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IZA DP No. 14442

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ABSTRACT

The Dynamics of Domestic Violence: Learning About the Match*

We present a dynamic lifecycle model of women's choices with respect to partnership status, labour supply and fertility when they cannot directly observe whether a given male partner is of a violent type or not. The model is estimated by the method of simulated moments using longitudinal data from the Avon Longitudinal Study of Parents and Children. The results indicate that uncertainty about a partner's abusive type creates incentives for women to delay fertility, reduce fertility overall, divorce more often and increase labour supply. We also study the impact of higher female wages, income support to single mothers, and subsidized childcare when the mother is working. While higher wages reduce women's overall exposure to abuse, both income support and subsidized childcare fail to do so because they encourage early fertility. Income support also leads to less accumulated labour market experience and hence higher abuse rates.

JEL Classification: J12, J13

Keywords: domestic violence, learning, fertility, ALSPAC

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* This research was funded by the British Academy (grant SG111103). We thank seminar participants at Collegio Carlo Alberto, Stony Brook, IDC, CESifo, ISER, Oslo, Leicester, Trondheim, Cambridge, Kings College, Mannheim, Royal Holloway, Bangor, Trinity College Dublin, Toulouse, Ariel University, Ecole Polytechnique, IWCEE, ESPE, EEA, and SEHO for helpful discussions and comments. We are especially grateful to Michael Keane and Ahu Gemici for comments that greatly improved the paper.

I Introduction

Freedom from violence is a fundamental human right. Yet violence by men towards their female partners is prevalent in every part of the world: WHO (2013) estimated that more than one third of all women in the world have been victims of physical or sexual violence, with far-reaching consequences for health, productivity, and well-being. Apart from its ubiquitous nature, domestic violence stands out as being the crime-category with the highest degree of repeat victimization. For instance, in the UK – which is the focus of the current paper – while seven percent of all women aged 16-59 experienced domestic abuse in 2009/10, repeat victimisation accounted for more than three-quarters of all incidents of domestic violence (Flatley et al., 2010).

Economics has recently seen a surge in research on domestic violence which has provided a wealth of useful insights. This research has focused on a range of environmental determinants of domestic abuse, including labour market conditions (Aizer, 2010; Tertilt and van den Berg, 2015; Anderberg et al., 2016; Tur-Prats, 2017), educational attainment (Erten and Keskin, 2018), culture and social norms (Alesina et al., 2020; Tur-Prats, 2019; González and Rodríguez-Planas, 2018; Guarnieri and Rainer, 2018), health and health innovations (Papageorge et al., 2019), gender ratios (Amaral and Bhalotra, 2017), and divorce laws (Stevenson and Wolfers, 2006; Garcia-Ramos, 2017). The literature has further focused on understanding motives for and triggers of abuse, including instant gratification (Tauchen et al., 1991), emotional cues (Card and Dahl, 2011), and instrumental abuse to change the victim's behaviour (Anderberg and Rainer, 2013) or to extract resources from the victim's family (Bloch and Rao, 2002). Finally, there has been a number of studies of the effect of policy on the incidence of domestic abuse, including law enforcement policy (Iyengar, 2009; Aizer and Dal Bó, 2009), and welfare and cash-transfers policy (Angelucci, 2008; Bobonis et al., 2013; Hidrobo and Fernald, 2013; Ramos, 2016; Hsu, 2017).

However, even with this flurry of contributions, a number of core questions – particularly of a dynamic nature – remain open. For instance, a question that has long been debated in the sociology and psychology literature is the dynamic link between a woman's labour supply and her exposure to abuse (Macmillan and Gartner, 1999; Riger and Staggs, 2004). This research has struggled with the fact that causality may go in both directions, and has been hampered by the use of relatively small and selective samples. Similarly, while there has been research into the relationship between domestic abuse and fertility, most of this research has focused particularly on abuse risk during pregnancy (Jasinski, 2004; Bowen et al., 2005). Finally, perhaps the most obvious dynamic response to abuse is whether or not a woman leaves her partner (Enander and Holmberg, 2008; Bowlus and Seitz, 2006).

The aim of this paper is to construct and estimate a dynamic lifecyle model of women's choices with respect to partnership status, fertility and labour supply in an environment where they are at risk of abuse from their partners and to use the estimated model to predict responses to changes in the economic environment, including policy. Our focus will be exclusively on modelling women's behavior. In contrast, we will model the behavior of men as non-strategic and stochastic. While this is a potential limitation, it is a modelling-choice motivated by a set of stylized facts. First, abuse, where it occurs, generally starts early in the relationship, typically within the first one to two years.[1] This suggests that violent men can/do not strategically control their behavior in order to conceal their nature. Second, we know from the work of Card and Dahl (2011) that incidents of abuse can be triggered by emotional cues causing a loss of control.

A starting point for our model is that women generally will, when meeting a new potential partner, not be able to directly observe his complete nature. Instead they will infer this by observing his behaviour over time. In our model we incorporate such learning in the simplest possible form. A man either has a "violent nature" or a "non-violent nature" where the former type is abusive with a high frequency and the latter only rarely. We allow the risk of abuse from "violent" men to depend on potential sources of "gender-tension". This way we can incorporate elements of proposed abuse theories – for instance exposure, identity, and bargaining theories – without assuming rational and strategic male behaviour. A woman holds beliefs over her partner's type which she updates based on observing his behaviour. If she experiences abuse her expectations about what the future within the relationship would hold worsen, potentially triggering divorce, and a change in labour supply, and/or fertility. In addition, a woman may delay fertility within a relationship until she is reasonably certain about her partner's nature.

To estimate the model, we use data from the Avon Longitudinal Study of Parents and Children (ALSPAC), a local longitudinal study that has followed a set of children – and their parents – from birth. Our sample population will include over 9,000 ALSPAC mothers who are followed for seven years starting from the study pregnancy. Importantly, the survey contains annual mea-

[1]Based on data from the British Crime Survey, Walby and Allen (2004) report that in relationships where domestic violence was going to become a repeated act, it had started during the first year of a relationship for 49 percent of women.

sures of intimate partner abuse, and we observe partnership, labour supply and fertility choices. The ALSPAC data, by surveying pregnant women, involves choice-based sampling, which as argued by Manski and Lerman (1977) and Cosslett (1981), has both advantages and drawbacks: it confers efficiency gains when some alternatives of particular interest are otherwise infrequently chosen but also poses challenges in terms of finding a suitable estimator that accounts for the nonrandom sampling. In our case child-bearing is an infrequent choice of central interest informing about women's investments within their relationships. In this respect, ALSPAC provides a clear advantage over other potential data sets of more general female populations.[2] We handle the nonrandom sampling by using the method of simulated moments. In particular, our estimation simulates lifecycle paths for a population of women and then computes moments on a portion of the simulated data selected using the ALSPAC sampling approach of tracking women from the moment they become pregnant.

We model a woman's choice of partnership status, labour supply, and child-bearing from her late teens until the end of her fertile period. As such, our model builds on an established literature developing lifecycle models of family decisions.[3] The relationship between our work and two contributions to this literature are worth noting in more detail. Brien et al. (2006) focus on the choice between marriage and cohabitation and a couple jointly learns about the true match quality of their match. Our learning setting is on the one hand simpler: women learn their partner's type with only a binary type space, and update beliefs based on abuse which is observed in the data. On the other hand, by endogenizing fertility and labour supply we study key behavioural responses to learning beyond partnership decisions. Bowlus and Seitz (2006) is the only contribution to date to estimate a lifecycle model with domestic violence. In their model, men rationally decide on abuse based on their preferences for violence. However, as women always know their partner's abuse preferences there is no learning. Moreover, fertility is treated as exogenous.

Our results indicate that violent men are high frequency repeat abusers. As a result learning is quite fast – within a few years most women will be quite certain about the nature of their

[2] It should also be noted that longitudinal data on domestic violence are extremely rare and most other datasets are small and highly selective in other ways, for instance often focusing on women seeking support after experiencing abuse. A drawback in our case is that the data will not have any information about the behaviour of women who choose to remain childless.

[3] Key contributions include van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2010), and Gemici and Laufer (2014).

partner – creating a strong incentive to delay fertility within a new relationship by one or a few years. The uncertainty and learning also mean that fertility is lower overall and divorces are higher than would be the case had male types been immediately observable. Our results further indicate that a woman is less at risk of abuse from a violent partner when she participates in the labour market. In contrast we find that an increase in a woman's *relative* earnings capacity has at most a modest effect of reducing the rate of abuse by a violent partner.

The latter finding does not imply that higher female wages would not reduce the equilibrium incidence of abuse. Indeed, our counterfactual simulations highlight a clear effect, but this effect occurs mainly through key behavioural responses: divorcing more frequently, delaying fertility, and working more frequently. In other words, better labour market opportunities imply that women are less likely to become trapped in abusive relationships as they are less likely to have children early in relationships and as they are financially better placed to leave bad relationships.

We also explore the potential effects of (i) an increase in the income support available to single mothers, and (ii) subsidized childcare available to households where the mother is working. In each of these two scenarios fertility is encouraged – with the former particularly encouraging single motherhood and the latter particularly encouraging fertility early in relationships. In addition, income support for single mothers leads to lower labour supply over the lifecycle. As a result, more generous income support provided to single mothers perhaps somewhat surprisingly leads to higher exposure to abuse overall. In contrast, subsidized childcare encourages labour force participation which mitigates the effect of early child bearing on exposure to abuse. A worrying unintended consequence of both policies however is that they lead to a higher incidence of abuse experienced by mothers in particular, implying that children are more likely to be exposed to abuse between their parents.

The paper is outlined as follows. Section II describes the ALSPAC sample and some of the key empirical facts that our empirical model will seek to replicate. Section III describes the model, starting with a simple illustrative version before outlining the full empirical version. Section IV outlines the estimation approach while Section V reports the model fit and the parameter estimates. Section VI presents the counterfactual experiments with perfect information, elimination of the gender pay gap, more generous child support and subsidized childcare. Section VII concludes.

II The ALSPAC Data and Key Empirical Features

The Avon Longitudinal Study of Parents and Children (ALSPAC), also known as "Children of the 90s" is a local UK cohort study conducted in the former England county of Avon. The initial recruits were pregnant women with estimated dates of delivery between April 1991 and December 1992.[4] While first and foremost a child development survey, ALSPAC also repeatedly surveyed the mothers of the study children (and their partners). Our female sample population is hence the mothers of the ALSPAC children and we exploit the fact that the mothers were surveyed roughly annually about key events in their lives, including their experience with abuse, up until when the survey child was about 6 years old, yielding a maximum of seven observation years for each female respondent.[5] An advantage to this form of data is that the years following the birth of a child is a key period when women's decisions regarding further fertility and if and when to return to work are particularly salient.

The ALSPAC data provides a unique opportuity for studying the dynamics of domestic abuse, both in terms of incidence and behaviour. To this end, we provide an extensive description of the sample used and the key dynamic patterns in the data in online Appendix A. Here we provide a brief overview of key features. ALSPAC recruited 14,541 pregnant women who returned at least one questionnaire or attended at least one clinic. After restricting the sample (see Data Appendix for details) to women of white ethnic origin, with complete information on basic demographics characteristics and at least one completed post-pregnancy questionnaire, we are left with 9,359 women, with a total of 56,926 person-year observations.

Marriage, Births and Labour Supply

In our analysis we make no distinction between formal marriage and cohabitation as learning about the nature of a partner can be expected to start when first living together. Hence we will use being "married" as synonyous to "living with a partner". The vast majority – 96 percent (Table A.1) – of the women in the sample live with a partner (are "married") at baseline, that

[4] Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees. For a detailed description of the ALSPAC cohort, see Boyd et al. (2013).

[5] The survey mothers completed multiple questionnaires during their pregnancy, one of which included the key questions on partner abuse. Post-birth they were asked to complete surveys with the abuse questions when the study child was aged 8, 21, 33, 47, 61 and 73 months respectively. After that the key abuse-related questions were no longer regularly asked.

is during the ALSPAC pregnancy. However, we observe both separations and entries into new partnerships (a 1.9 percent annual separation rate among with partners and a 12 percent annual partnership entry rate among those single, Table A.2). A concern with the particular data is that many of the women may effectively already have learned their partners' nature before entering the survey. To this end it is essential that many of the women in the sample are in relatively "new" relationships at baseline and we show that this is indeed the case: over 40 percent of women with partners at baseline have lived with those partners for no more than 3 years; similarly, 45 percent of the women in the sample have no previous children. Hence, close to half of the women are first-time mothers (Figure A.1).

