allowance transferable to his wife. This gave married men a somewhat larger tax free allowance than (married or unmarried) women and single men. The value of this MCA was repeatedly reduced, before it was abolished entirely in April 2000.

Figure 2: *Income tax schedule for married women*



Note: Assumes married women's partner at the 75th percentile of the 1992 male earnings distribution. All figures in April 1992 prices.
Source: author's calculations based on HM Treasury (2009).

2.6 times median female earnings compared to 1.1 times had the system of joint taxation continued to apply, substantially strengthening her incentive to be in work - especially full-time work - when married to a income tax paying partner.

To investigate what effects this reform had on the employment decisions of women, I adopt a difference-in-difference framework and compare changes in the employment rate of higher educated married women to that of similarly educated single women. Higher educated women are more likely to be affected by the reform than less educated women both as they - on average - have higher earnings and marry partners with higher earnings. Assuming women don't respond immediately to the reform by changing their marital status, higher educated single women can be used as a control group to identify the effect of the reform on higher educated married women.

Using data from the Family Expenditure Survey (FES) - a long running, repeated, cross-sectional household survey - Figure 3 compares changes in the employment rates of these groups relative to the period before 1990, when the reform

Figure 3: *Change in employment of women around abolition of joint assessment*

Note: Post-1990 dashed lines show the mean annual change in employment rates for groups relative to the period 1980–90. Sample restricted to women aged 20-59 who left education aged 18 or older.
Source: Author's calculations using data from the FES.

was fully implemented (shown by the vertical line).[7] It shows that the employment rates of married and single women evolved very similarly in the years before 1990, but diverge afterwards. While single women saw the same rate of employment growth in the years following the reform as the years before, married women saw employment growth that was - on average - 8% higher.

Although Figure 3 shows that the assumption of common trends between the groups appears to hold in the years preceding the reform, there are reasons to think that single women may not be a perfect control group for their married counterparts: for example, they are on average younger, and have fewer (younger) children. To account for some of these differences, I estimate a linear probability model at the individual level on pooled FES data for the years 1980–2000, with employment as the dependent variable. Table 1 reports the coefficient from the interaction of a treatment-group (married women who left education aged 18 or

[7]I restrict the sample of women to those aged 20-59 who left education after the age of 18. Similar results are obtained restricting the sample to those who left education after the statutory minimum. Further details on the FES are provided in appendix A.

Table 1: *Difference-in-difference regressions for employment*

	(1)	(2)	(3)	(4)	(5)
Post*Married* Left Edu 18+	0.0501*** (0.00826)	0.0425*** (0.00818)	0.0567*** (0.00794)	0.0558*** (0.00774)	0.0556** (0.0182)
N	95380	95380	95380	95380	95380
Controls:					
Age	✗	✓	✓	✓	✓
Kids	✗	✗	✓	✓	✓
Age of Youngest	✗	✗	✗	✓	✓
Pre-reform Trends	✗	✗	✗	✗	✓

Note: Data from the Family Expenditure Survey 1980-2000. Standard errors in parenthesis. *, **, and *** indicate statistical significance at the 5%, 1% and 0.1% levels respectively.

more) indicator with a variable that takes the value 1 if the year is 1990 or after. The estimates in columns 1–4 suggest that the reform led to an increase in the employment of high-educated married women of between 4 and 6%, where I successively add controls for age, the presence of children, and the age of the youngest child. In column 5, I also include controls for pre-reform trends (a series of time dummies for years before 1990 interacted with the treatment-group indicator), but these are all statistically insignificant and produce a similar estimate of the treatment effect.[8]

However, while 1990 saw the abolition of joint taxation in the UK, the measure was pre-announced in the 1988 Budget alongside some potentially confounding policy changes. These included cuts to the higher rates of income taxation applying to a very small group of very high earners, and significant reforms to working-age transfers.[9] While unlikely to have directly affected many of the women considered above, these reforms did alter the incentives to be in paid-work and may confound difference-in-difference estimates of the effects abolishing joint taxation had. In addition, from 1973 couples had the option of writing to HMRC - the British tax

[8]See Appendix Afor further details on the data used and the difference-in-difference results.

[9]1988 saw the introduction of Income Support (which provided an income floor for those not in work, but was less generous to the long-term unemployed than the benefit it replaced) and Family Credit (a payment available to low-income working families with children, tapered at a higher rate than the Family Income Supplement payment it replaced), as well as changes to the structure of Housing Benefit (which until then had awarded 100% of housing costs only to individuals who worked less than 30 hours a week).

authority - and asking to be assessed individually for income tax purposes, though very few took up this option even when beneficial. This further complicates the interpretation of any difference-in-difference estimates, as they may capture the effects of increased salience and reduced administrative burdens in addition to changes in financial incentives.

More fundamentally, the reform affected not only women who were married in 1990, but single women who at some point in the future could be married and face the higher marginal rates imposed by a system of joint taxation. One plausible response for such women is to increase their labour supply early in working life, so as to capture the increased net-of-tax return to experience later in life, thereby attenuating difference-in-difference estimates of the reform's effect on married women. Relatedly - as argued by Keane (2015), among others - the long-run impacts of permanent tax changes may be amplified by a human capital channel if future wages depend on accumulated experience. This is because a reduction in income tax increases both the current net-of-tax wage and the future returns to investment in human capital, generating a dynamic feedback loop between employment and wages. Women can also adjust to tax changes along margins other than labour supply, which if made at a lower frequency - like fertility decisions - may take time to respond but are crucial to consider in any assessment of the effects abolishing joint taxation had.

To investigate such longer run responses, and to explore the underlying mechanisms at play, I now adopt a more structural approach. The next section outlines a dynamic lifecycle model of women's education, employment, fertility and savings decisions.

3 A lifecycle model of education, employment, fertility and savings decisions

3.1 Overview

In the model I consider, there are 3 linked phases of life. In the first, women decide - aged 17 - between completing compulsory education, continuing to high-school or attending university. They then begin working life (aged 22 if they choose to attend university, 19 otherwise) deciding in each period how much to consume, whether to work full-time, part-time or not at all, and (until the age of 43) whether to try conceive. Partners arrive and leave stochastically (also until age 43) at rates that are dependent on education and the presence of children. At age 60, all women remaining in work retire and live for a further 10 years, choosing only how much to consume from their accumulated savings.

A key mechanism that induces dynamics in the model is feedback between work decisions and wages. I allow for a flexible experience process that depends not just on the work history of women, but also on the time since and type of education completed. The idea here is that at the beginning of working life, employers may care about what type of education people received, which feeds into wage progression. Later in working life, the amount and type of work experience obtained may become more important, and so education levels play a smaller role in determining wage progression. In addition, individuals are subject to persistent productivity shocks that depend on unobserved preferences for work and education. Individuals also differ ex ante in terms of their family background and the cost of education.

The UK tax and benefit system makes the budget constraint facing individuals non-linear. To accurately account for this and the incentives it creates for women, I use FORTAX, a UK tax and benefit microsimulation model (Shephard, 2009). Individuals also face a no-borrowing constraint, except to fund the costs of university. I now describe the model formally, beginning with the working life.

3.2 Working life

In each period of working life, women maximise their expected lifetime utility taking as given the state space X_t which summarises her economic and family circumstances at time t. This consists of her age (t), education (s), accumulated assets (a), human capital (e), productivity (v), family background (x_1, x_2) and tastes for work (θ_f, θ_p). Her family circumstances are described by the presence of a partner (m), his characteristics - education ($\bar{s}$), labour supply ($\bar{h}$), and wage ($\bar{w}$) - the presence of children (k) and the age of the youngest child (t^k).

The problem at time t during working life can be written in terms of the value function:

$$V_t(X_t) = \max_{\{h_j, c_j, z_j\}_{j=t,\dots\bar{t}}} E\left[\sum_{j=t}^{\bar{t}} \beta^{j-t} u(h_j, \tilde{c}_j, t_j^k) \mid X_t\right] \text{ s.t. the budget constraint} \tag{1}$$

where $\{h_j, c_j, z_j\}$ is a contingency plan of hours worked (discretised to represent zero, part-time, and full-time weekly hours), consumption, and the binary decision whether or not to try have a new child, respectively. Choosing to have a new child succeeds with probability $p_z(t)$, a function of age, which I estimate outside the model by fitting a third order polynomial to medical estimates of the share of women who are infertile by age (Menken et al., 1986). This risk of being unable to successfully conceive is an essential determinant of why women choose to have children when they do: deferring birth allows the accumulation of assets (which can be used to smooth consumption) and human capital (which increases earnings), but must be balanced against the fact that conception is physically possible only for a limited time.

These choices are made subject to the budget and borrowing constraints:

$$a_{t+1} = (1 + r_t)a_t + T(h_t, w_t, m_t\bar{w}_t\bar{h}_t, X_t) - c_t \tag{2}$$

$$a_{t+1} \geq \underline{a}_s,\ a_0 = 0,\ a_{\bar{t}+1} = 0 \tag{3}$$

where $T(\dots)$ is household income net of taxes and benefits (computed using FORTAX); and $\underline{a}_s$ is an education dependent borrowing limit, 0 for everyone unless they went to college, in which case it is the amount of student debt taken on.