All women, per construction of the data, have a birth between the first and the second period in the data. But we also observe the birth of further children. Close to half of the women in the sample have at least one further birth within the sample period: the observed annual fertility rate after the second period is 12 percent (Table A.2). The vast majority of women are not working immediately following the birth of the ALSPAC child. However, over time many return to work. Across all periods we have a 19.9 percent rate of transition from not working to working, either part- of full-time (Table A.2). We delineate three levels of educational attainment – "low", "medium" and "high" – of roughly equal-size based on a standard mapping of academic qualifications into National Vocational Qualification (NVQs) equivalents used by the Office for National Statistics (Table A.1). We impute hourly wages based on detailed information on current or most recent occupation, and we show that wages increase both with age and with qualification level, for both women and men (Table A.3).

The Incidence of Abuse

A key issue is the measurement of abuse. The literature typically advocates strict objective measures (Aizer, 2010; Tertilt and van den Berg, 2015) which is natural in contexts where the research aim is to understand the effect of various factors on the incidence of abuse. Our aim, in contrast, is to understand a woman's behavioural responses to her experience of abuse and the associated changes in her beliefs about the nature of her current partner. In line with this aim, we make use of a self-reported measure of physical and emotional abuse: whether the respondent reports that the partner has been "physically or emotionally cruel" to her since the last survey. Overall, we find that, across all observations, 2.4 and 8.7 percent of women report experiencing physical and emotional abuse respectively over the past year (Table A.4). For our analysis we combine the two into a single indicator of abuse of "any kind" with an average incidence rate of 9.2 percent. While the abuse-related questions are less specific than ones used in many dedicated domestic violence survey modules, it can be shown that the estimated incidence of physical and emotional abuse in our sample is very similar to the best available evidence from the Crime Survey for England and Wales. We also show that the measured abuse is, as expected, higher among younger women than among older women, and higher among the less qualified women than among the more qualified women (Figure A.2).

The value of using longitudinal data becomes clear when we consider the persistence of abuse. We find evidence of a very high persistence: of women reporting experiencing abuse in some period t, 49.5 percent report experiencing abuse again in the following period (Table A.4). A key modelling challenge is capturing this high rate of persistence of abuse experienced by some women.

The incidence of abuse decreases monotonically with partnership duration, from 16 percent in relationships with 0-1 years duration down to 8 percent in relationships with durations of 6 or more years (Figure A.2). This relationship is of course highly endogenous as women select out of relationships based on their experience. As we will show below, this duration-pattern will be instrumental both to understanding the prevalence of violent males and to women's responses to abuse.

As noted above, key discussion in the literature is the relationship between labour supply and abuse. A complication is that this relationship may be bi-directional. Using the longitudinal nature of the data we highlight that there is a U-shaped relationship between labour supply at $t-1$ and abuse experienced between $t-1$ and t: 10 percent of women who were not working a year ago report experiencing abuse over the past 12 months, while those who were working part-time and full-time report abuse at rates of 8 and 9 percent respectively (Figure A.2).

Choices Following Abuse

The longitudinal nature of the data also allows us to explore how women's choices with respect to partnership status, child-bearing and labour supply reflect their experience of abuse.

A controversial question is whether women who experience abuse stay in their relationships. We find that the rate of separation following a period of abuse is about five times (6.3 percentage points) higher than the corresponding rate following a period without abuse (Table A.5). In other words, the data suggests that women do systematically leave abusive partners at a substantially higher rate. However, at the same time it also suggests that women who experience abuse are, in any given period, far more likely to stay than to leave.

What is unique about the current data is that it allows us to consider the dynamic relationship between abuse and fertility. Here we find that the fertility hazard is reduced by about a third (4.6 percentage points) after a period of experiencing abuse. This suggests that a strong response to abuse is to reduce fertility (Table A.5). In general, the dynamic relationship between fertility and abuse will be a central feature of the estimated full model.

Finally, when we look at how women may respond to abuse in term of their labour supply – relating the experience of abuse between $t-1$ and t to labour supply status at time t – the data suggests an increase in labour force participation though the response appears rather modest in the short run (0.5 - 2 percentage points, Table A.5).

III Model

We develop a model of the behaviour of women in an environment where there is heterogeneity among males with respect to their propensity to engage in abuse: some men have a "violent" nature and some do not. We model abuse as non-strategic occurrences of loss of control, though possibly influenced by an underlying gender-tension. A woman who meets a new prospective partner does not directly observe his type; instead she forms a belief which she updates based on her observations of his behaviour.

Women also choose labour supply and fertility. The interaction between learning and fertility is particularly interesting as it leads to the possibility that a woman becomes "trapped" in abusive relationships. Once a woman has children either childcare costs have to be incurred or she will have to lower her labour supply and forego earnings. This makes it more financially difficult for her to divorce once children are present and as a consequence she will be more prone to stay even if that means suffering abuse. To avoid this she can delay fertility until she knows her husband's type better and also use that delay to gain further labour market experience. Thus delaying fertility and building labour market experience act as a type of insurance that increases her flexibility in case she discovers that her partner is of the violent type.

Before presenting the full empirical model we will begin by presenting a simple illustrative version that ignores labour supply and fertility but introduces the core learning structure. In particular, we will use this simple model to highlight how the main type- and learning structure allows us to replicate key features in the data relating to the incidence of abuse.

A Simple Illustrative Version

Consider a population of women who are facing an infinite time horizon, $t = 1, 2, ...$, and who in any given period t are either single or married, $m_t \in \{0, 1\}$. Normalize the instantaneous utility of being single to zero and the systematic utility of being married, denoted ψ^m, to unity. Additionally, let ε_t^m be a temporary marriage utility shock which is normally distributed with zero mean and variance σ_m^2.

A currently married woman can either remain married or divorce. Single women receive marriage offers at rate ς from randomly drawn prospective partners. Men are of two possible types, $r \in \{0, 1\}$, who differ in their propensity for abuse: a "non-violent type" $(r = 1)$ and a "violent type" $(r = 0)$. A woman receiving a marriage offer does not observe the male's type. Let $\phi_b = E[r] \in (0, 1)$ be the probability of him being non-violent. ϕ_b thus also represents the woman's initial beliefs.

Let $z_t \in \{0, 1\}$ indicate abuse in period t and let $\chi_r = \Pr(z_t = 1|r)$ denote the probability that a type-r male is abusive. We assume that $0 < \chi_1 < \chi_0 < 1$. A woman updates her beliefs based on her husband's behaviour. Under standard Bayesian updating, a woman who holds beliefs ϕ_{t-1} going into period $t - 1$ and who *does not* experience any abuse in that period will hold the next period belief

$$\phi_{t|z_{t-1}=0} = \frac{\phi_{t-1}(1-\chi_1)}{\phi_{t-1}(1-\chi_1) + \left(1-\phi_{t-1}\right)(1-\chi_0)}, \tag{1}$$

whereas if she *does* experience abuse her next period belief will be

$$\phi_{t|z_{t-1}=1} = \frac{\phi_{t-1}\chi_1}{\phi_{t-1}\chi_1 + \left(1-\phi_{t-1}\right)\chi_0}. \tag{2}$$

Abuse is associated with a instantaneous disutility $\psi^z > 0$. Hence the expected disutility from abuse in period t for a married woman with current beliefs ϕ_t are $\pi(\phi_t)\psi^z$, where $\pi(\phi_t) = \phi_t\chi_1 + (1-\phi_t)\chi_0$. Letting δ denote the discount rate, the model can be solved using basic dynamic programming. In particular, there will be a present discounted value $V^m(\phi_t)$ associated with entering a period as married with belief ϕ_t and a value V^s associated with entering a period as single.[6] A woman with current belief ϕ_t will choose marriage over singlehood if

$$\psi^m + \varepsilon_t^m - \pi(\phi_t)\psi^z + \delta\left[\pi(\phi_t)V^m\left(\phi_{t+1|z_t=1}\right) + (1-\pi(\phi_t))V^m\left(\phi_{t+1|z_t=0}\right)\right] \geq \delta V_s, \tag{3}$$

[6] Formally, $V^m(\phi_t)$ and V^s satisfy

$$V^m(\phi_t) = E_{\varepsilon_t^m}\left[\max\left\{\psi^m + \varepsilon_t^m - \pi(\phi_t)\psi^z + \delta\left[\pi(\phi_t)V^m\left(\phi_{t+1|z_t=1}\right) + (1-\pi(\phi_t))V^m\left(\phi_{t+1|z_t=0}\right)\right], \delta V_s\right\}\right]$$

and $V^s = \varsigma V^m(\phi_b) + \delta(1-\varsigma)V^s$ respectively.

which means that there will be a threshold ε_t^m below which she will divorce. Moreover, this threshold value will be a decreasing function of ϕ_t, creating a positive link between abuse and divorce.

The model can be easily calibrated and doing so is instructive as it illustrates how some of the core parameters are identified from key empirical moments in the data. Such a calibration is shown in Table 1.[7] The observed overall annual divorce rate is 1.9 percent (Table A.2), but it is substantially higher following abuse than following non-abuse (7.5 percent and 1.4 respectively – see Table 2 below). These moments are informative about ψ^z and σ_m^2. The fact that women who experience abuse are markedly more likely to divorce than those who don't, while at the same time also being more likely to remain married than to divorce, indicate that the disutility term ψ^z is substantial but also below the (normalized) systematic utility of marriage, ψ^m. The frequency of divorce after non-abuse is informative about the size of the match quality shocks.

Calibrated Moments		**Parameter**	
Singlehood duration	7 yrs	$\varsigma = 0.15$	Meeting rate
Divorce rate after non-abuse	0.014	$\sigma_m^2 = 2.72$	Match quality shock variance
Divorce rate after abuse	0.075	$\psi^z = 0.34$	Abuse disutility
Abuse persistence	0.495	$\chi_0 = 0.58$	Abuse rate: violent males
Abuse rate at zero duration	0.162	$\chi_1 = 0.02$	Abuse rate: non-violent males
Abuse rate overall	0.092	$\phi_b = 0.72$	Proportion non-violent

Table 1: A calibration of the simple illustrative model.

The duration of singlehood relates to ς. We do not have any direct measure of this duration in the data, but based on the rate of entry into new partnerships (Table A.2) and on the average age at first birth (see Table B.1 below), we can approximate this as about seven years. Not all marriage proposals are accepted, but most are, whereby ς is closely above the inverse of this duration.[8]

The final three parameters – χ_0, χ_1 and ϕ_b – can be set to match key empirical moments of abuse. First, in order to generate a high abuse persistence (Table A.4), it has to be that some males are high repeat abusers, in particular χ_0 has to be well above 0.5. Second, the incidence at the start of a relationship (Figure A.2, panel c) is a direct linear combination of three parameters, $\phi_b\chi_1 + (1-\phi_b)\chi_0$, whereas the overall incidence rate (Table A.4) is significantly lower due to selective divorces.

[7] In this calibration we have set the discount parameter to $\delta = 0.95$.

[8] Note that a woman is as likely to accept a new partner as she is to remain married at belief ϕ_b.

The calibrated parameters are highlighted in Table 1. As we will see, the insights from this simple exercise will carry over to the main model below. For instance, the estimated main model will suggest a similar size of disutility of abuse relative to the systematic utility of marriage, and similar values for the abuse rates by male types, and a similar type frequency among males.

This also means that the current simple model can be used to gauge the speed of learning. Given the sharply different behaviours of violent and non-violent males, learning will generally be quite fast. Consider for instance a large set of women who all marry randomly selected partners at some time t and remain married for at least three periods. Using the calibrated values of χ_0, χ_1 and ϕ_b, after three periods, close to 70 percent of the women will have not experienced any abuse and will hold a belief that the partner is non-violent that is well-above 0.95. Conversely, close to 20 percent of the women will have experienced two or three periods of abuse and will hold a belief that is below 0.01. In other words, within three periods of marriage, the vast majority of women will be nearly certain about the true nature of their partners, in either direction.

The Full Empirical Model

While the illustrative model was useful for setting the stage for the learning environment and for highlighting how heterogeneity among men is essential for understanding the dynamic patterns of the incidence of abuse, it is also limited due to its focus on a stationary environment. In order to build in key dimensions, such as fertility and the accummulation of work experience, and in order to make our model more useful for policy analysis, we need a lifecycle model.

Setup

The full version that we take to the data models women's choices with respect to marital status, employment status and child-bearing from the time of entry into adulthood until the end of their fertile period, age 16 to 44, a total of $T = 29$ periods. In each period $t = 1, ..., 29$ there are three mutually exclusive employment states $k_t \in \{0, 1, 2\}$, representing not-working, working part-time and working full-time respectively. As before $m_t \in \{0, 1\}$ indicates whether the woman lives with a male partner ("married") or not, and we let $f_t \in \{0, 1\}$ indicate the choice whether or not to conceive a child at time t.

Each woman maximizes her present value of lifetime utility, discounted at rate δ. The utility flow in period t is specified as

$$U_t = \frac{\mu^{k_t} C_t^{1-\lambda}}{1-\lambda} + \left(\Psi_t^m - \bar{\Psi}_t^z\right) m_t + \Psi_t^n, \tag{4}$$

where C_t is her level of consumption, μ^{k_t} varies with the employment state k_t, and λ is the parameter of relative risk aversion. μ^0 is normalized to unity while μ^1 and μ^2 are constrained to the unit interval to capture disutility of work effort. The following term, which is enjoyed by the woman only if she chooses to be married in period t, includes the direct utility of marriage Ψ_t^m and the expected disutility from abuse $\bar{\Psi}_t^z$. The final term, Ψ_t^n, captures the direct utility of children. The Ψ-terms will be further specified below.

Since the unit of time is taken to be a year, consumption and earnings are annual values. The consumption enjoyed by the woman at time t is

$$C_t = \begin{cases} \tau\left(w_t + w_t^h - c_t\right) & \text{if } m_t = 1 \\ w_t - c_t & \text{if } m_t = 0 \end{cases}, \tag{5}$$

where w_t and w_t^h are her own and her husband's annual earnings at t respectively, τ is an income sharing parameter, and, c_t represents annual child-related costs and incomes (specified further below).

Wages, Experience and Child-Related Costs

When not working the woman receives a fixed basic unearned income $w^0 > 0$. If she is in work, her earnings associated with part- and full-time work are

$$w_t^k = \exp\left(\beta_0^k + \beta_1^k a + \beta_2^k x_t + \beta_3^k x_t^2 + \varepsilon_t^k\right), \text{ for } k = 1, 2, \tag{6}$$

respectively, where $a \in \{0, 1\}$ is a fixed individual characteristic that captures permanent heterogeneity among women in earnings capacity and where x_t measures her accumulated work experience. A woman's permanent productivity type a is assumed to be stochastically related to her observed educational attainment level, which, as described in Section II, is either "low", "medium", or "high", $q \in \{0, 1, 2\}$. We specify the relationship between q and a to be logistic,

$$\Pr(a = 1|q) = \frac{\exp\left(\beta_0^a + \beta_1^a d_{q=1} + \beta_2^a d_{q=2}\right)}{1 + \exp\left(\beta_0^a + \beta_1^a d_{q=1} + \beta_2^a d_{q=2}\right)}, \tag{7}$$

where d_q is a dummy for educational attainment level q and where low educational attainment is the base category.

Work experience, which is accumulated according to,

$$x_{t+1} = x_t + k_t, \tag{8}$$

starts from the initial condition of zero. Her work experience thus increases by one unit if she works part-time and by two units if she works full-time. Finally, the part-time and full-time wage offers at time t include distinct temporary productivity shocks, ε_t^k, $k = 1, 2$.

The husband's earnings in equation (5) is specified in a similar way as

$$w_t^h = \exp\left(\beta_0^h + \beta_1^h a + \beta_2^h t + \beta_3^h t^2 + \varepsilon_t^h\right), \tag{9}$$

where ε_t^h is also a temporary productivity shock. The presence of the woman's own permanent productivity type a in the husband's wage offer equation (9) captures a systematic spousal wage correlation, representing assortative mating on ability. Married couples also tend to be similar in age and we assume for simplicity that they are of the same age. Since men are assumed to always be working FT in our model, their experience increases linearly with time t.

The distribution of the temporary productivity shocks is joint normal, $(\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^h) \sim N(0, \Sigma)$ with covariance matrix $\Sigma = AA'$ where A is the Cholesky decomposition. A is restricted for identification reasons so that

$$A = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{h1} & 0 & a_{hh} \end{bmatrix}. \tag{10}$$

The child-related costs and incomes c_t have two basic components. The first component is childcare costs. The maximum childcare costs are assumed to be quadratic in the number of children. A fraction ρ^{k_t} of the maximum childcare cost is incurred at labour supply level k_t, where we normalize $\rho^2 = 1$ and estimate ρ^1 and ρ^0. The second component of c_t is income support that accrues to single mothers. Such income may come from alternative sources, including out-of-work benefits, in-work benefits, and child-support payments from the biological father.[9] Given the potential multiple sources, we will model child-related income to single mothers in the simplest possible way as a quadratic function of the number of children and include it in the

[9] During the period of study, "Income Support" (IS) was the main out-of-work benefit in the UK, with a maximum benefit that depended on the number and ages of children and that also included a lone-parent premium. Eligibility for IS was conditional on not working more than 16 hours/week. The in-work benefit system at the time was "Family Credit" (FC) which was designed for families with children where at least one person is working more than 16 hours/week. Lone mothers were a main recipient group for both IS and FC.

estimation. Hence we specify the two components of c_t as follows

$$c_t = \rho^{k_t} \left(\beta_1^{cc} n_t + \beta_2^{cc} n_t^2\right) - \left(\beta_1^{ci} n_t + \beta_2^{ci} n_t^2\right)(1 - m_t)\,, \tag{11}$$

where the first term enters positively as it represents a cost and the second negatively as it represents income.

Marriage, Abuse, and Learning

The marriage and learning side of the model follows the simplified version above. A woman who enters period t as married can choose to remain married or divorce. A single woman meets a new prospective partner with probability $\varsigma \in (0,1)$, with men being of two possible types, $r \in \{0,1\}$.[10] The fraction of encountered men who are of the non-violent type is ϕ_b^q, where the superscript q indicates that we allow the male type distribution to depend on the woman's level of qualification.

Abuse $z_t \in \{0,1\}$ is realized after the woman has decided on her current level of labour supply k_t and made her current conception decision f_t. Hence a married woman makes these decisions under uncertainty about potential exposure to abuse. In the simple version above, the probability of abuse, χ_r, depended on the male's type only. In the full model we retain the feature that non-violent males ($r = 1$) are abusive with some small fixed probability χ_1. However, for the violent type ($r = 0$), we extend our modelling so as to allow for various factors to influence the abuse probability. Specifically, we model the abuse realization as a combination of an underlying "gender tension" component and a random emotional cue. The systematic gender tension element allows us to incorporate aspects of various abuse theories, including exposure, bargaining and gender-identity theory, whilst the emotional cue element allows us to model the incidence of abuse as a stochastic loss of control.

Consider first the systematic gender tension element. Pure exposure theory (Dugan et al., 2003) would suggest that tension depends on the woman's labour supply: the more she works, the less time she spends in the household and thus the lower is exposure. Bargaining theory would suggest that improvements in her relative earnings capacity would strengthen her bargaining position and enable her to secure a reduction in the incidence abuse. Conversely, however, gender identity theory would suggest that the woman working more and/or having a higher relative

[10] Note that we are not using any time subscript on the husband's type to indicate that his type is fixed. Nevertheless, it should be clear that if a woman remarries, her next husband may be of a different type.

earnings capacity may challenge the male's identity and thereby increase gender tension. As the different theories make opposing predictions, we will model gender tension in a general fashion as

$$\varrho_t\left(k_t, \overline{w}_t^2, \overline{w}_t^h, t\right) = \alpha + \sum_{k=1,2} \chi_0^k d_t^k + \chi_0^w \log\left(\overline{w}_t^2\right) + \chi_0^h \log\left(\overline{w}_t^h\right) + \chi_0^t t, \tag{12}$$

where d_t^k is a dummy indicating whether $k_t = k$, and where $\overline{w}_t^2$ is the deterministic part of the woman's potential full-time earnings and $\overline{w}_t^h$ correspondingly is the deterministic component of the husband's current earnings. Exposure theory would suggest that $\chi_0^2 < \chi_0^1 < 0$ as the woman working more reduces tension by reducing exposure. In contrast, gender identity theory would suggest that her working increases tension. If $\chi_0^w = -\chi_0^h$, only *relative* earnings capacity would matter, and bargaining theory would suggest that $\chi_0^w < 0$ while gender identity theory would suggest the opposite. The final term in allows for a direct effect of time of age, allowing for instance for the possibility that young men are more susceptible to losing control.

While gender tension ϱ_t increases the *probability* of abuse, the realization of abuse is also driven by random emotional cues, denoted ϵ_t, which we take to be i.i.d. extreme value distributed across individuals and time periods. Abuse is assumed to occur when the combination of ϱ_t and ϵ_t "tips over" and becomes positive, $\varrho_t + \epsilon_t \geq 0$. Using the extreme value distribution of the emotional cues, it follows that the current risk of abuse from a violent partner is given by the logit function

$$\chi_0\left(k_t, \overline{w}_t^2, \overline{w}_t^h, t\right) = \frac{\exp\left(\varrho_t\left(k_t, \overline{w}_t^2, \overline{w}_t^h, t\right)\right)}{1 - \exp\left(\varrho_t\left(k_t, \overline{w}_t^2, \overline{w}_t^h, t\right)\right)}. \tag{13}$$

The dependence of the abuse probability on the woman's earnings capacity and labour supply generates potentially important incentive effects. For instance a woman who experiences abuse may switch to a level of labour supply with relatively low abuse risk and/or she may choose to increase her labour supply in order to build up her work experience and future earnings capacity.

A woman's beliefs ϕ_t are updated exactly as in (1) and (2) while taking into account that χ_0 is given by (13). The expected disutility from abuse for a married woman with current belief ϕ_t in (4) is given by $\bar{\Psi}_t^z = \pi\left(\phi_t, k_t, \overline{w}_t^2, \overline{w}_t^h, t\right)\psi^z$ where

$$\pi\left(\phi_t, k_t, \overline{w}_t^2, \overline{w}_t^h, t\right) = \phi_t \chi_1 + (1 - \phi_t)\chi_0\left(k_t, \overline{w}_t^2, \overline{w}_t^h, t\right), \tag{14}$$

is her perceived probability of experiencing abuse in the current period and where

$$\psi^z = \psi_0^z + \psi_a^z a, \tag{15}$$

is the direct disutility of abuse. In order to allow for potential heterogeneity in "tolerance" of abuse, we allow in (15) for the possibility that high productivity type women ($a = 1$) have a different disutility of abuse compared with low productivity type women ($a = 0$).

Conceptions

If a woman decides to become pregnant at time t, she will give birth before the start of the following period. Thus letting n_t denote her number of children, we have that

$$n_{t+1} = n_t + f_t. \tag{16}$$

The direct utility from children and conception in (4) is specified as

$$\Psi_t^n = \beta_1^n n_t - \beta_2^n n_t^2 + f_t \varepsilon_t^f, \tag{17}$$

where ε_t^f is a temporary utility shock from conceiving a child, assumed to be normally distributed with zero mean and variance σ_f^2. As in the simple model we assume that the (direct) utility of marriage has a deterministic and a stochastic part so that

$$\Psi_t^m = \psi^m + \varepsilon_t^m, \tag{18}$$

where ε_t^m is normally distributed with zero mean and variance σ_m^2. The random utility can be interpreted as a temporary match quality shock. The utility shocks ε_t^f and ε_t^m are assumed to be independent of the earnings shocks and of each other.

Before proceeding to the estimation, it is worth highlighting some of the key restrictions imposed on the model in particular with respect to how abuse interacts with children. Note first that the specified abuse probability function in (13) does not depend on the presence or number of children. We will argue below that the model fits the data very well without any such direct link. In particular, we will show that (i) as an empirical stylized fact, women experience an increase in the incidence of abuse following their first birth and that the current model replicates this finding, and (ii) there is no strong empirical relationship between abuse and number of children among mothers and that this is also replicated with the current parsimonious specification. Second, note also a woman's disutility from abuse, specified in (15), does not depend on the children. This restriction mainly reflects that it is difficult to identify any such effect using the current data as all women in the data either are or are about to become mothers.[11]

[11] We have made attempts at including the number of children as a determinant of the disutility of abuse but found that the fertility then become overly sensitive to this parameter.

IV Estimation

The model is estimated using the method of simulated moments (McFadden, 1989; Pakes and Pollard, 1989). This approach entails, for any trial parameters, first solving the model using backwards induction. In doing this we are using a full numerical solution method, solving the $Emax$ function at every $t = 1, ..., T$ (Keane and Wolpin, 1994). The deterministic part of state space at time t is $\{n_t, \phi_t, x_t, m_{t-1}, k_{t-1}, t, q, a\}$. After solving, the model is then forward-simulated to obtain simulated panel data with lifecycle paths for a large number of individuals with a distribution of observable characteristics that correspond to those observed in the data.