Within period utility $u(h_t, \tilde{c}_t, t^k_t)$ is intertemporally separable, and depends on hours worked, equivalised consumption ($\tilde{c}_t$), family circumstances and ex-ante heterogeneity. It is non-separable in consumption and leisure, and given at time t by:

$$u(\dots) = \frac{\tilde{c_t}^{1-\gamma}}{1-\gamma} \exp\left\{U(h_t, \theta, Z_t) + g(k_t, m_t, s, \bar{s}_t)\right\} \tag{4}$$

where $U(\dots)$ are a set of demographic factors and unobserved tastes that shift the marginal utility of consumption when in work, and likewise $g(\dots)$ when children are present in the household. These are parametrised as:

$$g(k_t, m_t, s, \bar{s}_t) = \begin{cases} 0, & \text{if } k_t = 0 \text{ (no children)} \\ \omega_s & \text{if } k_t = 1, m_t = 0 \text{ (lone mother)} \\ \omega_m + \omega_{s,\bar{s}_t} & \text{otherwise} \end{cases} \tag{5}$$

$$U(h_t, \theta, Z_t) = \begin{cases} 0, & \text{if } h_t = 0 \text{ (out-of-work)} \\ \theta_h + Z_t'\alpha(h_t), & \text{otherwise} \end{cases} \tag{6}$$

$$\alpha(h_t) = \alpha_{FT} + \alpha_{PT}.\mathbf{1}(h_t = P) \tag{7}$$

where Z_t' is a set of family characteristics (marital status, whether a partner is working, the age of the youngest child in bands, and family background) interacted with education dummies, and $\theta = (\theta_F, \theta_P)$ are dichotomous variables that reflect unobserved tastes for full- and part-time work, taking either the value 'high' or 'low'.

Partners arrive and depart stochastically with a probability that depends on the woman's own education level, age, marital status last period, and the presence of children. They are characterised by their education ($\bar{s}$), which determines their productivity draw $\bar{\upsilon}_t$ and so the probability that they work full-time, given by:

$$\Pr(\bar{h}_t = FT|X_t) = \begin{cases} \Pr(\bar{\upsilon}_t > b_1(t, \bar{s}_t, \bar{h}_t) & \text{if } m_{t-1} = 1 \\ \Pr(\bar{\upsilon}_t > b_0(t, \bar{s}_t) & \text{if } m_{t-1} = 0 \end{cases} \tag{8}$$

as well as their measured wage ($\bar{w}_t$), which is a function of age, productivity and normal iid measurement error ($\bar{\xi}_t$):

$$\ln \bar{w}_t = \bar{b}_{\bar{s}} + \bar{\gamma}_{\bar{s}} \ln(t - 18) + \bar{\upsilon}_t + \bar{\xi}_t \tag{9}$$

$$\bar{\upsilon}_t = \bar{\rho}_{\bar{s}} \bar{\upsilon}_{t-1} + \bar{\zeta}_t \tag{10}$$

Productivity follows an AR(1) process, with an initial draw and innovations $\bar{\zeta}_t$ that are normally distributed but differ by the education level of the man.

While wages are exogenous for men, a key source of dynamics in the model comes from the feedback between work decisions today and wages tomorrow for women. The wage process is described by equations 11–13:

$$\ln w_t^m = b_{s,0} + b_{s,1}x_1 + b_{s,2}x_2 + (\gamma_{s,0} + \gamma_{s,1}x_1 + \gamma_{s,2}x_2) \ln(1 + e_t) + \upsilon_t + \xi_t \tag{11}$$

$$\ln w_t = \ln w_t^m - \xi_t \tag{12}$$

$$\upsilon_t = \rho_s \upsilon_{t-1} + \zeta_t \tag{13}$$

where w_t^m is the observed wage rate, w_t is the wage rate that informs women's decisions, and ξ_t is normal iid measurement error. The observed wage rate depends on education (s), family background (x_1, x_2), accumulated human capital (e_t)

and individual productivity (v_t), which follows an AR(1) process with normally distributed shocks (ζ_t).[10]

Human capital (e) accumulation is determined by the history of education and employment decisions. It follows the law of motion:

$$e_t = e_{t-1}(1-\delta_s) + E_{0,s}^{-\lambda_s.(t-t_{0,s})}.k(h_{t-1}) \tag{14}$$

which says that human capital today is given by that yesterday (e_{t-1}) less depreciation at an education specific rate δ_s, plus experience gained in the previous period $k(h_{t-1})$ scaled by the stock of education capital $E_{0,s}^{-\lambda_s.(t-t_{0,s})}$ remaining. This flexible process is designed to account for different trade-offs between working or not across life. For example, skills acquired in education may be particularly productive early in working life, creating a complementarity between education and experience accumulation in the years immediately after completing schooling.

Education capital $E_{s,t} > 1$ depreciates with the time elapsed since completing education ($t - t_s$), and provides a mechanism which - alongside accumulating savings to smooth consumption across periods of life - may help explain why some women defer having children until later in life: a simpler model of experience accumulation without this feature (i.e. where $E_{s,t} = 1$) suggests that women should try take time out of the labour market and have kids at the beginning of working life, when their stock of experience is bounded by zero and so cannot depreciate. $E_{s,0}, \lambda_s, \delta_s$ and $k(h_{t-1} = PT)$ are all key parameters to be estimated within the model, with $k(h_{t-1} = FT)$ normalised to 1.

3.3 Education

Women decide at age 17 whether leave education with the legal minimum ($s = 1$), complete secondary-school ($s = 2$) or continue to higher education ($s = 3$). This determines the age at which they enter working life: 19 for those with secondary-

[10] These are education specific, with an initial shock that is determined by a mixture distribution whose means depend on unobserved tastes for work θ.

school education or lower, and 22 for those with a degree. The optimal choice is given by

$$s = \underset{s\in 1,2,3}{\text{argmax}}\{W_s(X_{17}) - B_s(X_{17})\} \tag{15}$$

where $W_s(X_{17})$ is the discounted expected value of lifetime utility for choice s, and $B_s(X_{17})$ is the utility cost of the education investment. These terms are defined as

$$W_s(X_{17}) = \begin{cases} E[V_{19}(X_{19})|X_{17}, s] & \\ & \text{if } s = 1,2 \\ E[\underset{c_{19},c_{20},c_{21}}{max}\{\sum_{t=19}^{21}\beta^{t-19}u(c_t, F; \theta, Z_{17}) & \\ +\beta^{22-19}V_{22}(X_{22})\}|X_{17}, s] & \\ & \text{if } s = 3 \end{cases}$$

where $V_t(X_t)$ is the discounted expected lifetime utility at age t, and $u(\dots)$ is the same instantaneous utility as for those in full-time work (equation 4); and

$$B_s(X_{17}) = \pi_{1s}f_1 + \pi_{2s}f_2 + \pi_{5s}y_p + \bar{\omega}_s \tag{16}$$

where (f_1, f_2) are continuous background factors (discretised as x_1, x_2 in working life), y_p is a liquidity shock to parental income and $\bar{\omega}_s$ is the unobserved utility cost of education option s (normally distributed with variance σ_s^2).

Tuition costs (D) and consumption during higher education are funded by a student loan, meaning the optimal decisions to the education problem is made subject to the budget constraint:

$$\begin{aligned} &a_{19} = a_{17} = 0 \\ &a_{22} = -(1+r)^2c_{19} - (1+r)c_{20} - c_{21} - D \qquad \text{if } s = 3 \end{aligned}$$

4 Model solution, fit and counterfactual simulations

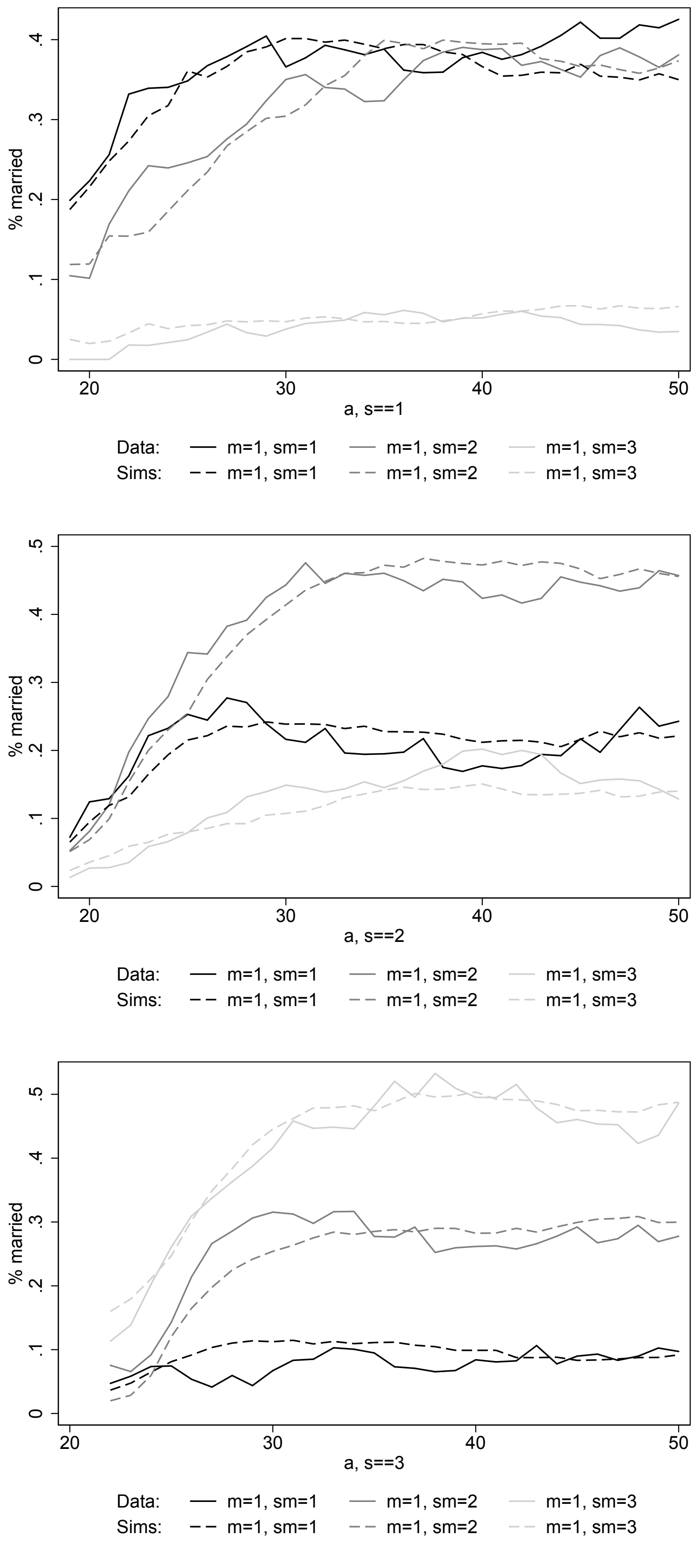
Given its complexity, there is no analytical solution to the lifecycle problem set out above. Instead, the approach I take is to numerically approximate policy functions for labour supply, consumption, fertility and education over all possible combinations of state variables recursively. Details of the solution algorithm and its computational implementation are given in Appendix B.

To estimate the parameters of the model I follow a two-step procedure. The first-step involves estimating some parameters outside of the model or setting them with reference to the literature. Equations determining the exogenous features of the model that I estimate are the probability a partner arrives, departs, works and (if he works) his earnings. This is done separately for women by education, using 18 waves of the British Household Panel Survey (BHPS), a longitudinal household survey that collected detailed information on demographics, education, and incomes for a random sample of 5,050 households.[11] Figure 4 shows that the estimated profiles of partner arrival and departure capture the patterns of assortative matching observed in the data. Women are much more likely to marry men of the same education level than they are men of higher or lower education, while high (low) educated women are very unlikely to marry low (high) educated men.

Two key preference parameters are set with reference to the literature: the coefficient of risk aversion, γ, to 1.56 - consistent with evidence from Blundell et al. (1994) and Attanasio and Weber (1995) who both allow for the non-separability of consumption and leisure as here - and the discount factor, β, to 0.98 - as is common in the literature (e.g. Attanasio et al., 2008). The risk-free rate of interest is set slightly lower than the discount rate - to 0.015 - so that agents are somewhat

[11]Appendices A and C provide further details of these data and estimates respectively.

Figure 4: *Women cohabiting, by age (a), own (s) and partner's education (sm)*



Note: Panels show proportion of women cohabiting with spouse of given education level (1=secondary, 2=high school, 3=university) by age and their own education level. Simulations are shown by the dashed and data (BHSPS) by the solid line.

present biased. The parameters governing the wage process are calibrated to the values estimated by Blundell et al. (2016) for the same sample of women.[12]

The remaining parameters - determining preferences and the dynamics of human capital accumulation - are estimated by the method of simulated moments. I first solve the lifecycle problem for an initial set of parameters, then simulate lifecycle profiles for women under the history of tax and benefit systems faced in the BHPS.[13] I select an observation window for these simulations so that they match the age-time structure of the BHPS, then compute moments for both the simulated and observed data. The parameter estimates are finally obtained by minimising an objective function that sums the standardised difference between these simulated and data moments. Further details of this estimation procedure are provided in Appendices B.

4.1 Parameter estimates

Table 2 presents estimates of preferences for children: the ω terms from equation 5. It shows these are decreasing in education, both when single and married, with university educated women valuing children least and high-school educated women valuing them most. The utility from children is highest for women of any education level when married to a man of the same education level, mirroring the patterns of assortative matching seen in Figure 4 for partnering.

Table 3 contains estimates of the parameters determining the human capital accumulation process (Equation 14). It shows that the lowest education group face the fastest rate of human capital depreciation when out-of-work, though also accumulate experience when part-time at the highest rate. The middle education group see the least human capital depreciation when out of work but the slowest

[12] These parameters are contained in Appendix C. Figure 8 shows that the model succeeds in closely matching the evolution of log wages across the lifecycle, both on average and at various points across the distribution.

[13] The BHPS data cover the period 1991-2008. For computational simplicity, I use the April 1995, 1999, 2002 and 2005 systems and assume they applied in the intervening years. These years are chosen to stylistically represent the tax and transfer regime in operation over these years, with monetary variables adjusted to remove the effects of inflation and growth.

Table 2: *Parameter estimates: preferences for children*

		Education level (s)		
		s=1	s=2	s=3
Estimated disutility from children when:				
(1)	Single	-0.010	0.000	0.001
(2)	Married	-0.238	-0.219	-0.151
(3)	Married, to man s=1	-0.035	-0.022	-0.100
(4)	Married, to man s=2	-0.021	-0.049	-0.100
(5)	Married, to man s=3	0.000	0.050	-0.042

Note: value function minimised so that positive (negative) values reflect disutility (utility) from presence of children. Parameters additive across family type.

rate of accumulation when working part-time. While the rate of human capital depreciation is quite fast for those in the highest education group, they take fewer breaks from the labour market, in part explaining their higher wages across the lifecycle. But as the estimates for $E_{0,s}$ show, a higher rate of human capital accumulation in the years immediately after schooling is part of the explanation too. The much larger estimate of this parameter tells us that part of the reason wages are steeper for university educated women is because their education is especially complementary with human capital acquired on the job.[14]

Parameter estimates of preferences for work and education are contained in Tables 8 and 7 in Appendix C. These show that family background is an important determinant of education choices, and that the estimated disutility of work is greatest for university educated women, especially when married with children. This suggests that the higher earnings they receive in work underlie their much higher employment rates across the lifecycle rather than some stronger preference for work, and helps rationalise some of the findings of the counterfactual simulations presented below.

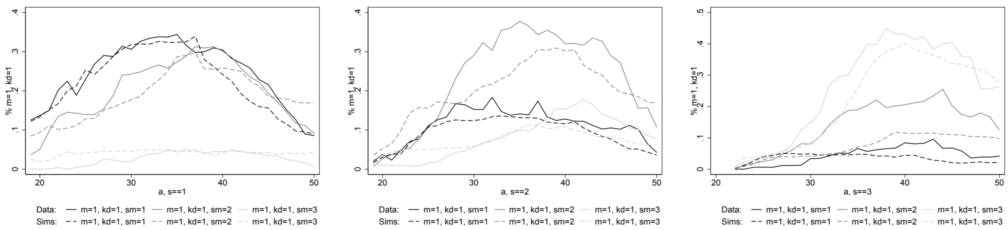
4.2 Model fit

Figure 5 shows how the fit of key moments from the simulations compare to those from the BHPS. The model matches the presence of children across the lifecycle

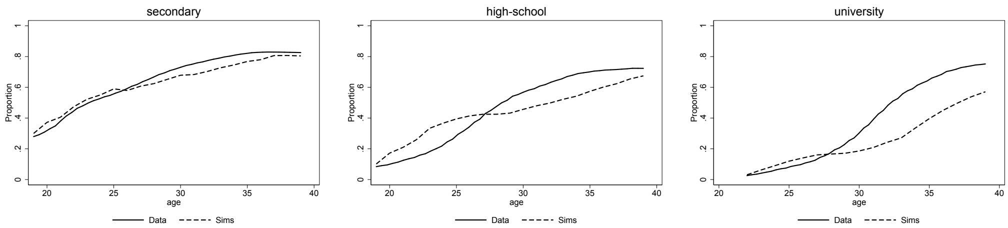
[14]See Figure 8 in Appendix C for these log-wage profiles.

Figure 5: *Fit of key lifecycle moments*

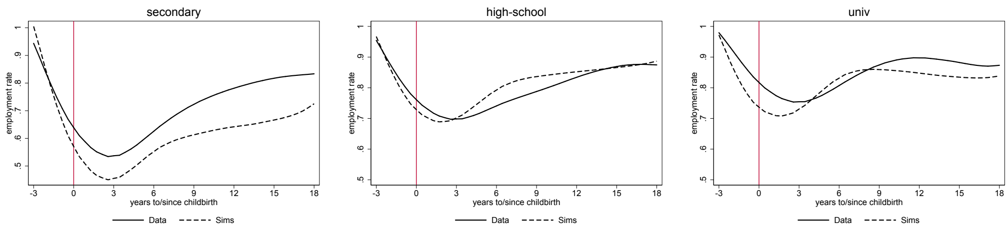
a. Women with children, by age (a), own (s) and partner's education (sm)



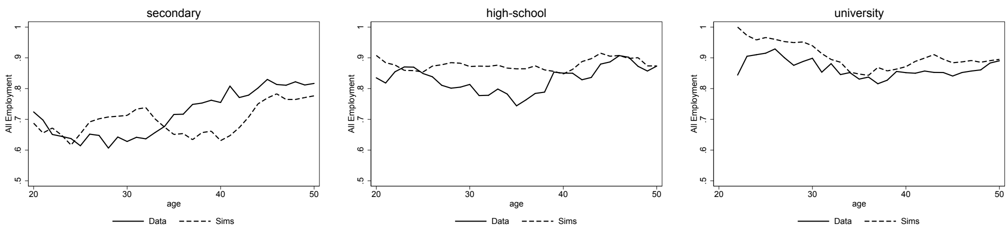
b. Women who have had children, by age (a) and education (s)



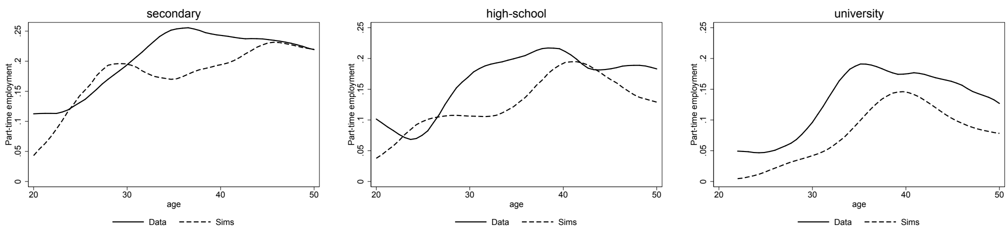
c. Employment rate by time to/since childbirth, by education (s)



d. Employment rate, by age (a) and education (s)



e. Part-time employment rate, by age (a) and education (s)



Each row displays average proportions by age for secondary, high-school and university educated women. Solid lines show proportions from the British Household Panel Survey, while dashed lines show proportions from the lifecycle profiles simulated using the model, as described in the main text.