Simulated Population and Sampling

For any trial parameters outcomes are simulated for 15,000 women with a distribution of academic qualifications – the only source of observed initial heterogeneity – as observed in the data. When computing the simulated moments we focus on outcomes between the ages 17 to 40 to help correct for the initial conditions problem and end-of-horizon effects.

To account for the choice-based sampling frame used by the ALSPAC, we adopt a corresponding sampling frame on our simulated data. In particular, when computing the matched moments on the simulated data, we include every birth from the moment of conception along with the following six periods for that woman.[12] This places us as close as possible to the timing of the ALSPAC sampling frame, where women are first observed a few months into the study pregnancy.[13]

Identification

Overall, 47 parameters are estimated using 93 empirical moments that are both static and dynamic in nature. Here we discuss how the model parameters are identified.

[12] The fact that we match the distribution of the number of children among mothers also means that the births included in our simulated moments have the same distribution of birth order as the ALSPAC survey children.

[13] Standard errors are obtained by taking the square root of the diagonal elements of the variance-covariance matrix $Q_S(W) = \left(1 + \frac{1}{S}\right)\left[\frac{\partial b(\theta_0)'}{\partial \theta} W^* \frac{\partial b(\theta_0)'}{\partial \theta}\right]^{-1}$ where $\partial b(\theta_0)' / \partial \theta$ is the first derivative of the vector of moments b with respect to the parameter vector θ. S is the number of simulations $(15,000*24)$ and W is the weighting matrix. We use the identity matrix for W and set $1/S = 0$, given the large number of simulations $(1/S = 0.000003)$. Use of the identity matrix rather than an ideal weighting matrix only reduces efficiency. $\partial b(\theta_0)' / \partial \theta$ is numerically approximated using parameter bump sizes that vary between .01% and 1% depending on the sensitivity of the moments.

In the simple version of the model above, we argued that the type frequency ϕ_b and the type-specific behaviours, χ_1 and χ_0, were identified from the persistence of abuse, the abuse risk in the early stages of a relationship, and the overall level of abuse. The same logic continues to apply in the full model. More generally, with longitudinal data, the binary male type distribution in the within and across distribution of abuse. In particular, with two types of males, some women will experience a low abuse frequency while others will experience a high abuse frequency. Hence the count distribution of abuse over the seven periods of data is strongly informative about the core type structure.[14] The underlying heterogeneity among men is further identified from the women's observed behaviour within marriage by shaping the learning environment. Hence, for instance, the general fertility delay within marriage and the fertility response to abuse and non-abuse – reflect their speed of learning which in turn provides information about the distribution and behaviour of male types.

Also as in the simple version, the overall divorce probability and the divorce probability specifically after abuse help identify the size of the marital utility shocks and the disutility of abuse.[15] Note that the rate at which women selectively divorce abusive males will also be strongly identified by the empirical relationship between abuse risk and partnership duration. The rate at which single women marry also continue to identify the arrival rate of potential partners.

In the full model we allow the male type frequency to vary with the woman's qualification level and to identify this variation we match abuse rates by qualification. In order to identify the parameters of the gender-tension function (12), we match how abuse risk varies with labour supply, age, and potential earnings.

The remaining set of moments included in estimation can be broadly split into two main groups by what they help to identify. The first group contains moments related to employment (employment transitions and employment status by age, marital status, and qualifications) and wages (by employment level and qualification level, and for husbands). These moments strongly identify the parameters associated with the wage offer functions, the unobserved ability structure, the disutility of work effort, income associated with non-employment, and the correlation

[14]For instance, we will argue below that the observed count distribution would be inconsistent with all men being of a single type.

[15]Interestingly, the observed rates of abuse help identify the marital utility shock, which has been difficult to identify in discrete choice dynamic programming models that do not incorporate domestic abuse data (see e.g., Keane and Wolpin (2010) and Sauer (2015)).

between per-period earnings shocks. The identified earnings structure combined with the observed marriage rate further identifies the sharing parameter. The second main group of empirical moments relates to fertility, including average age and average partnership duration at first birth, the distribution of completed fertility, the proportion of out-of-wedlock births, and birth rates for single and married women. These moments help identify the utility of children, conception utility shocks, child-related costs, and the level of income-support for lone mothers.[16]

The discount factor and the parameter of relative risk aversion are not estimated but rather fixed at levels consistent with previous literature. The discount factor δ is set at 0.95 and the parameter of relative risk aversion λ is set at 0.7. Identification of δ and λ is a common problem in discrete choice dynamic programming models.

As noted above, we expect the speed of learning to be quite high. Hence it is important that we observe a large number of women making decisions in the early stages of partnerships. Fortunately, about 20 percent of all our person-year observations – close to 12,000 observations – are for partnerships with a current duration of no more than four years. Moreover, these observations account for about a third of all subsequent births and also about a third of all divorces. As a check that our estimated full model fits the behaviour of women in the earlier stages of partnerships we will also present the fit to empirical moments specifically for first time mothers.

V Estimation Results

In this section, we report the results from the estimation of the full model presented in Section III. We first present the moments included in the estimation and the estimated model's fit to these moments. We then present the fit to a further set of moments, including moments relating to the association between children and abuse. Finally, we present and discuss the parameter estimates.

[16] As an auxiliary moment we include the fraction of women who remain childless. As this empirical moment, per construction, cannot be computed in the ALSPAC data, we obtain it from Table 3 in ONS (2013).

Moments and Model Fit

Fitted Moments

A comparison of empirical and simulated moment values are presented in Table 2 below along with Tables B.1 to B.3 in Appendix B. Table 2 presents abuse-related moments. Table B.1, B.2, and B.3 presents moments related to marriage/fertility, employment (labour supply status by age, qualification level and marital status, and employment transitions), and hourly wages (by labour supply status, of husbands, and by qualification level respectively).

We focus here particularly on how the model fits core moments in relation to abuse. Looking first at abuse, Panel A of Table 2 shows that, in line with the simple illustrative model above, the full empirical model replicates quite closely the overall level of abuse and the abuse transitions. Closely related, the model predicts very well also the count distribution of abuse incidents (Panel B) over the seven periods.[17] Importantly for the identification of the type-structure and selective divorce behaviour, Panel C shows that the model captures well how the incidence of abuse varies with partnership duration.

Panel D shows that the model somewhat over-predicts the qualification gradient in abuse. It should be noted that the model predicts that high qualified women experience a markedly lower rate of abuse even though the parameter estimates do not suggest that they meet violent men at a particularly lower rate (see below). Instead, their lower incidence of abuse for high qualified women reflect them more frequently working and having fewer children and having them later.

The model captures that abuse declines with age, but somewhat under-predicts the particularly high abuse incidence among young mothers (Panel E). It further replicates the U-shaped relationship between the level of labour supply and exposure to abuse (Panel F), implying that part-time work is the labour supply status least associated with abuse. As will be seen below, the estimated abuse-probability function indicate very little direct difference between part- and full-time work. Instead, the observable difference is explained by endogenous labour supply choices: part-time work tends be chosen by women with more positive beliefs about their

[17] The shape of the count distribution, just as the persistence of abuse, lends strong support to the two-type specification. For instance, a standard χ^2 goodness-of-fit test can be used to reject that the observed count distribution is generated by a binomial process where abuse is i.i.d. over all women and periods. Specifically, a binomial distribution with seven draws and an abuse probability given by the mean abuse rate would have a significantly lower incidence of zero occurrences and also of three or more occurrences. In the ALSPAC data, this moment is computed on the subsample of women who are available for the full seven periods.

Panel A: Abuse Rate and Abuse Transitions			
	Mean	No Abuse at $t+1$	Abuse at $t+1$
No abuse at t	0.904	0.943	0.057
	0.908	*0.943*	*0.057*
Abuse at t	0.096	0.505	0.495
	0.092	*0.549*	*0.451*
Panel B: Count Distribution of Abuse Incidents			
0	1-2	3-4	5+
0.748	0.169	0.057	0.026
0.704	*0.192*	*0.068*	*0.036*
Panel C: Abuse Rate by Partnership Duration in Years			
0-1	2-3	4-5	7+
0.162	0.117	0.093	0.079
0.194	*0.157*	*0.124*	*0.067*
Panel D: Abuse Rate By Qualification Level			
Low Qual.	Medium Qual.	High Qual.	
0.101	0.094	0.085	
0.113	*0.105*	*0.055*	
Panel E: Abuse Rate By Age Group			
Age 17-24	Age 25-32	Age 33-40	
0.144	0.087	0.085	
0.102	*0.087*	*0.091*	
Panel F: Abuse Rate By Labour Supply at $t-1$			
Not Working	Part-Time	Full-Time	
0.101	0.084	0.106	
0.097	*0.082*	*0.100*	
Panel G: Abuse Rate By Potential Income Quartile			
Q1	Q2	Q3	Q4
0.105	0.097	0.087	0.074
0.124	*0.118*	*0.069*	*0.058*
Panel H: Divorce and Birth Rate by Abuse Status at $t-1$			
Divorce Rate if		Birth Rate if	
Non-Abused	Abused	Non-Abused	Abused
0.014	0.075	0.126	0.075
0.011	*0.049*	*0.099*	*0.073*

Table 2: Matched moments: abuse.

partners' nature, with longer partnership duration, and with a larger number of children. In contrast, full-time work is more relatively more commonly chosen by women with less positive expectations about their partners' nature, with shorter marriage duration and with fewer children.

Panel G highlights the relationship between potential earnings (hourly full-time wage) quartile and incidence of abuse, showing a clear negative gradient. The estimated model exhibits a similar, thought somewhat steeper, gradient. Finally, Panel H shows that the model predicts well that women who experience abuse at time t are substantially – about five times – more likely to divorce in the following period, and also substantially less likely to conceive a further child.

The fit to all other moments used in the estimation are presented in Tables B.1 to B.3 in Appendix B. Table B.1 shows that the model fits the marital transitions well. The empirical annual birth rates are for the periods following the birth of the ALSPAC child and hence capture births of subsequent siblings, and the simulated birth rates are computed in the corresponding way. The model slightly overpredicts births to single women but predicts well the proportion of women who remain childless and the distribution of number of children among those who do have children. Importantly, the model predicts the timing of first births very well, both in terms of the mother's age and in terms of partnership duration. It also replicates fairly accurately the average duration at divorce.

Table B.2 shows the model's fit to labour supply moments. The table shows that the model replicates a key set of stylized facts well: (i) the majority of transitions into employment in the specific population of mothers with young children are into part-time employment; (ii) younger mothers are the least likely to work whereas older mothers are the most likely to work part-time; (iii) single mothers work less than married mothers, and that married mothers are particularly likely to work part-time; (iii) more qualified mothers work more than less qualified mothers. Table B.3 shows that the model correctly predicts that the accepted wages of full-time workers exceed those of part-time workers. The model also predicts a realistic qualification gradient for accepted hourly wages.

Additional Moments

As an important check we also consider the fit to a number of unmatched moments. Consider first the relationship between abuse and children. We refrained from making the gender-tension function (13) depend on the presence/number of children. In the top panel of Table B.4 in Appendix B we compare the model-predicted incidence of abuse by number of children to the corresponding moments in ALSPAC. In the data, this relationships is very weak, only exhibiting a very modest U-shape. A similar small U-shape is predicted by the model.

More interesting is how the incidence of abuse evolves around child-birth. Figure 1 plots the incidence of abuse over time for first time mothers starting in pregnancy ($Time = 0$). In terms of the ALSPAC data, the initial observation is based on the reports by first time mothers to be from the early stages of their pregnancies, with the 12-month period in question thus relating mainly to abuse experience pre-pregnancy. We compare this to the model-simulated abuse in the last period before a woman becomes first-time pregnant. Both in ALSPAC and in the simulated data, the rate of abuse increases substantially between pre- and the post-pregnancy. It is striking that the model replicates this pattern almost perfectly without these moments being matched and without having the abuse probability function depending on the presence of children. The logic behind this however is a reverse causality relating to the underlying learning structure. Women in the model choose to conceive in response to positive beliefs about the partner's nature induced by the absence of abuse. Stated differently, pregnancies and births do not per se increase women's exposure to abuse – they occur as a response to an initial absence of abuse.