Table 3: *Parameter estimates: human capital accumulation process*

		Education level (s)		
		s=1	s=2	s=3
(1)	δ_s: human capital depreciation rate	0.080	0.056	0.072
(2)	$k(\dots)$: experience accumulation rate	0.151	0.096	0.116
(3)	$E_{0,s}$: $k(\dots)$ scaling factor	1.501	1.501	2.999
(4)	λ_s: depreciation rate of $E_{0,s}$	1.050	1.050	1.050

Note: parameters for human capital accumulation process, given by Equation 14. Stock of human capital depreciates at education specific rate δ_s when not working. Rate of experience accumulation normalised to 1 for full-time work, with $k(PT)$ the estimated relative experience accumulation rate when working part-time. Experience accumulates at a faster rate in the years immediately following the completion of education, with $k(\dots)$ scaled by $E_{0,s}^{-\lambda_s.(t-t_{0,s})}$.

for women of each education group (Panel a), and likewise the timing of first births for women in these groups (Panel b). Lower educated women are more likely to have children early in life, with most higher educated women waiting until their 30s to have children: particularly those married to a higher educated spouse.

Panel c shows that the model also captures the dip in employment rates around childbirth, which is most pronounced for those in the lowest education group (those with only secondary education), with high-school and university educated women seeing much higher rates of employment following childbirth. The simulated life-cycle profiles of employment (Panel d) match the data closely, though those for part-time employment (Panel e) are a little low - especially at ages 30-40 - for all education groups. Appendix D contains the full set of 303 moments used to estimate the parameters.

4.3 Counterfactual simulations

I use the lifecycle model to examine the long run effects of the UK's move to independent taxation. Specifically, I compare outcomes under the 1992 tax and transfer system - where each individual had their own tax free personal allowance above which they faced the basic rate of 25% - to a world in which couples' incomes were jointly assessed and a 27% basic rate of income tax continued to apply. The

Table 4: *Abolition of joint income tax assessment: overall impact*

	Baseline	Reform	effect (%)
Employed	0.817	0.828	1.4%
In part-time work	0.158	0.124	-21.4%
In full-time work	0.659	0.704	6.8%
Secondary only	0.206	0.203	-1.2%
High-school	0.399	0.400	0.1%
University	0.395	0.397	0.5%
Ever has child	0.683	0.669	-2.0%

Note: baseline and reform proportions are averages across lifecycle of 19,505 simulations using the model described above. Final column shows the difference between proportions.

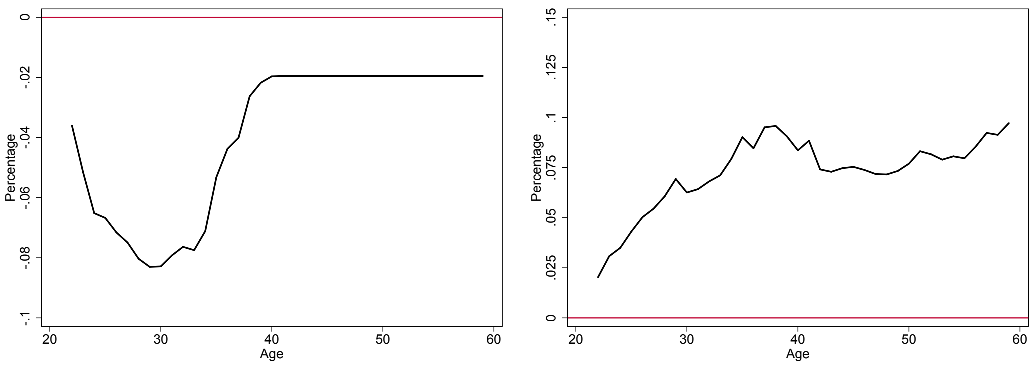
two systems - adjusted for inflation - are assumed to apply for the entirety of individuals' lives to isolate the effects of the reform.

Table 4 shows the impact of the reform on women's employment, education, and fertility decisions on average. Abolishing joint taxation leads to a modest 1.4% increase in the proportion of women in work, from 0.817 under a jointly assessed income tax system to 0.828 under an individually assessed one. But as the next two rows show, the reform has much larger effects on the intensive margin, with an increase of 6.8% in the full-time employment rate more than offsetting a decline of around a fifth in part-time work. The reform also leads to a 1.2% increase in the proportion of women leaving school with more than secondary education, reflecting the greater returns to education in the form of higher after-tax earnings. Finally, the last row shows that there is a 2% increase in the proportion of women who choose never to have children in response to the reform.

This increase is related to the more pronounced responses observed across the lifecycle. The left panel of Figure 6 shows that the reform leads many women to delay the point at which they first have children, with the share of women that have had a child by age 30 falling 8%: four-times the reduction in the share of women that ever have children. As fertility decisions are in part stochastic,

Figure 6: *Impact of reform across the lifecycle: fertility and employment*

(a) *Share who have given birth* (b) *Share working full-time*



Panels show the simulated impact of the reform by age in percentage terms for a) the share of women who have had children and b) the proportion working full-time. All panels constructed from lifecycle profiles of 19,505 simulations using the model described in the text.

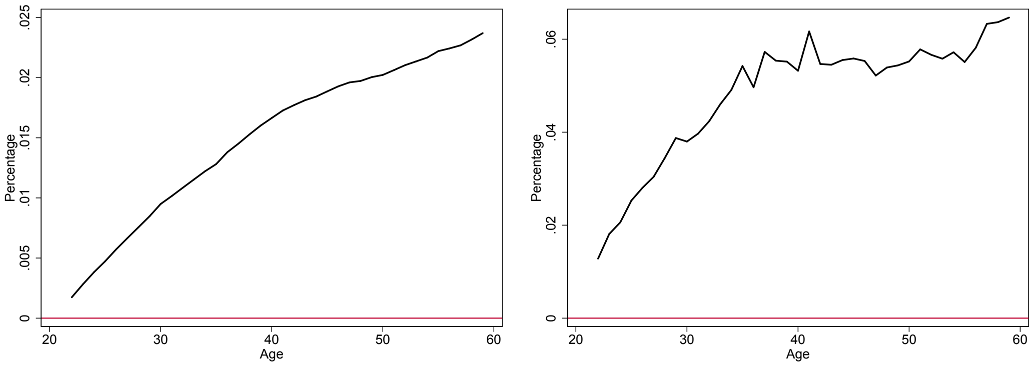
with fecundity declining in age, this delay contributes to fewer women going on to successfully have children.

The delay is itself related to a large rise in full-time employment among women, shown in the right panel of Figure 6, which peaks at 10% around age 38 and is sustained throughout the remainder of working life. Up to age 30, this mainly reflects women choosing to postpone having children and to instead work full-time, in response to both higher post-tax earnings today and increased returns to experience that will feed into higher pre-tax wages in the future. It is the latter human capital channel that amplifies the effects of the reform, and results in responses that grow with age. By inducing higher labour supply today, a permanent tax cut leads to higher pre-tax wages and so even higher labour supply tomorrow, which will in turn increase wages further, and so on.

This channel is particularly important for university educated women, who see the largest fertility responses. As discussed in Section 4.1, university educated women do not have stronger underlying preferences for work, but work more because their potential earnings are higher. Intuitively, we should therefore expect that they would respond more to a policy change that raises after-tax wages, particularly at higher levels of earnings.

Figure 7: *Impact of reform across the lifecycle: wages and earnings*

(a) *Hourly wages* (b) *Earnings*



Panels show the simulated impact of the reform by age in percentage terms for a) hourly wages and b) weekly earnings. All panels constructed from lifecycle profiles of 19,505 simulations using the model described in the text.

The dynamic feedback between wages and employment can be clearly seen in Figure 6, which plots the average percentage change in hourly wages (panel a) and annual earnings (panel b) across the lifecycle as a result of the reform. The average effect on hourly wages is monotonically increasing in age, reaching more than 2% by the end of working life. These higher hourly wages, combined with the rise in full-time employment across the lifecycle, result in pre-tax earnings that are on average 6% higher for women by the end of working life. This translates into a 2 percentage point reduction in the gender pay gap at median earnings, from 28.2% to 26.2%.

5 Conclusion

When assessed against couples' joint incomes, a progressive income tax can impose high marginal rates on second earners, typically women. This paper has shown that the long-run effects of such policies is to suppress the labour supply of women, particularly along the intensive margin. I first presented reduced form evidence that the UK's abolition of joint taxation led to an increase in participation rates of married women in the short-run. To investigate longer-run responses, and to unpack the underlying mechanisms, I then developed a dynamic lifecycle model of women's education, employment, fertility and savings decisions. Counterfactual simulations using this model suggest that abolishing joint taxation led to more women working, completing post-compulsory education, and deciding not to have children. Moreover, it resulted in far more women working full-time through their 30s and delaying the point at which they first had children, helping to substantially boost wages and earnings later in life. These effects are driven by the dynamic feedback between wages and human capital, whereby a rise in labour supply today sparked by higher after-tax earnings leads to higher (pre- and post-tax) wages and so further increases in labour supply tomorrow.

The findings lend support to recent policy proposals in the United States for a second earners' deduction aimed at increasing the employment rates of married women (e.g. Kearney and Turner, 2013; LaLumia, 2017), a measure included in both President Obama's final budget proposal to Congress and the tax plan published by then Republican presidential candidate Jeb Bush in 2016.[15] By increasing the point at which second earners face the higher rates of income tax, thereby increasing the post-tax returns to experience, these measures would improve the incentives that married women have to remain in the labour force. The simulations here suggest such policies can have large, long-run impacts on labour market participation that grow over time.