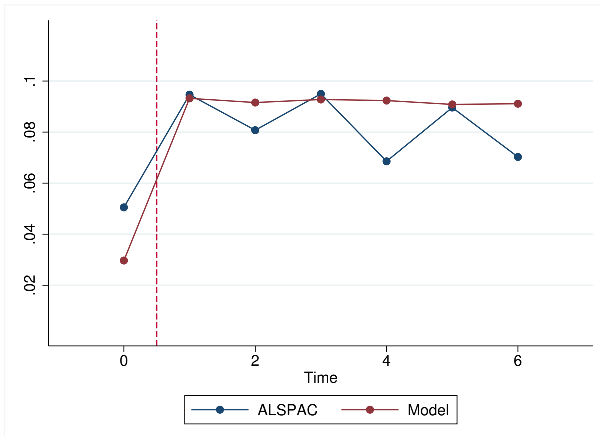


Figure 1: Abuse frequency by period relative to time of first birth.

The estimated model further did not match how the married rates and divorces varied across qualification levels for women. The lower panel of Table B.4 first shows the proportion married by qualification level. There is a marked positive gradient in the data and a similar gradient occurs in the simulated model, reflecting a stronger financial incentive for more qualified women to marry under the assumed assortative mating. The table also reports the empirical and predicted divorce rates, both following abuse and non-abuse, by qualification level. In the absence of abuse, and mirroring the marriage incentives, the divorce rate decreases with qualifications in the data. Part of this gradient is replicated in the simulated model. There is no strong qualification pattern in the divorce rate following abuse neither in the data nor in the simulated model.

It can be argued that first time mothers, who have, on average, spent shorter time with their partners, may experience a different pattern of abuse and may react differently. Table 3 explores how the estimated model fits the data for first time mothers in particular by focusing on the subsample of ALSPAC women who were pregnant with their first child at baseline. The top panel reports the abuse incidence and dynamics. While the average abuse rate is slightly lower for first time mothers, the most striking finding is that the abuse dynamics are effectively the same for first time mothers as for the women in the full ALSPAC sample (Table 2).[18] The fact that the abuse dynamics are not systematically different for first time mothers lends support to the assumption that men with a violent type do not (or fail to) strategically conceal their abusive nature early on in relationships.

The lower panel of Table 3 reports on the divorce and subsequent fertility behaviour of the first time mothers. The observed divorce behaviour of the first time mothers is not markedly different to that for all women in the sample (see Table 2), neither after abuse nor after non-abuse. The observed subsequent birth rates are, by nature, higher for first time mothers than for women with previous children. Hence the birth rates reported in Table 3 differ in level to those in Table 2. Nevertheless, the observed proportional reductions in fertility following abuse are similar for first time mothers compared to all women in the sample. This observed similarity of responses to abuse by first time mothers is well replicated by the estimated model.[19]

Panel A: Abuse Incidence			
		Time $t-1$	
Time t	Mean	Not Abused	Abused
Abuse Rate (any)	0.078	0.053	0.456
	0.090	*0.058*	*0.430*

Panel B: Divorce and Birth Rate by Abuse Status at $t-1$			
Divorce Rate if		Birth Rate if	
Not Abused	Abused	Not Abused	Abused
0.013	0.076	0.202	0.124
0.009	*0.043*	*0.184*	*0.133*

Table 3: Moments for first time mothers.

Parameter Estimates

The estimated parameters are reported in Tables 4 and 5, with Table 4 presenting the β-coefficients from equations (6), (7) (9), (11) and (17), and Table 5 reporting all remaining

[18]The overall incidence rate for mothers with previous children at baseline was 10.0 percent, their onset rate was 5.9 percent and their persistence rate was 49.5 percent.

[19]We have further explored whether women who divorce after reporting abuse are more likely to report abuse also in any future relationships. However, the sample proved too small to determine any such relationship: less than fifty women were observed in new relationships after divorcing with a history of abuse.

parameters.

Panel A: Wage Offer Functions				
	Non-Emp.	PT Emp.	FT Emp.	Husband
	$log(w^0)$	$log(w_t^1)$	$log(w_t^2)$	$log(w_t^h)$
Constant	7.266	7.204	7.775	9.525
	(0.107)	(0.002)	(0.002)	(0.001)
a		0.690	0.831	0.043
		(0.001)	(0.001)	(0.000)
x_t		0.106	0.106	
		(0.000)	(0.000)	
$x_t^2/100$		-0.206	-0.206	
		(0.000)	(0.000)	
age_t				0.017
				(0.000)
$age_t^2/100$				-0.001
				(0.000)
Panel B: Child-Utility, Childcare Costs and Income Support				
	Child Utility	Childcare Cost	Income Support Single Mothers	
n_t	0.756	5,168.91	3,029.83	
	(0.001)	(0.129)	(0.041)	
n_t^2	-0.004	-212.95	-664.28	
	(0.000)	(0.022)	(0.012)	
Panel C: Ability Probability Function				
Constant	0.255			
	(0.002)			
$q = 1$	0.418			
	(0.001)			
$q = 2$	0.996			
	(0.000)			

Table 4: Parameter estimates: linear equations.

Consider first the earnings regressions in Panel A of Table 4. The female earnings equations imply that high-ability women earn 2 - 2.3 times as much as low ability women. The annual earnings growth ranges from about 20 percent for FT working women at the early career states down to zero for women who have worked FT for fifteen years. The estimated maximum childcare costs presented in Panel B (incurred in full if working FT) are substantial, ranging from close to £5,000 per year with one child to over £13,000 with three children. The estimated child-related income available to single mothers is also substantial, ranging from £2,300 per year with one child to over £3,000 with 2 or 3 children.

Panel C presents the estimated relationship between the observable qualifications and the unobservable ability types. The probabilities of being high ability ($a = 1$) if low-, medium-, and high-qualified are 0.56, 0.66 and 0.78 respectively. Hence the low ability women are a minority group concentrated among the low and medium qualified.

Panel A: Preference Parameters				
Marriage		Fertility	Work Effort Cost	
ψ^m	σ_m^2	σ_f^2	μ_1	μ_2
338.87	773.95	1.703	0.999	0.958
(0.005)	(0.027)	(0.001)	(0.000)	(0.000)
Panel B: Abuse Parameters - Types/Disutility				
$\phi_b^{q=0}$	$\phi_b^{q=1}$	$\phi_b^{q=2}$	ψ^z	ψ_a^z
0.636	0.645	0.675	152.58	11.000
(0.001)	(0.002)	(0.001)	(0.015)	(0.002)
Panel C: Abuse Parameters - Abuse Freq.				
χ_1	χ_0^0	χ_0^1	χ_0^2	χ_0^t
0.029	0.969	0.240	0.208	-0.006
(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
χ_0^w	χ_0^h			
0.002	-0.002			
(0.000)	(0.000)			
Panel D: Sharing, Cost Fractions, Meeting Rate				
Sharing	Childcare		Meeting Pr.	
τ	ρ^0	ρ^1	ς	
0.705	0.056	0.302	0.141	
(0.003)	(0.000)	(0.001)	(0.000)	
Panel E: Cholesky Terms				
a_{22}	a_{32}	a_{33}	a_{h2}	a_{hh}
-0.031	0.060	0.011	0.304	0.032
(0.000)	(0.000)	(0.000)	(0.001)	(0.001)

Table 5: Parameter estimates continued: remaining parameters.

Consider now the parameters presented in Table 5. Comparing the systematic utility from marriage ψ^m and the disutility from abuse ψ^z shows that, in line with the simple model above, the abuse is a large-scale negative utility shock – close to half of ψ^m. The estimated ψ_a^z is, in contrast, relatively small suggesting that the disutility of abuse is felt almost equally by low- and high ability women. The marriage utility shocks are large, with the variance σ_m^2 being more than twice the size of ψ^m, again, similar to the simple model.

The estimates of ϕ_b^q indicate that there is no marked difference across qualification groups in the rate of meeting violent men. The estimated abuse probability for non-violent males, χ_1, is, as in the simple model, low. The remaining parameters presented in Panel C are those for the tension-function (12) that underlies the abuse probability $\chi_0(\cdot)$ for the violent type (13). In order to interpret the implied effects, note that the probability of abuse from a violent partner for a woman who is currently not working, aged 27, and with an earnings capacity that is the same as that of her husband is $\chi_0(\cdot) = 0.71$, which is somewhat higher than the calibrated value of χ_0 in the simple version above. Table 6 then highlights how the abuse risk $\chi_0(\cdot)$ varies with labour supply, hourly wage and age.

The estimates indicate a significantly higher risk of abuse for women who are not working: the estimated probability that a violent male engages in abuse is close to 17 percentage points lower when the woman works part-time relative to when she is not working. Further increasing her labour supply to full-time does not substantially additionally reduce the risk of abuse. While we have seen that the incidence of abuse decreases both with age and partnership duration (see Table 2), the estimates suggests at most a modest direct effect of age: increasing age by 10 years reduces the $\chi_0(\cdot)$ by only 1.5 percentage points.

The positive estimated parameter for the own earnings capacity and the negative for that of the husband would be consistent with gender-identity theory. However, the estimated effects are also very modest: Table 6 highlights the effect of increasing each partner's earnings capacity by the interquartile range. In either case, the effect is less than a third of a percentage point (in absolute value) and hence only very minor in relation to the baseline value of $\chi_0(\cdot)$.

Labour Supply		**Age**	**Own FT Wage**	**Husband Wage**
NW to PT	PT to FT	$\Delta t = 10$	Q_1 to Q_3	Q_1 to Q_3
-0.169	-0.008	-0.015	0.003	-0.002

Table 6: Variation in abuse risk from violent partners.

The estimated meeting rate ς is also effectively unchanged from the simple model. Conception utility shocks are important in the model, suggesting a fair amount of randomness in the timing of fertility: the estimated variance σ_f^2 is more than twice as large as the (annual) marginal utility of a child (see Panel B of Table 4). Childcare costs are nearly eliminated for women who do not work and only about 30 percent of the maximum cost for women who work part-time rather than full-time. The "sharing" parameter τ indicates close to equal sharing.[20]

[20] It should be noted however that τ can also capture household public goods whereby the sum of her consumption as a proportion of total household income (τ) and his corresponding consumption as a proportion of total income can exceed unity.

VI Counterfactual Experiments

In this section we use the model to explore two distinct sets of questions. First, we explore the overall effect of uncertainty and learning on behaviour and outcomes. To do this we re-simulate the model under the counterfactual information structure where women can immediately observe any male's type as they meet. Second, we explore the effect of changes in the economic environment, focusing particularly on aspects that economically "empower" women in general and mothers in particular. These experiments include (i) raising female wages to close the gender pay gap, (ii) increasing the child-related income available to single mothers, and (iii) providing subsidized child-care to households where the mother is working.

The simulations highlight how the interplay between labour supply and fertility in particular is key to the predicted impact of policy on the incidence of abuse. Indeed, a central theme to emerge is that both fertility and labour supply are more responsive to policy than is partnership status, a finding well in line with the literature. The empirical literature on the effect of financial incentives on marriage has generally used variation in marriage penalties or bonuses arising from the tax-benefit code. While the estimated effects, if any, go in the expected direction, studies generally find that the effects on marriage are modest at best.[21] The corresponding literature on the effect of financial incentives on fertility finds larger effects. This holds for incentives generated by the tax-benefit system, by public childcare policy, as well as for explicit pro-natalist policies.[22] However, this literature faces the challenge of separating out responses that represent a shift in the *timing* of fertility from the longer run impact on *completed* fertility. Hence the general conclusion from this literature is that fertility responds significantly to financial incentives, at least in terms of its timing.

Whereas in the model estimation we focused on the population of mothers in order to match the ALSPAC sample, the focus in this section is on the entire female population between the

[21] Key contributions include Dickert-Conlin and Houser (2002), Eissa and Hoynes (2000), Eissa and Hoynes (2003) and Fisher (2013). For instance, Eissa and Hoynes (2000) find that reducing the marriage tax penalty by $1,000/year would increase the married rate by 0.4 percent *when the alternative is cohabitation*, whereas Dickert-Conlin and Houser (2002) find little or no effect of the EITC on marriage.

[22] Baughman and Dickert-Conlin (2009) studies the effect of the US Earned Income Tax Credit, Brewer et al. (2012) the effect of the UK welfare reforms in the late 1990s, and Laroque and Salanie (2014) study the effect of incentives generated by the French tax system. Bauernschuster et al. (2016) study the effect of public childcare in Germany. A leading example of an analysis of pro-natalist policies is Milligan (2005) who studies the Allowance for Newborn Children introduced in Quebec in 1998.

ages of 17 and 40. We do however also consider the incidence of abuse experienced by mothers and non-mothers respectively. This is of specific interest as a substantial literature argues that there are negative effects on children's outcomes and behaviours of witnessing abuse between parents (McTavish et al., 2016).

The results from the counterfactual simulations are presented in Table 7 and Figures 2 - 4. Table 7 presents results for a set of statistics computed across the women's lifetimes. Figure 2 highlights some more details of the dynamics of the responses by presenting various outcomes – relative to the baseline model – by age. Figure 3 focuses in particular on the timing of conceptions relative to first marriage. Figure 4 focuses specifically on labour supply responses by qualification group.

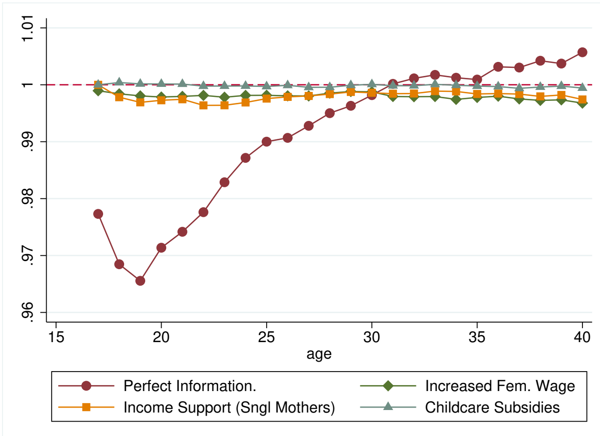
	Baseline Model	Perfect Information	Increased Female Wages	Income Support Single Mothers	Subsidized Childcare
Age at First Marriage	21.80	21.92	21.81	21.80	21.80
Divorce Rate	0.017	0.016	0.018	0.018	0.017
Age at First Birth	27.02	25.38	28.33	24.47	25.60
Proportion Childless	0.182	0.158	0.199	0.051	0.061
Average Nr of Children: All	1.821	2.287	1.714	2.615	2.220
Low Qualified	2.074	2.373	1.895	2.816	2.383
Medium Qualified	1.977	2.336	1.834	2.723	2.329
High Qualified	1.474	2.172	1.456	2.355	1.988
Non-Employed	0.340	0.317	0.246	0.474	0.318
Working Part-Time	0.197	0.283	0.191	0.225	0.251
Working Full-Time	0.463	0.399	0.563	0.301	0.432
Average Own Earnings (if working)	11,169	10,631	12,741	11,566	10,811
Average Husb. Earnings	18,847	18,868	18,845	18,847	18,847
Abuse Frequency: All	0.118	0.098	0.116	0.120	0.118
Low Qualified	0.126	0.105	0.122	0.128	0.126
Medium Qualified	0.122	0.102	0.119	0.124	0.122
High Qualified	0.108	0.089	0.107	0.108	0.109
Mothers	0.093	0.048	0.080	0.111	0.118
Non-Mothers	0.148	0.179	0.150	0.144	0.119

Table 7: Counterfactual simulations: lifetime outcomes.

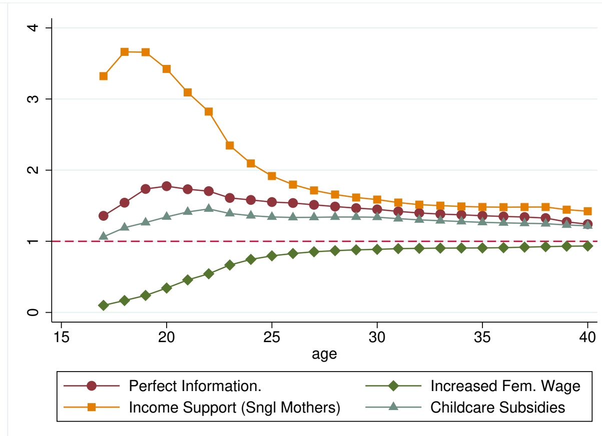
The Effect of Uncertainty

In the first counterfactual simulation we explore how uncertainty about males' types affects women's choices and outcomes. We focus here on the extreme opposite scenario relative to the baseline case, namely the case where any woman can immediately observe the type of any potential new partner.[23]

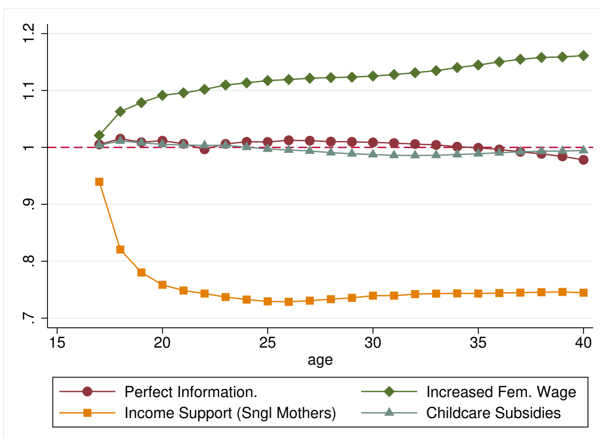
[23] We have further explored intermediate cases where a woman receives a binary signal $s \in \{0,1\}$ which is correlated with the male's true type, $\Pr(s=1|r=1) = (1+\epsilon)/2$ and $\Pr(s=1|r=0) = (1-\epsilon)/2$ for some value $\epsilon \in [0,1]$. Based on the signal s she can then decide whether or not to marry this male. ϵ parameterizes



(a) Relative Married Rate



(b) Relative Nr of Children



(c) Relative Experience

Figure 2: Proportion married, number of children, and labour market experience relative to the baseline economy.

There are two immediate behavioural consequences of the unobservability of a partner's nature. First, when male types are not observable, women cannot directly reject marriage proposals from violent types. As that would be possible with perfect information, a lack of information increases the proportion of women who are married in early adulthood. As shown in Figure 2, the proportion of women who are married is higher under uncertainty below the age of 30.[24] However, divorces are also higher when types are not directly observable; as a

the precision of the signal with $\epsilon = 0$ corresponding to the baseline model (no information) and $\epsilon = 1$ the full information case. The results from these simulations indeed suggest that behaviour and outcomes with positive but imperfect information is, as expected, "between" the cases of no information and full information.

[24]The drop in married rates is rather modest. This reflects that, even with perfect information, many marriage

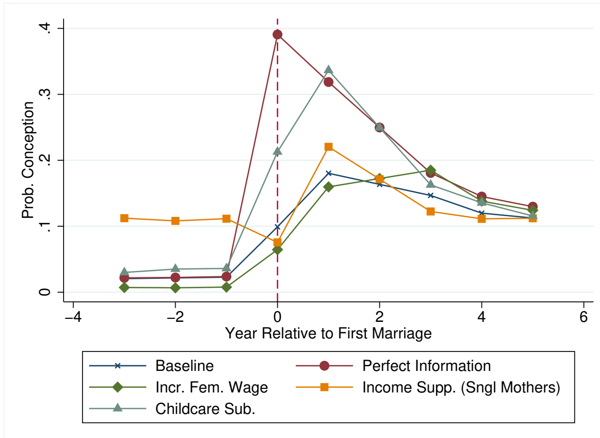


Figure 3: Conception rate in years around year of first marriage.

consequence the proportion married is lower under uncertainty above the age of 30.

Second, uncertainty about a partner's type also affects fertility incentives. In particular, it creates an incentive for delaying fertility within marriage in order to observe the partner's behaviour. From the simple model above we know that learning occurs quite fast, providing a strong incentive to delay fertility by one or more years. This effect of uncertainty is highlighted in Figure 3 which plots the conception rate in years around first marriage (where $year = 0$ indicates the year of first marriage). With uncertainty, the conception rate is higher in the subsequent years following marriage than in the first year of marriage. In contrast, under perfect information there would be a spike in conceptions immediately upon marriage, followed by a monotonic reduction in the conception rate thereafter.

Uncertainty not only delays fertility, it also decreases overall fertility (Table 7), both in terms of increasing the proportion of women who remain childless and lowering the average number of children. The latter effect is particularly pronounced among high qualified women. This also has implications for labour supply, with part-time work being less frequent under uncertainty than it would be under perfect information. As can be seen from Figure 4 this is particularly pronounced for the high-qualified women.

Finally, when male types are not observable women are naturally also more exposed to abuse. The overall abuse rate is 20 percent higher in the baseline model with uncertainty than it is

offers from violent men are accepted due to the direct utility of marriage and the income that the husband brings. Note also that the rejection rate of marriage offers must, per construction, be of a similar magnitude to the divorce rate which is quite low even when women are near certain that the partner has a violent nature. Marriages to violent men however are substantially more short-lived and have lower associated fertility.

Figure 4: Counterfactual simulations: labour supply by qualification group.

in the perfect information scenario (Table 7). For mothers, the effect is even stronger with the abuse rate under uncertainty being close to double that under perfect information.

The Effects of Wages and Policy

We now revert back to the case where males' types are unobserved in order to focus on changes in the economic environment. Before highlighting differences between these cases two commonalities are worth noting. First, in all the cases considered, the impact on marriage rates is small. Figure 2 shows that the impact of any of the experiments in this section on the proportion married is less than half a percentage point at any age. This should come as no surprise given that the literature has found married rates to be fairly unresponsive to financial incentives and given that none of the below experiments provide direct financial incentives for or against marriage. Second, all the simulated environments considered here share the feature of the baseline economy that the rate of conception is higher in the *years following* marriage than in the *actual year* of first marriage (Figure 3). Hence in each case where there is learning about the partner's nature, women delay fertility *within* marriage.

Eliminating the Gender Wage Gap

In this simulation we raise female earnings to the point where the average full-time earnings are the same for both genders. This involved a 15 percent increase. Part-time earnings were increased by the same proportion. In policy terms, this experiment could be thought of as representing a gender-specific wage subsidy.

Higher female wages encourage women to work more in the labour market. Labour market experience continuously grows faster than in the baseline economy, and by age 40 the average experience is more than 15 percent higher than in the baseline economy (Figure 2). Figure 4 further shows that the increase in labour supply comes in particular from an increased labour force participation among the low- and medium qualified women.

Improved earnings opportunities for women also delay fertility. From Table 7 we also see that the average age at first birth increases by over a year and Figure 2 shows that below age 25 the average number of children is well-below that in the baseline economy. It also delays fertility within marriage, with the conception rate peaking three years post first marriage (Figure 3). Over time, fertility largely catches up so that, by age 40, the proportion childless is only marginally higher and the average number of children is only about five percent lower than in the baseline economy, with the decrease coming mainly from low- and medium-qualified women.

Turning to abuse, we see that the overall incidence of abuse decreases by 0.3 percentage points or 2.5 percent relative to baseline. This decrease is driven by the increased labour force participation, which also explains why the decrease in abuse is larger among the low- and medium-qualified women. The prediction that improved wages for women reduces exposure to abuse is in line with the findings in Aizer (2010), though the mechanism here is directly via increased labour supply rather than intra-household bargaining.[25]

While abuse reduces for women overall, this is particularly pronounced among mothers who experience a 14 percent reduction in abuse. This effect reflects that fertility, by being further delayed due to strengthened labour supply incentives, is based on better information and, by being lower overall, also is more selective. Hence, an important consequence of improved earnings opportunities for women is that children become less exposed to abuse between parents.

[25] Aizer's estimates imply that a 15 percent increase in the relative wages of women would reduce women's exposure to assault by about 10 percent.

Income Support for Single Mothers

The estimated model includes child-related income support, $\beta_1^{ci} n_t + \beta_2^{ci} n_t^2$, available to single mothers, as a catch-all for either in- or out-of-work welfare benefits and potential child-support payments. At first glance, more generous income support to single mothers could potentially enable them to leave abusive relationships and could hence be a policy option for reducing domestic abuse.

However more generous support will also boost fertility incentives and lower labour supply through an expected income effect. Taking such broader responses into account, it is less clear that a generous child-related support policy would indeed reduce the incidence of abuse. To explore this, we simulate the effect of an increase in the child support parameter, β_1^{ci}, by 20 percent relative to the baseline.

A first main effect is to increase fertility by every measure: reducing the age at first birth, reducing the proportion who remain childless, and increasing the average number of children (Table 7). Age at first birth reduces by about two and a half years on average and, as can be seen from Figure 3, pre-marital conceptions increase substantially to the point where the conception rate is fairly flat over the time of marriage. This reflects the decreased financial importance to the mother of being married (whilst leaving of course the direct benefit unaffected).