A Data

The Family Expenditure Survey (FES)

The Family Expenditure Survey (FES) is a cross-sectional survey that collects information on household and personal incomes alongside a detailed 14-day expenditure diary.[16] It ran annually from 1961 until 2001, when alongside the National Food Survey it was replaced by the Expenditure and Food Survey (EFS), known since 2008 as the Living Costs and Food Survey (LCFS).

[15] For a summary of these proposals, see Greenberg (2016).

[16] UK Data Service GN33057, https://discover.ukdataservice.ac.uk/series/?sn=200016.

In my reduced-form analysis (Section 2), I use FES data between the years 1980 and 2000 when information on the age that individuals ceased education was collected. For Figure 3, I restrict the sample to women aged between 20 and 59 who left education aged 18 or older, and calculate employment rates (including self-employment) for women who report their marital status as married or cohabiting and single. The annual change in these employment rates plotted is normalised by the average within-group change over the years 1980-1989 (so that positive numbers indicate higher than average employment growth and vice versa).

Table 1 summarises the results of the following regression, estimated on the FES for the sample of women aged 20-59 over the years 1980 and 2000:

$$E_i = \beta_0 + \beta_1 \text{treated}_i * \text{post}_i + \beta_2 \text{treated} + \boldsymbol{\alpha} \sum_{t=1980}^{2000} \mathbb{1}(\text{year}_i = t) + \boldsymbol{\gamma} \boldsymbol{X}_i \qquad (17)$$

where the dependent variable is an indicator for whether a women is employed or not; the reported treatment effect β_1 is the coefficient from the interaction of a treatment group and post-1990 dummy; β_2 is the coefficient on the treatment group dummy; $\boldsymbol{\alpha}$ is a vector of coefficients on year dummies; and $\boldsymbol{X}$ is a vector of demographic variables that are added successively to the specification, including age, the presence of children, and the (banded) age of a woman's youngest child.

The British Household Panel Survey (BHPS)

To estimate the parameters of the structural model, I use all 18 waves of the British Household Panel Survey (BHPS) carried out annually between 1991 and 2008.[17] This collected detailed information on demographics, education, and incomes for a random sample of 5,050 households in England, Wales and Scotland (south of the Caledonian canal) containing 9,092 adults. Individuals in these households were followed over time, with others marrying or born onto original interviewees added over time, along with regional and ethnic minority booster samples.

[17] UK Data Service SN5151, http://doi.org/10.5255/UKDA-SN-5151-1.

I use the same unbalanced panel of 3,901 women as Blundell et al. (2016): those observed while aged 19 to 50, dropping those in self-employment to avoid measurement issues created by the unreliability of hours and earnings. Three-fifths of this sample are observed for more than 5 years, with a third of these observed for more than 10 years.

I use a three-way education classification, defining 'secondary' as those with compulsory schooling or lower; 'high-school' as those obtaining A-level or equivalent qualifications; and 'university' as those with three-year degrees or higher). Employment decisions are discretised, with those working 21 hours or more per week (including overtime) categorised as full-time and those working 5-20 hours per week as part-time. Hourly wages are constructed for those in full- or part-time work by dividing usual gross weekly earnings by reported hours (capped at 70 per week), then trimmed at the 2nd and 98th percentiles to limit the degree of measurement error.

All monetary variables are first deflated by the Consumer Price Index (CPI) to remove the effects of inflation. These real quantities are then rescaled to strip out the effects of aggregate growth using a wage index constructed by regressing a set of time and region dummies on log wages.[18] This procedure is applied not only to earnings and wages, but the parameters of the tax and transfer system, and savings (which are defined as financial assets and housing less of debt, excluding private and public pensions).

B Computational details

Given its complexity, there is no analytical solution to the lifecycle problem outlined in Section 3. Instead, I numerically approximate policy functions for consumption, education, employment and fertility decisions recursively, conditional on the information in the state space. This involves simultaneous discrete-continuous

[18] These regressions are run separately by education group, with the aggregate index given by the coefficients associated with the time dummies weighted by the distribution of these education groups across the sample.

choices at each age during working life which can create kinks in the value function that propagate backwards through time, meaning its smoothness and concavity - which ensures the existence of a unique, continuous, solution - is not assured.

One approach taken in the literature is to discretise the space of the continuous choice, thereby bypassing the challenges that simultaneous discrete-continuous decisions pose (e.g. French and Jones, 2011; Adda et al., 2016; O'Dea, 2018). Another, adopted by Fella (2014); Iskhakov et al. (2015) and Blundell et al. (2016) is to allow uncertainty to concavify the expected value function and smooth out the kinks that arise from discrete choices. This is the approach I follow, exploiting the rich sources of uncertainty embedded in my model which include wages, a partner's arrival, departure, employment and earnings, along with the realisation of stochastic fertility decisions.

Numerically solving the model requires finding expressions for expected value and expected marginal utility at time t as a function of the state space, which can be partitioned into that which is known conditional on choices at $t-1$ ($\Omega = \{\theta, x_1, x_2, s, a_t, e_t\}$) and that which is uncertain ($\omega = \{v_t, k_t, t_t^k, m_t, \tilde{s}_t, \tilde{l}_t, \tilde{v}_t\}$). These expressions can be written as $EV_t(\Omega_t, \omega_{t-1})$ and $Eu_t'(\Omega_t, \omega_{t-1})$ respectively, and are obtained by the following algorithim:

1. **Approximate the policy function for consumption conditional on labour supply and fertility choices**. For each possible labour supply and fertility decision, at each point of the state space:

   (a) calculate (after tax and transfer) household resources I_t;

   (b) compute next period's experience e_{t+1}, then interpolate expected marginal utility $Eu_t'(\Omega_{t+1}, \omega_t)$ at e_{t+1};

   (c) Using (a) and (b) above, solve for the root of the Euler equation

$$c_t(X_t : l_t, z_t) = (u_{l,z}')^{-1}.\beta R E\left[u'\left(c_{t+1}(X_{t+1})\right)|X_t, l_t, z_t\right] \tag{18}$$

by linear interpolation at $t_{t+1} = I_t - c_t(X_t : l_t, z_t)$, where $(u'_l)^{-1}$ is the analytical inverse of the utility function evaluated at $Eu'_t(\Omega_{t+1}, \omega_t)$.

(d) Use (c) to compute the value function conditional on labour supply and fertility decisions, $V_t(X_t; l_t = l; z_t = z)$

2. **Compute the unconditional optimum** by selecting l_t and z_t that maximise $V_t(X_t; l_t; z_t)$. Store the value function $(V_t(X_t))$ and marginal utility of consumption $(u'_t(X_t))$ associated with this optimal choice.

3. **Calculate** $EV_t(\Omega_t, \omega_{t-1})$ **and** $Eu'_t(\Omega_t, \omega_{t-1})$ by integrating out $(V_t(X_t))$ and $(u'_t(X_t))$ over the distribution of productivity shocks; whether conception successful; the arrival/departure of a spouse; and whether a spouse works or not.

Having solved the model, I simulate lifecycle profiles for 3,901 women using the initial conditions observed in the BHPS along with random sequences of unobserved shocks. Women make education decisions given these draws on the basis of the expected value of each choice, then begin working life. Simulating forwards, optimal savings-consumption decisions are calculated conditional on fertility and employment decisions by solving the Euler equation, then the unconditional optimal computed, interpolating over human capital, future assets, and productivity shocks.

The two-step estimation procedure involves first estimating some parameters outside of the model or calibrating them with reference to the literature as described in Appendix C below. Parameters determining preferences and the dynamics of human capital formation are estimated iteratively within the model as follows. I first solve and simulate 5 replications of the model for an initial set of parameters under the April 1995, 1999, 2002 and 2005 tax and transfer systems - selected to stylistically represent the tax and transfer regime in operation over the BHPS sample period (1991-2008) - with monetary variables deflated to strip out the effects of inflation and macroeconomic growth using the wage index described above. I then select an observation window for these simulations so that they match the age-time structure of the BHPS, and compute moments for both the simulated and observed data, including the proportions employed and presence of children by age and education.[19]

These are used to estimate 76 parameters by minimising an objective function that sums the standardised difference between these simulated and data moments weighted by the inverse variance-covariance matrix of the data moments; that is, finding the set of parameter values Θ that solve:

$$\hat{\Theta} = \underset{\Theta}{argmin} \sum_{k=1}^{K} \frac{(M^d_{kN} - M^m_{ks}(\Theta))^2}{\mathrm{var}(M^d_{kN})} \tag{19}$$

where M^d_{kN} and M^m_{ks} are the k^{th} moments calculated from N data observations and s model simulations respectively. I use the Bound Optimization By Quadratic Approximation (BOBQA) approach of Powell (2009) to find this minimum, implemented in FORTRAN by NAG.[20].

C Model parameters

Parameters governing the arrival and departure of a partner are estimated outside the model, along with the probability he works and his earnings in work.

Arrival rates for partners of a given education level (secondary, high-school, and university) are estimated separately for women by education, first fitting a fourth-order polynomial in age to arrival rates observed for single women in the BHPS. I then set these to 0 from age 55, and calibrate rates for the first period of working life to those observed in the data. Departure rates are estimated separately by women's education level and the presence of children, fitting a fourth order polynomial in age on the relevant sample aged 20 to 69. Finally, I scale the arrival probabilities so that the proportion of women married or cohabitating with

[19] The full set of 303 moments are contained in Tables 9-21 in Appendix D).