As a result of having more children – and also due to the expected non-labour income effect – women work less, with low- and medium qualified women in particular being more likely to be out of the labour force (Figure 4). Furthermore, with less work experience pre-marriage, they are more likely to be out of the labour force when they eventually do get married. Given that being out of the labour force is associated with a higher rate of abuse from violent men, the reduced incentives for working indirectly increase exposure to abuse. Indeed, Table 7 indicates an increase of 0.2 percentage points in the overall incidence of abuse, with the increase being concentrated among the low- and medium-qualified women. Hence rather than reducing exposure to abuse, taking all behavioural responses into account – most notably fertility and labour supply responses – more generous income support to single mothers leaves women, not less, but more exposed to abuse. Moreover, the increase in the abuse rate is particularly large for mothers for whom the abuse rate increases by close to 20 percent. This result is largely driven by the increase in pre-marital fertility, which implies that children are frequently present during the critical early partnership stages.

Subsidized Childcare when the Mother is Working

The estimated childcare costs, $\beta_1^{cc} n_t + \beta_2^{cc} n_t^2$, apply equally to married and single mothers; however they are incurred in full only if the mother is working full-time, $\rho^2 = 1$, and partially at rate ρ^1 (estimated to 0.30, see Table 5) when she works part-time. Here we consider the effect of subsidized childcare for households with working mothers. To do so we reduce each fraction, ρ^2 and ρ^1, of the full childcare cost incurred when the mother is working full- and part-time respectively by 20 percent.

Subsidised childcare has two main direct effects. First, it reduces the cost associated with working and hence encourages labour force participation among mothers. Second, it directly encourages fertility by reducing the overall expected cost associated with having children. As fertility and labour supply are negatively associated, this indirectly reduces labour supply, leaving the overall net effect on labour supply ambiguous.

The positive effect on fertility can be seen from Table 7: age at first birth decreases by over a year, the proportion who remain childless reduces substantially, and the average number of children increases and, naturally, most strongly so for the high-qualified women. In contrast to increased income support for single mothers, subsidized childcare does not particularly encourage pre-marital conceptions but instead encourages fertility early in new relationships (Figure 3). The overall effect on labour supply is modest, with small predicted reductions in the proportion not working and working full time (Table 7). Consequently, the predicted impact on overall incidence of abuse is negligible, a conclusion that holds in each qualification category.

Given that subsidized childcare is a popular policy option for simultaneously encouraging both fertility and labour supply, this would appear to be a positive conclusion, suggesting that such a policy can be used without increasing women's exposure to abuse. However, the result comes with an important caveat: as can be seen from Table 7 the incidence of abuse among mothers – and hence the exposure to abuse of children – increases substantially, by over 25 percent. This large effect is driven particularly by increased fertility early in relationships: note from Figure 3 that fertility in the first three years of marriage ($time = 0, 1, 2$) increases quite sharply relative to the baseline case.

VII Conclusions

Starting a relationship with a new intimate partner usually comes with hopes of a happy, long-lasting and well-functioning relationship. However, in far too many cases, such dreams fail to materialize as it is gradually disclosed that the new partner has a violent nature and will repeatedly engage in verbal and physical abuse. In formal modelling terms, this suggests that there is heterogeneity in male "violence types" which is not directly observable at the outset of a new partnership but is only revealed over time. Focusing on the impact of such uncertainty for women this paper has addressed two broad sets of questions.

First, what is the effect of uncertainty about a partner's violent nature on a woman's dynamic behaviour? For instance, does it lead to a delay in investments within marriage, most notably in fertility? Relatedly, what are the labour supply responses of women facing possible domestic violence? Do certain labour supply choices lead to an increased risk of abuse?

Second, what is the effect of female "economic empowerment" in the form of earnings opportunities and financial resources on the incidence of abuse? In particular, how do higher female wages affect women's choices and their exposure to abuse? What are the overall effects of better income support to single mothers and of subsidized childcare available to households in which the mother is working.

To address these questions, we constructed and estimated a dynamic lifecycle model where women meet and marry men, learn about their husbands' nature, and make decisions about fertility, labour supply, and about continued marriage or divorce. The core mechanism of the model is a learning process where a woman updates her beliefs about her husband's true nature by observing, over time, whether or not he engages in abusive behaviour. As the partner's type is gradually revealed, her perceived utility of continued marriage changes over time. But learning also indirectly affects fertility incentives. Children impose costs – either in the form of direct childcare costs or in terms of foregone earnings – which are shared whilst married. Hence, separating from a partner is more costly when children are present potentially trapping mothers in abusive relationships. Learning therefore implies an incentive for delayed child-bearing until more information is available about the partner's nature. It further affects labour supply decisions over time. A higher risk of divorce provides an incentive to build up labour market experience and earnings capacity in anticipation of potential singlehood. Moveover, in so far as some labour supply choices are more associated with abuse, a women may avoid these particular choices early in relationships when the partner's nature is still largely unknown.

In order to study the various effects of uncertainty and learning on women's choices and outcomes, we used a counterfactual simulation of the model where a woman is provided with full information about the nature of any prospective new partner at the very moment they meet. In doing so, we uncovered some important interactions between learning and labour supply, marriage duration and fertility. Specifically, we found that, compared to the full-information scenario, the learning environment is associated with (i) more early marriages, more frequent divorces, delayed fertility, and lower completed fertility, (ii) increased labour supply to avoid possible abuse and to build up labour market experience, and, of course, (iii) substantially higher rates of abuse.

Counterfactual simulations were similarly used to analyse the effects of female economic empowerment in the form of access to higher wages, increased income support provided to single mothers, and subsidized childcare when working.

Higher female wages were, unsurprisingly, found to increase female labour supply. However, it was found to only modestly decrease the incidence of abuse due to having only a minor direct effect and also small effects via marriage and divorce decisions. Indeed, the predicted reduction in abuse comes largely from a lower probability of abuse by violent men towards women who work either part- or full-time.

Perhaps more surprising were the findings regarding more generous income support for single mothers and subsidized childcare. Such policies could, in principle, make mothers more financially independent and hence more able to walk away from abusive partners. However, we found that both policies also encourage fertility – either premarital fertility or early-in-marriage fertility – and the former policy in particular also decreases labour supply. With these policies, women more frequently find themselves in the early stages of relationships with children and with less accumulated labour market experience. As a result, they find it more difficult to leave abusive partners. Hence, we found that neither policy decreases abuse towards women in general, and more worryingly, both policies can actually increase the incidence of abuse towards mothers in particular.

The current model is the first to formally estimate a model where women learn the potentially abusive nature of their partners. To accomplish this, a set of assumptions have been imposed, including for instance rational (Bayesian) learning. Our model also does not incorporate any measure of health or well-being and does not consider any impacts on children beyond their existence. Hence there are many obvious directions in which this work could be extended.

References

Aizer, A. (2010), 'The gender wage gap and domestic violence', *American Economic Review* **100**(4), 1847–1859.

Aizer, A. and Dal Bó, P. (2009), 'Love, hate and murder: Commitment devices in violent relationships', *Journal of Public Economics* **93**(3), 412–428.

Alesina, A., Brioschi, B. and La Ferrara, E. (2020), 'Violence against women: A cross-cultural analysis for Africa', *Economica* . Forthcoming.

Amaral, S. and Bhalotra, S. (2017), 'Population sex ratios and violence against women: The long-run effects of sex selection in India', University of Essex.

Anderberg, D. and Rainer, H. (2013), 'Economic abuse: A theory of intrahousehold sabotage', *Journal of Public Economics* **97**(C), 282–295.

Anderberg, D., Rainer, H., Wadsworth, J. and Wilson, T. (2016), 'Unemployment and domestic violence: Theory and evidence', *Economic Journal* **126**(597), 1947–1979.

Angelucci, M. (2008), 'Love on the rocks: Domestic violence and alcohol abuse in rural mexico', *B E Journal of Economic Analysis & Policy* **8**(1), Article 43.

Bauernschuster, S., Hener, T. and Rainer, H. (2016), 'Children of a (policy) revolution: The introduction of universal child care and its effect on fertility', *Journal of the European Economic Association* **14**(4), 975–1005.

Baughman, R. and Dickert-Conlin, S. (2009), 'The Earned Income Tax Credit and fertility', *Journal of Population Economics* **22**(3), 537–563.

Bloch, F. and Rao, V. (2002), 'Terror as a bargaining instrument: A case study of dowry violence in rural India', *American Economic Review* **92**(4), 1029–1043.

Bobonis, G. J., González-Brenes, M. and Castro, R. (2013), 'Public transfers and domestic violences: The roles of private information and spousal control', *American Economic Journal: Economic Policy* **5**(1), 179–205.

Bowen, E., Heron, J., Waylen, A., Wolke, D. and ALSPAC Team (2005), 'Domestic violence risk during and after pregnancy: Findings from a British longitudinal study', *BJOG: An International Journal of Obstetrics & Gynaecology* **112**(8), 1083–1089.

Bowlus, A. and Seitz, S. (2006), 'Domestic violence, employment, and divorce', *International Economic Review* **47**(4), 1113–1149.

Boyd, A., Golding, J., Macleod, J., Lawlor, D. A., Fraser, A., Henderson, J., Molloy, L., Ness, A., Ring, S. and Smith, G. D. (2013), 'Cohort profile: The children of the 90s - the index offspring of the Avon longitudinal study of parents and children', *International Journal of Epidemiology* **42**(1), 111–127.

Brewer, M., Ratcliffe, A. and Smith, S. (2012), 'Does welfare reform affect fertility? Evidence from the UK', *Journal of Population Economics* **25**(1), 245–266.

Brien, M. J., Lillard, L. A. and Stern, S. (2006), 'Cohabitation, marriage, and divorce in a model of match quality', *International Economic Review* **47**(2), 451–494.

Card, D. and Dahl, G. (2011), 'Family violence and football: The effect of unexpected emotional cues on violent behavior', *Quarterly Journal of Economics* **126**(1), 103–143.

Cosslett, S. (1981), Efficient estimation of discrete choice models, *in* C. F. Manski and D. McFadden, eds, 'Structural Analysis of Discrete Data with Econometric Applications', MIT Press.

Dickert-Conlin, S. and Houser, S. (2002), 'EITC and marriage', *National Tax Journal* **55**(1), 25–40.

Dugan, L., Rosenfeld, R. and Nagin, D. S. (2003), 'Exposure reduction or retaliation? The effects of domestic violence resources on intimate-partner homicide', *Law and Society Review* **37**(1), 169–198.

Eissa, N. and Hoynes, H. (2000), 'Tax and transfer policy, and family formation: Marriage and cohabitation', University of California, Berkeley.

Eissa, N. and Hoynes, H. (2003), 'Good news for low income families? Tax-transfer schemes, and marriage', University of California, Berkeley.

Enander, V. and Holmberg, C. (2008), 'Why does she leave? The leaving process(es) of battered women', *Health Care for Women International* **29**(3), 200–226.

Erten, B. and Keskin, P. (2018), 'For better or for worse? Education and the prevalence of domestic violence in Turkey', *American Economic Journal: Applied Economics* **10**(1), 64–105.

Fisher, H. (2013), 'The effect of marriage tax penalties and subsidies on marital status', *Fiscal Studies* **34**(4), 437–465.

Flatley, J., Kershaw, C., Smith, K., Chaplin, R. and Moon, D. (2010), 'Crime in England and Wales 2009/10', Home Office Statistical Bulletin.

Francesconi, M. (2002), 'A joint dynamic model of fertility and work of married women', *Journal of Labor Economics* **20**(2), 336–380.

Garcia-Ramos, A. (2017), 'Divorce laws and intimate partner violence: Evidence from Mexico', University of Birmingham.

Gemici, A. and Laufer, S. (2014), 'Marriage and cohabitation'. Royal Holloway, University of London.

González, L. and Rodríguez-Planas, N. (2018), 'Gender norms and intimate partner violence', Universitat Pompeu Fabra, Mimeo.

Guarnieri, E. and Rainer, H. (2018), 'Female empowerment and male backlash', CESifo Working Paper No. 7009.

Hidrobo, M. and Fernald, L. (2013), 'Cash transfers and domestic violence', *Journal of Health Economics* **32**(1), 304–319.

Hsu, L. C. (2017), 'The timing of welfare payments and intimate partner violence', *Economic Inquiry* **55**(2), 1017–1031.

Iyengar, R. (2009), 'Does the certainty of arrest reduce domestic violence? Evidence from mandatory and recommended arrest laws', *Journal of Public Economics* **93**(1), 85–98.

Jasinski, J. L. (2004), 'Pregnancy and domestic violence: A review of the literature', *Trauma, Violence, and Abuse* **10**(9), 961–990.

Keane, M. P. and Wolpin, K. I. (1994), 'The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte carlo evidence', *The Review of Economics and Statistics* **76**(4), 648–672.