[20] For more details, see entry for routine E04JCF in NAG Library Manual (Mark 24), available at https://www.nag.com/numeric/fl/nagdoc_fl24/html/E04/e04jcf.html

Table 5: *Estimated employment probabilities and wage rates for partners*

	Education level of partner		
	Secondary	High-School	University
		Employment probabilities	
New couples	0.74	0.87	0.83
	(0.02)	(0.02)	(0.03)
Existing couple: intercept	0.05	0.37	0.58
	(0.02)	(0.02)	(0.04)
Existing couple: employed $t-1$	1.52	1.40	1.28
	(0.03)	(0.03)	(0.06)
		Wage equation	
Log wage	1.94	2.07	2.05
	(0.07)	(0.08)	(0.15)
Log partner's age -18	0.09	0.18	0.35
	(0.04)	(0.03)	(0.07)
St. deviation of innovation to productivity	0.37	0.36	0.39
(new couples)	(0.12)	(0.13)	(0.18)
St. deviation of innovation to productivity	0.12	0.10	0.10
(existing couples)	(0.04)	(0.03)	(0.50)

Note: employment probabilities estimated by probit regression separately for new and existing couples. Wage rates deflated by wage index described in Appendix A. Standard errors in parenthesis.

men of each education level match those observed in the data (shown in Figure 4 in the main text).

Employment probabilities for partners are estimated separately by education, whether the couple has been newly formed and (if not) whether the man was employed in the previous period. The first three rows of Table 5 show these are quite persistent and are broadly increasing with education. Similarly, the estimates show that the age profile of log wages is steeper for those with high-school and university education.

The parameters governing the wage process in Equations 11-13 are set equal to those estimated by Blundell et al. (2016) for the same sample of women and wage process. These are displayed in Table 6, with rows 1-6 showing that both the initial level of wages and returns to experience are increasing in education. The final four rows imply that while wages are quite persistent (with ρ taking a

Table 6: *Calibrated wage equation parameters*

	Education level		
	Secondary	High-School	University
Intercept: $b_{s,0}$	5.406	5.547	6.949
Increment, high factor 1: $b_{s,1}$	0.005	0.018	0.061
Increment, high factor 2: $b_{s,2}$	0.014	-0.186	0.045
Baseline: $\gamma_{s,0}$	0.152	0.229	0.306
Increment, high factor 1: $\gamma_{s,1}$	0.054	0.014	-0.002
Increment, high factor 2: $\gamma_{s,2}$	-0.002	0.029	-0.006
Autocorrelation coefficient: ρ_s	0.925	0.916	0.880
Productivity innovation: $\sqrt{\text{var}(\zeta_t)}$	0.125	0.154	0.139
Initial productivity: $E(\upsilon_{0,s}\|\text{type I})$	0.140	0.111	0.306
Initial productivity: $\sqrt{\text{var}(\upsilon_t)}$	0.145	0.202	0.223

Note: parameter estimates reported in Table VIII of Blundell et al. (2016), used to calibrate the wage process described by equations 11-13.

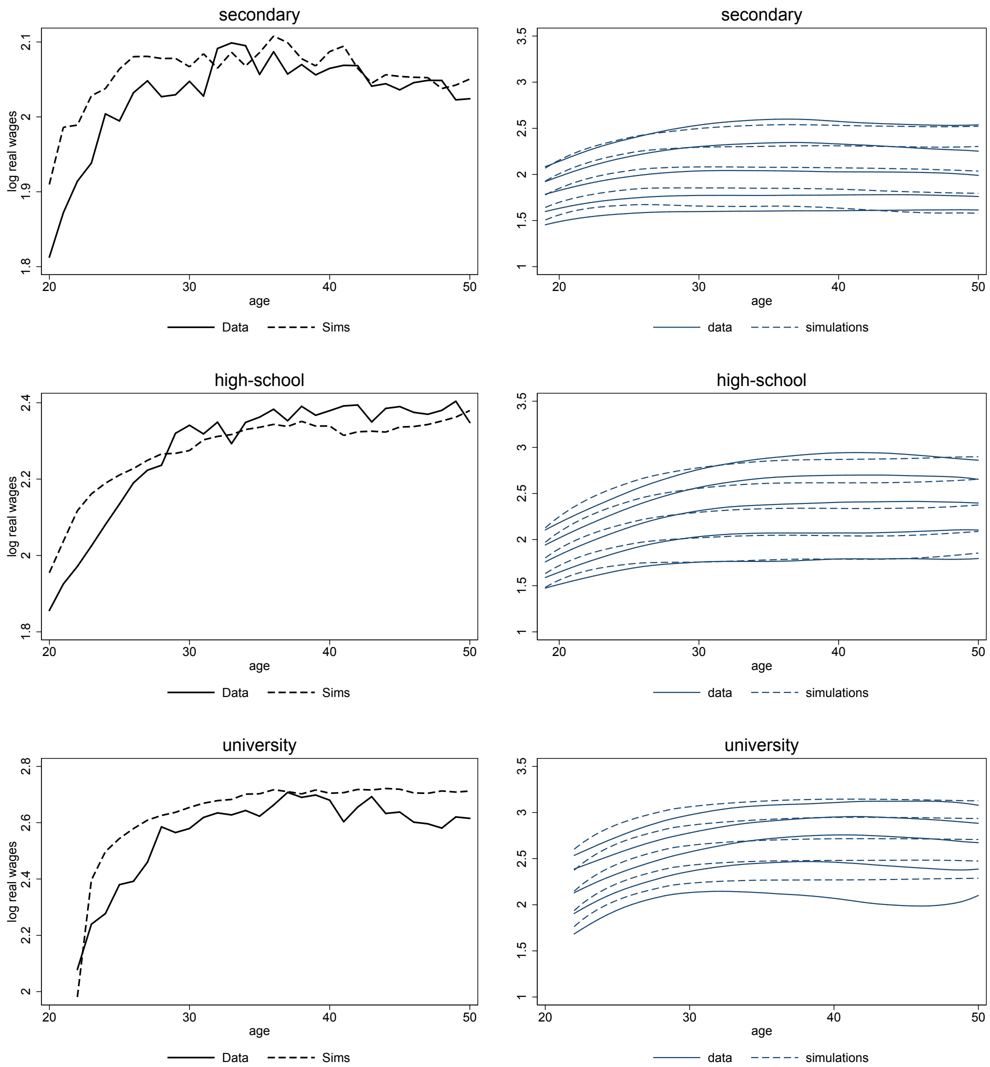
value of about 0.9 for the three education groups), they are also subject to a high degree of uncertainty ($\sqrt{\text{var}(\zeta_t)}$) and hetrogeneity (the υ terms).

In addition, two key preference parameters are set with reference to the literature: the coefficient of risk aversion, γ, to 1.56 (consistent with evidence from Blundell et al. (1994) and Attanasio and Weber (1995), who both allow for the non-separability of consumption and leisure as here) and the discount factor, β, to 0.98 as is common in the literature (e.g. Attanasio et al., 2008). The risk-free rate of interest is set slightly lower than the discount rate - to 0.015 - so that agents are somewhat present biased.

The remaining parameters - determining preferences and the dynamics of human capital formation - are estimated by the method of simulated moments as described in Appendix B. Tables 2 and 3 in the main text contain, respectively, estimates of preferences for children (the ω terms from equation 5) and the parameters determining the human capital accumulation process (Equation 14), and are discussed in Section 4.1.

Estimates of preferences for work and education are contained in Tables 7 and 8. The first of these shows that family background and parental liquidity at age 16 are important determinants of whether or not women go to university, as

Figure 8: *Log wages, by age (a) and education (s)*



Left-hand panels show mean log-wages by eduation and age for women in the British Household Panel Survey estimation sample (solid lines) and simulations from the dynamic model described in Section 4 (dashed lines). Right-hand panels show quintiles of log-wages for these groups.

Table 7: *Parameter estimates: preferences for education*

	Education level (s)	
	High-school (s=2)	University (s=3)
Intercept	-0.053	0.681
Background factor $f1$	0.225	0.366
Background factor $f2$	0.010	0.302
Parental liquidity shock when 16	0.303	0.694
St. deviation of unobserved utility cost	1.576	1.049

Note: value function minimised so that negative (positive) values reflect utility (disutility) from education.

are the unobserved (random) utility cost of attending. Table 8 shows that the estimated disutility of work is greatest for university educated women, especially when married with children. This suggests that the higher earnings they receive in work are behind their much higher employment rates across the lifecycle rather than some stronger preference for work.

D Moments

Tables 9-21 contain the 303 data and simulated moments used to estimate the parameters of the model, grouped by education level: the coefficients from a regression of log wages (Table 9); the distribution of log wages (Tables 11-11); the proportion of women with children by age (Tables 13-15); employment rates by age (Tables 16-18); and part-time employment rates by age (Tables 19-21). Standard errors are calculated by drawing 1,000 bootstrap replications (with replacement) from the data estimation sample.

Table 8: *Parameter estimates: preferences for work*

		Full-time (α^{FT})	Part-time (α^{PT})
Estimated disutility of work if:			
(1)	Single, s=1	0.326	-0.304
(2)	Single, s=2	0.338	-0.317
(3)	Single, s=3	0.453	-0.386
Additional disutility if:			
(4)	Children present, s=1	0.494	-0.135
(5)	Children present, s=2	0.461	-0.134
(6)	Children present, s=3	0.580	-0.116
(7)	Child aged 0-2	0.184	-0.096
(8)	Child aged 2-5	0.081	-0.068
(9)	Child aged 6-10	0.042	-0.039
(10)	Spouse present, s=1	0.250	-0.189
(11)	Spouse present, s=2	0.233	-0.158
(12)	Spouse present, s=3	0.259	-0.177
(13)	Child & spouse present, s=1	0.320	-0.216
(14)	Child & spouse present, s=2	0.262	-0.198
(15)	Child & spouse present, s=3	0.286	-0.197
(16)	Spouse works	-0.074	0.078
(17)	High background factor $f1$	-0.011	0.009
(18)	High background factor $f2$	-0.002	0.002
(19)	Of (unobserved) type I	-0.093	-0.053
Estimated probability of:			
(20)	Being type I	0.255	(0.000)

Note: value function minimised and parameters additive across both family and work type so that e.g. disutility of full-time work for secondary educated single women with kids is $0.326 + 0.494 = 0.820$, greater than the disutility of part-time work for same woman $0.326 + 0.494 - 0.304 - 0.135 = 0.130$.

Table 9: *Log-wage regressions*

Moment	Data	Simulated	SE data	No. SE diff
s = 1				
Constant	0.43268	0.45023	0.03976	0.44145
Family background: $H1$	0.02938	0.03259	0.00716	0.44864
Family background: $H1$	-0.00633	-0.00423	0.00653	0.32086
$\ln w_{t-1}$	0.74493	0.73952	0.01549	0.34922
Cumulated human capital, t	0.07308	0.20790	0.07419	1.81724
Cumulated human capital, $t-1$	-0.03955	-0.17847	0.06510	2.13392
Variance of residuals	0.04985	0.05231	0.00221	1.11324
Autocorrelation of residuals	-0.01008	-0.01060	0.00088	0.59054
s = 2				
Constant	0.37370	0.29993	0.03213	2.29604
Family background: $H1$	0.00963	0.01093	0.00675	0.19242
Family background: $H2$	0.00210	0.00765	0.00629	0.88307
$\ln w_{t-1}$	0.79904	0.81492	0.01125	1.41164
Cumulated human capital, t	0.18771	0.32053	0.05950	2.23233
Cumulated human capital, $t-1$	-0.15062	-0.28167	0.05031	2.60485
Variance of residuals	0.05019	0.05299	0.00196	1.42878
Autocorrelation of residuals	-0.01037	-0.01038	0.00077	0.01143
s = 3				
Constant	0.60643	0.46670	0.05676	2.46181
Family background: $H1$	-0.00935	0.00650	0.01096	1.44581
Family background: $H1$	0.00059	-0.00404	0.00888	0.52131
$\ln w_{t-1}$	0.76046	0.73834	0.02071	1.06815
Cumulated human capital, t	0.08810	0.61178	0.06981	7.50149
Cumulated human capital, t	-0.06889	-0.53652	0.05816	8.04044
Variance of residuals	0.04346	0.04629	0.00248	1.13942
Autocorrelation of residuals	-0.00746	-0.00789	0.00100	0.42992

Table shows coefficients from an OLS regression of log-wages by education along with the variance and first-order autocorrelation of the residual terms, for both the BHPS estimation sample and simulations from the model. Standard errors calculated by drawing 1,000 bootstrap replications from the data estimation sample. Final column shows the difference between data and simulated moments in terms of the data standard error.

Table 10: *Distribution of log-wages (s=1)*

Moment	Data	Simulated	SE data	No. SE diff
Mean log wages, full-time	2.08376	2.11756	0.01111	3.04217
Mean log wages, part-time	1.90184	1.87624	0.01143	2.23975
pQ10, full-time	0.10013	0.09049	0.00571	1.68749
pQ25, full-time	0.25004	0.20024	0.01080	4.61137
pQ50, full-time	0.49993	0.44472	0.01416	3.89914
pQ75, full-time	0.75011	0.72076	0.01322	2.21992
pQ90, full-time	0.90001	0.89591	0.00918	0.44628
pQ10, part-time	0.09967	0.12441	0.00723	3.42143
pQ25, part-time	0.24991	0.25883	0.01240	0.71933
pQ50, part-time	0.50018	0.44729	0.01686	3.13730
pQ75, part-time	0.75009	0.75514	0.01490	0.33891
pQ90, part-time	0.90033	0.94597	0.00980	4.65687
Mean log wage, type $H1$	2.07310	2.11601	0.01404	3.05653
Mean log wage, type $H2$	2.02026	2.04270	0.01368	1.64059

Table contains means, variances and quintiles of log wages for groups indicated.

Table 11: *Distribution of log-wages (s=2)*

Moment	Data	Simulated	SE data	No. SE diff
Mean log wages, full-time	2.29797	2.32320	0.01143	2.20757
Mean log wages, part-time	2.08873	1.97533	0.01972	5.75066
pQ10, full-time	0.09999	0.08801	0.00602	1.99067
pQ25, full-time	0.24990	0.23003	0.01046	1.89996
pQ50, full-time	0.50007	0.47898	0.01359	1.55186
pQ75, full-time	0.74997	0.73888	0.01229	0.90248
pQ90, full-time	0.90001	0.88708	0.00802	1.61233
pQ10, part-time	0.09972	0.11560	0.00943	1.68413
pQ25, part-time	0.25014	0.27472	0.01684	1.45981
pQ50, part-time	0.50028	0.58306	0.02336	3.54358
pQ75, part-time	0.75042	0.86827	0.01987	5.93119
pQ90, part-time	0.90028	0.98387	0.01260	6.63445
Mean log wage, type $H1$	2.25097	2.27494	0.01411	1.69860
Mean log wage, type $H2$	2.27823	2.29606	0.01655	1.07754

Table contains means, variances and quintiles of log wages for groups indicated.

Table 12: *Distribution of log-wages (s=3)*

Moment	Data	Simulated	SE data	No. SE diff
Mean log wages, full-time	2.55501	2.65391	0.01461	6.76954
Mean log wages, part-time	2.47400	2.42281	0.04019	1.27359
pQ10, full-time	0.09987	0.05358	0.00949	4.87826
pQ25, full-time	0.24994	0.16328	0.01476	5.87108
pQ50, full-time	0.50013	0.39893	0.01870	5.41155
pQ75, full-time	0.75006	0.68332	0.01563	4.26976
pQ90, full-time	0.90013	0.84291	0.00983	5.82101
pQ10, part-time	0.09864	0.01951	0.01912	4.13884
pQ25, part-time	0.25000	0.20098	0.03449	1.42142
pQ50, part-time	0.50000	0.64054	0.04033	3.48483
pQ75, part-time	0.75000	0.89481	0.03550	4.07916
pQ90, part-time	0.90136	0.97562	0.02604	2.85170
Mean log wage, type $H1$	2.52505	2.62388	0.01630	6.06341
Mean log wage, type $H2$	2.53009	2.63028	0.01923	5.21011

Table contains means, variances and quintiles of log wages for groups indicated.

Table 13: *Proportion of women living with children, by age (s=1)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.47785	0.47007	0.02789	0.27908
23	0.54128	0.52259	0.02854	0.65475
24	0.55255	0.54917	0.02838	0.11927
25	0.58671	0.58897	0.02696	0.08375
26	0.62881	0.57767	0.02545	2.00943
27	0.65535	0.60563	0.02454	2.02592
28	0.69139	0.62408	0.02189	3.07482
29	0.72581	0.65154	0.02121	3.50178
30	0.74286	0.67857	0.02007	3.20322
31	0.76667	0.68299	0.01913	4.37411
32	0.78947	0.70298	0.01839	4.70293
33	0.81460	0.72715	0.01678	5.21132
34	0.82093	0.74543	0.01675	4.50741
35	0.83992	0.76812	0.01624	4.42143
36	0.84306	0.77984	0.01647	3.83844
37	0.82424	0.80637	0.01705	1.04833
38	0.80777	0.64879	0.01823	8.72059
39	0.80085	0.62136	0.01874	9.57795
40	0.77201	0.60944	0.02009	8.09198
41	0.74115	0.60440	0.02065	6.62249
42	0.69977	0.54676	0.02236	6.84291

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 14: *Proportion of women living with children, by age (s=2)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.17906	0.25678	0.01968	3.94917
23	0.20533	0.33124	0.02081	6.05023
24	0.23575	0.36571	0.02207	5.88854
25	0.29064	0.39405	0.02310	4.47660
26	0.34722	0.41480	0.02372	2.84906
27	0.40135	0.42529	0.02395	0.99979
28	0.47321	0.42479	0.02398	2.01917
29	0.53273	0.43209	0.02403	4.18806
30	0.57965	0.45666	0.02316	5.31052
31	0.61726	0.47978	0.02284	6.01944
32	0.63938	0.49779	0.02217	6.38660
33	0.68212	0.52232	0.02171	7.36060
34	0.71395	0.54257	0.02152	7.96356
35	0.75179	0.57396	0.02058	8.64089
36	0.74217	0.60140	0.02068	6.80689
37	0.74755	0.62347	0.02044	6.07044
38	0.74016	0.59153	0.02198	6.76215
39	0.73743	0.58870	0.02260	6.58083
40	0.74499	0.58195	0.02288	7.12571
41	0.74336	0.57333	0.02320	7.32874
42	0.75081	0.51251	0.02420	9.84707

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 15: *Proportion of women living with children, by age (s=3)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.01299	0.03067	0.00933	1.89495
23	0.03061	0.06269	0.01240	2.58682
24	0.06303	0.08974	0.01588	1.68222
25	0.07438	0.11862	0.01728	2.56023
26	0.08400	0.13939	0.01843	3.00522
27	0.12450	0.16025	0.02131	1.67754
28	0.16733	0.16606	0.02405	0.05278
29	0.27347	0.17136	0.02871	3.55665
30	0.33333	0.18603	0.03010	4.89362
31	0.42544	0.20831	0.03223	6.73697
32	0.52093	0.24248	0.03325	8.37440
33	0.58294	0.27094	0.03300	9.45457
34	0.61538	0.33484	0.03219	8.71499
35	0.68137	0.39636	0.03249	8.77220
36	0.71875	0.45108	0.03245	8.24882
37	0.72626	0.49715	0.03356	6.82697
38	0.74251	0.53881	0.03277	6.21607
39	0.74118	0.57109	0.03235	5.25792
40	0.77844	0.59292	0.03079	6.02532
41	0.74843	0.57215	0.03231	5.45597
42	0.75641	0.55565	0.03245	6.18666

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 16: *Employment rate, by age (s=1)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.65705	0.67627	0.02816	0.68270
23	0.64724	0.65029	0.02758	0.11076
24	0.64653	0.61967	0.02653	1.01259
25	0.60465	0.65480	0.02583	1.94171
26	0.64804	0.69094	0.02569	1.66985
27	0.64380	0.70110	0.02499	2.29274
28	0.60241	0.70778	0.02403	4.38505
29	0.63134	0.71010	0.02398	3.28451
30	0.64537	0.71286	0.02267	2.97694
31	0.65553	0.73333	0.02126	3.65961
32	0.64228	0.73800	0.02185	4.38090
33	0.66667	0.70104	0.02032	1.69165
34	0.69355	0.67493	0.02149	0.86623
35	0.72817	0.65086	0.01951	3.96277
36	0.72837	0.65385	0.01971	3.78102
37	0.75456	0.63395	0.01936	6.22974
38	0.75770	0.65684	0.01941	5.19647
39	0.77331	0.66158	0.01933	5.78008
40	0.77602	0.63090	0.01956	7.41916
41	0.81153	0.64698	0.01850	8.89470
42	0.78588	0.67338	0.02011	5.59417
43	0.79418	0.70752	0.01937	4.47388
44	0.81030	0.75036	0.01914	3.13151
45	0.83991	0.76934	0.01678	4.20542
46	0.81681	0.78291	0.01772	1.91291
47	0.80882	0.76471	0.01789	2.46585
48	0.81720	0.76462	0.01802	2.91765
49	0.80973	0.77089	0.01801	2.15639
50	0.81720	0.77647	0.01780	2.28817

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 17: *Employment rate, by age (s=2)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.83425	0.87712	0.01939	2.21086
23	0.85405	0.86074	0.01844	0.36278
24	0.87696	0.85872	0.01700	1.07296
25	0.83663	0.85486	0.01902	0.95858
26	0.83565	0.87305	0.01832	2.04139
27	0.82127	0.87746	0.01856	3.02734
28	0.82022	0.88444	0.01906	3.36944
29	0.81050	0.88250	0.01891	3.80759
30	0.82063	0.87186	0.01820	2.81480
31	0.81069	0.87306	0.01865	3.34399
32	0.80942	0.87239	0.01886	3.33903
33	0.82327	0.87628	0.01770	2.99466
34	0.81030	0.86667	0.01866	3.02072
35	0.77372	0.86435	0.02084	4.34880
36	0.79756	0.86456	0.01999	3.35175
37	0.79353	0.87401	0.01964	4.09776
38	0.81167	0.86082	0.01978	2.48468
39	0.85185	0.85601	0.01883	0.22073
40	0.86127	0.84768	0.01845	0.73647
41	0.85329	0.86250	0.01853	0.49703
42	0.83498	0.88783	0.02126	2.48609
43	0.84775	0.89731	0.02028	2.44361
44	0.88603	0.91514	0.02009	1.44876
45	0.88973	0.90525	0.02018	0.76928
46	0.90038	0.90776	0.01892	0.38999
47	0.90734	0.89805	0.01894	0.49071
48	0.86957	0.90062	0.02195	1.41438
49	0.87347	0.87387	0.02086	0.01936
50	0.86667	0.87362	0.02234	0.31093

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 18: *Employment rate, by age (s=3)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.86093	1.00000	0.02835	4.90547
23	0.91623	0.97239	0.02060	2.72612
24	0.90678	0.95884	0.01945	2.67658
25	0.92149	0.96690	0.01784	2.54521
26	0.93852	0.95972	0.01586	1.33661
27	0.92276	0.95280	0.01712	1.75438
28	0.88980	0.94970	0.02045	2.92895
29	0.88797	0.95165	0.01976	3.22279
30	0.87826	0.93943	0.02133	2.86786
31	0.85841	0.91383	0.02274	2.43690
32	0.87793	0.89474	0.02254	0.74565
33	0.85167	0.88579	0.02418	1.41095
34	0.86893	0.85363	0.02297	0.66622
35	0.86500	0.84730	0.02314	0.76476
36	0.86842	0.84316	0.02427	1.04061
37	0.86207	0.86876	0.02628	0.25452
38	0.85629	0.85757	0.02677	0.04794
39	0.86826	0.86342	0.02579	0.18773
40	0.88485	0.87128	0.02483	0.54655
41	0.88387	0.88842	0.02609	0.17450
42	0.89404	0.89921	0.02503	0.20660
43	0.88194	0.91063	0.02674	1.07309
44	0.90441	0.89549	0.02500	0.35665
45	0.88489	0.88400	0.02684	0.03302
46	0.89209	0.88690	0.02551	0.20348
47	0.90000	0.89136	0.02650	0.32585
48	0.89683	0.88571	0.02693	0.41276
49	0.89516	0.89093	0.02766	0.15305
50	0.90833	0.89510	0.02589	0.51082

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 19: *Part-time employment rate, by age (s=1)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.13782	0.07982	0.01933	3.00038
23	0.14110	0.12181	0.01937	0.99600
24	0.13897	0.11688	0.01835	1.20364
25	0.13663	0.13523	0.01852	0.07552
26	0.17877	0.16343	0.02049	0.74864
27	0.17678	0.18623	0.01987	0.47551
28	0.16386	0.18943	0.01823	1.40249
29	0.19355	0.22108	0.01879	1.46532
30	0.19824	0.19000	0.01908	0.43187
31	0.19833	0.17823	0.01785	1.12598
32	0.21138	0.19715	0.01843	0.77230
33	0.23154	0.16971	0.01826	3.38594
34	0.24194	0.16057	0.01902	4.27790
35	0.26786	0.16337	0.01912	5.46481
36	0.24748	0.18435	0.01889	3.34197
37	0.25558	0.17109	0.01940	4.35528
38	0.24846	0.19437	0.01998	2.70721
39	0.26059	0.19556	0.02071	3.13995
40	0.24434	0.18598	0.02081	2.80442
41	0.24390	0.19918	0.02124	2.10566
42	0.24374	0.20000	0.02140	2.04393
43	0.23490	0.21448	0.02035	1.00321
44	0.22482	0.23367	0.02038	0.43435
45	0.23026	0.22774	0.01957	0.12891
46	0.23060	0.23810	0.01950	0.38437
47	0.21849	0.23119	0.01916	0.66285
48	0.22366	0.22423	0.01966	0.02920
49	0.21987	0.21902	0.01942	0.04376
50	0.21935	0.21765	0.01908	0.08925

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 20: *Part-time employment rate, by age (s=2)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.09669	0.05339	0.01522	2.84495
23	0.05405	0.08497	0.01191	2.59634
24	0.08901	0.10007	0.01462	0.75674
25	0.06436	0.09652	0.01242	2.58911
26	0.08565	0.10659	0.01363	1.53596
27	0.10860	0.10747	0.01464	0.07715
28	0.13034	0.10587	0.01542	1.58659
29	0.16438	0.11244	0.01723	3.01424
30	0.19058	0.10741	0.01880	4.42383
31	0.19376	0.10143	0.01850	4.99074
32	0.19507	0.10234	0.01900	4.88067
33	0.24385	0.10969	0.02007	6.68441
34	0.22482	0.10561	0.01951	6.11017
35	0.21655	0.12202	0.02051	4.60908
36	0.22439	0.14035	0.02098	4.00568
37	0.20647	0.15047	0.02078	2.69500
38	0.21220	0.16566	0.02141	2.17384
39	0.22222	0.19332	0.02232	1.29492
40	0.21387	0.19868	0.02239	0.67863
41	0.19461	0.21083	0.02138	0.75881
42	0.18482	0.18809	0.02236	0.14639
43	0.17647	0.18182	0.02278	0.23478
44	0.18382	0.18985	0.02362	0.25535
45	0.16730	0.16710	0.02272	0.00892
46	0.16475	0.14828	0.02328	0.70765
47	0.17375	0.14359	0.02385	1.26476
48	0.16206	0.14424	0.02305	0.77314
49	0.14694	0.12703	0.02279	0.87376
50	0.15000	0.11993	0.02323	1.29461

Standard errors calculated by drawing 1,000 bootstrap replications of the data.

Table 21: *Part-time employment rate, by age (s=3)*

Age	Data	Sims.	Data SE	No. SE diff
22	0.06623	0.00000	0.02022	3.27547
23	0.03141	0.00672	0.01261	1.95825
24	0.07627	0.00607	0.01725	4.06940
25	0.03306	0.01172	0.01174	1.81736
26	0.04098	0.02302	0.01284	1.39892
27	0.03252	0.03043	0.01115	0.18702
28	0.06122	0.03697	0.01501	1.61561
29	0.07884	0.03366	0.01722	2.62371
30	0.10435	0.04326	0.02062	2.96250
31	0.09735	0.04030	0.01894	3.01227
32	0.13146	0.05576	0.02357	3.21152
33	0.14833	0.06218	0.02454	3.51048
34	0.19903	0.07254	0.02793	4.52886
35	0.23000	0.10331	0.03077	4.11720
36	0.20526	0.10756	0.02868	3.40641
37	0.17241	0.14194	0.02896	1.05214
38	0.17365	0.14393	0.02983	0.99619
39	0.17964	0.15495	0.03050	0.80944
40	0.20000	0.14562	0.03245	1.67595
41	0.17419	0.15352	0.02996	0.68980
42	0.15232	0.13059	0.02921	0.74402
43	0.17361	0.12511	0.03038	1.59639
44	0.13971	0.10451	0.03013	1.16840
45	0.11511	0.09916	0.02702	0.59037
46	0.13669	0.09237	0.02886	1.53584
47	0.14615	0.08914	0.02994	1.90426
48	0.14286	0.08381	0.03069	1.92410
49	0.10484	0.08012	0.02767	0.89354
50	0.10833	0.06993	0.02846	1.34926

Standard errors calculated by drawing 1,000 bootstrap replications of the data.