Keane, M. P. and Wolpin, K. I. (2010), 'The role of labor and marriage markets, preference heterogeneity and the welfare system in the life cycle decisions of black, hispanic and white women', *International Economic Review* **51**(3), 851–892.

Laroque, G. and Salanie, B. (2014), 'Identifying the response of fertility to financial incentives', *Journal of Applies Econometrics* **29**(2), 314–332.

Macmillan, R. and Gartner, R. (1999), 'When she brings home the bacon: Labor force participation and the risk of spousal violence against women', *Journal of Marriage and the Family* **61**(4), 947–958.

Manski, C. F. and Lerman, S. R. (1977), 'The estimation of choice probabilities from choice based samples', *Econometrica* **45**(8), 1977–1988.

McFadden, D. (1989), 'A method of simulated moments for estimation of discrete response models without numerical integration', *Econometrica* **57**(5), 995–1026.

McTavish, J. R., MacGregor, J. C., Wathen, C. N. and MacMillan, H. L. (2016), 'Children's exposure to intimate partner violence: an overview', *International Review of Psychiatry* **28**(5), 504–518.

Milligan, K. (2005), 'Subsidizing the stork: New evidence on tax incentives and fertility', *The Review of Economics and Statistics* **87**(3), 539–555.

ONS (2012), 'Ethnicity and national identity in England and Wales: 2011'. Office for National Statistics report.

ONS (2013), 'Cohort fertility', Statistical Bulletin. December 5th.

Pakes, A. and Pollard, D. (1989), 'Simulation and the asymptotics of optimization estimators', *Econometrica* **57**(5), 1027–1057.

Papageorge, N., Pauley, G., Cohen, M., Wilson, T., Hamilton, B. and Pollak, R. (2019), 'Health, human capital and domestic violence', *Journal of Human Resources* .

Ramos, A. (2016), 'Household decision making with violence: Implications for conditional cash transfer programs', Universitat Autonoma de Barcelona.

Riger, S. and Staggs, S. (2004), 'Welfare reform, domestic violence, and employment', *Violence Against Women* **10**(9), 961–990.

Sauer, R. M. (2015), 'Does it pay for women to volunteer?', *International Economic Review* **56**(2), 537–564.

Stevenson, B. and Wolfers, J. (2006), 'Bargaining in the shadow of the law', *Quarterly Journal of Economics* **121**(1), 267–288.

Tauchen, H. V., Witte, A. D. and Long, S. K. (1991), 'Violence in the family: A non-random affair', *International Economic Review* **32**(2), 491–511.

Tertilt, M. and van den Berg, G. (2015), 'The association between own unemployment and violence victimizations among female youth', *Journal of Economics and Statistics* **235**(4-5), 499–513.

Truman, J. L. and Morgan, R. E. (2014), 'Nonfatal domestic violence, 2003 - 2012', U.S. Department of Justice, Bureau of Justice Statistics, Special Report.

Tur-Prats, A. (2017), 'Unemployment and intimate partner violence: A gender-identity approach', Universitat Pompeu Fabra.

Tur-Prats, A. (2019), 'Family types and intimate-partner violence: A historical perspective', *Review of Economics and Statistics* **101**(5), 878–891.

van der Klaauw, W. (1996), 'Female labour supply and marital status decisions: A life-cycle model', *The Review of Economic Studies* **63**(2), 199–235.

Walby, S. and Allen, J. (2004), 'Domestic violence, sexual assault and stalking: Findings from the British Crime Survey'. Home Office Research Study 276.

WHO (2013), 'Global and regional estimates of violence against women: Prevalence and health effects of intimate partner violence and non-partner sexual violence', WHO ref. nr: 978 92 4 156462 5.

Online Appendix A: Data and Illustrative Dynamics

This appendix describes the ALSPAC data used in the estimation of the model along with some illustrative dynamic patterns in the data.

Sample Population

ALSPAC recruited 14,541 pregnant women who returned at least one questionnaire or attended at least one clinic. The pregnancies resulted in 14,062 live births and 13,988 children who were alive at 1 year of age. We impose a set of restrictions on the sample. Avon is the South-West region of England where, in the UK context, the population is known to be of predominantly white ethnic origin ONS (2012). In order to avoid issues with small cell sizes, we drop all women who are of Asian, Black or other/unknown ethnic origin, dropping 2,614 women. We then remove all women for whom basic demographic information on age and/or academic qualification level is missing, dropping a further 508 women. We keep only women who completed at least one post-pregnancy questionnaire, dropping 672 women. We then eliminate person-year observations with missing information on the key time-varying variables: partnerships status, births, and abuse eliminating a further 1,312 women. We further eliminate women who were pregnant with the ALSPAC child below the age of 17 (32 women) or above 40 (44 women) in order to be consistent with our lifecycle model below. This leaves a sample of 9,359 women, with a total of 56,926 person-year observations, with over 80 percent of the sample women observed for the complete seven years. After imposing these sample restrictions we are left with 9,359 women, with a total of 56,926 person-year observations.

We start by characterizing the demographic characteristics of the sample population at baseline. Note that at this stage, all the women in the sample are pregnant. Table A.1 gives basic information about the population at this stage. The sample women were, on average, 28 years old at the start of the survey. The vast majority, 96 percent, of the women lived with a male partner at baseline, and had done so for over four and a half years on average. 55 percent of the sample women already had at least one child at baseline and the average number of existing children was 0.78.

For partnership status we make no distinction between marriage or cohabitation and refer to a woman as “married” if she currently lives with a male partner either as married or cohabiting, and as "single" otherwise.[26] We will correspondingly refer to the event of a woman separating from her partner as "divorcing" and the event of forming a new partnership as "marrying". The focus on live-in partnership status rather than formal marital status is natural given our focus on women's learning about their partners. Such learning can naturally be expected to start from the moment they live together.

We delineate three ordered qualification groups – denoted "low", "medium" and "high" – of roughly equal size using a standard mapping from academic qualifications. Our delineation of qualification groups draws on the standard mapping of academic qualifications into National Vocational Qualification (NVQs) equivalents used by the Office for National Statistics. The "low" qualification group includes respondents without any formal qualification or a basic CSE or low GCSE (grades D-G). The "medium" qualification group includes respondents holding an O-level degree or a "high" GCSE (grades A*-C). The "high" qualified group includes respondents holding an A-level degree or a university undergraduate degree or higher.

Variable	**Mean**	**Std. Dev.**	**Variable**	**Mean**	**Std. Dev.**
Age in Years	28.1	4.55	Nr Children	0.782	0.895
Has Partner ("Married")	0.962	0.192	Low Qualification	0.244	0.430
Years with Partner	4.84	3.53	Medium Qualification	0.381	0.486
Any Child	0.553	0.497	High Qualification	0.374	0.486
Obs.			9,359		

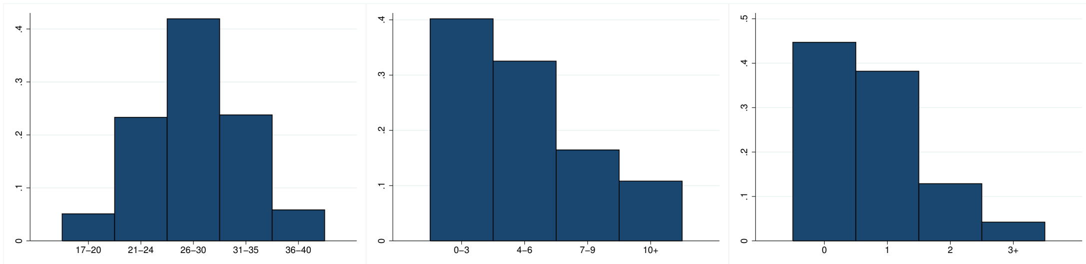
Table A.1: Demographic characteristics of the ALSPAC sample at baseline.

Figure A.1 provides further details of age, partnership duration and children at baseline. The left hand figure shows that many of the women were in their mid to late 20s when entering the survey. The middle figure shows that 40 percent of the women in the sample had a current partnership duration of no more than 3 years. The right hand figure shows that for about 45 percent of the women in the sample, the ALSPAC child represented a first birth, and a further 38 percent had only one previous child.

Partnership Status, Children and Labour Supply

Panel A of Table A.2 notes that, across all person-year observations, some 94 percent of women are married, which is lower than at baseline; indeed, the proportion married drops monotonically

[26] The vast majority of observed partners are also the natural father to the child that the woman is pregnant with at the start of the survey; however, we make no formal distinction between biological fathers and other male partners.



(a) Age (b) Partnership Duration (c) Nr of Children

Figure A.1: Distribution of age, partnership duration and number of children at baseline.

over time and reaches 90 percent by the end of the sample period. Panel A further notes that the overall divorce rate is little less than 2 percent, whereas single women "marry" – that is, start living with a new partner – at an annual rate of 12 percent.

Panel A: Partnership Status				
		Time $t+1$		
Time t	**Mean**	**Single**	**Married**	
Single	0.063	0.880	0.120	
Married	0.937	0.019	0.981	
Obs.		56,926		
Panel B: Birth Incidence				
		Time $t+1$		
Time t	**Mean**	**No Birth**	**Birth**	
No Birth	0.879	0.856	0.144	
Birth	0.121	0.926	0.074	
Obs.		37,876		
Panel C: Labour Supply				
			Time $t+1$	
Time t	**Mean**	**Not Working**	**Working PT**	**Working FT**
Not Working	0.471	0.801	0.166	0.033
Working PT	0.345	0.183	0.703	0.114
Working FT	0.184	0.229	0.302	0.469
Obs.		53,746		

Table A.2: Marriage, births and labour supply.

The birth dummy variable indicates the event of a birth between the previous and the current period. All women in the sample, per construction, give birth to the ALSPAC child between the first and the second period. The birth rates reported in Panel B of Table A.2 are therefore computed using data from period three onwards. As such it measures the arrival of subsequent siblings to the ALSPAC child. Nearly half of the women in the sample have some further birth in the years that follow and the average annual birth rate from sample period 3 onwards is 0.12. The table shows that a woman is less likely to have a birth in any given period if she had one in the previous period, reflecting that the spacing of births is typically more than one year. Children born within the sample period are added to each woman's existing children at baseline, thereby keeping track of how many children she has at any moment in time.[27]

Information on hours of paid work is available in each wave and we use this information to classify the female participant's current labour supply status as not-working, working part-time or working full-time, where the latter two categories are defined as working $1-25$ or 25 hours/week or above, respectively. Part-time work is common in the data, across all periods. Full-time work on the contrary has a stronger time profile. About 40 percent of the women work full-time at baseline. This then drops sharply in conjunction with the birth of the ALSPAC child before gradually picking up again over time. By the end of the sample period, close to a quarter of the women are in full-time paid work. This feature of the data should also be kept in mind when interpreting the observed transition rates in panel C of Table A.2. Notably, the fact that the majority of women observed in full-time employment have left this state by the following period is a reflection of them reducing labour supply in conjunction with a birth. Also, the low rate of direct transitions from being out of the labour force to full-time employment reflects that many of the women in the sample re-enter employment more gradually via part-time employment.

The model estimated below will focus on annual earnings. For that purpose we will assume that part-time and full-time work correspond to 20 and 40 hours/week for 50 weeks/year. As individual earnings are not observed in the data, hourly wage are imputed for each individual and year based on their most recently observed occupation according to the standard SOC90 classification system at the 3-digit level. We use this information to impute an hourly wage for each person-year observation, based on the respondent's most recent occupation in the listing of over 300 possible occupations. Specifically, for each occupation in the classification system, we compute and use the average hourly wage among all women aged 18-59 observed in the UK Labour Force Survey between 1993 and 1999. An hourly wage is then assigned to each observation (individual and year) based on the individual's most recently observed occupation.

[27]The focus on own biological children to the female respondent means that we include children who potentially have left home but not children of the partner who may reside within the household. These issues are likely to be relatively minor. First, since each woman is pregnant at the beginning of the sample period, few of them will have children old enough to have moved out. Second, as a stylized fact, the vast majority of children from separated parents live with their natural mothers.

Panel A in Table A.3 provides summary statistics on these imputed hourly wages by age and qualification. The wages of male partners are imputed in the same way using the partner's occupation, and summary statistics by age and qualification are provided in panel B of Table A.3.

Panel A: Female Wages by Age and Qualification					
Age Group	**Mean**	**Std. Dev.**	**Qualification**	**Mean**	**Std. Dev.**
Aged 17-24	5.55	1.79	Low Qualification	5.37	1.62
Aged 25-31	6.48	2.38	Medium Qualification	6.05	1.89
Aged 32-45	7.49	2.87	High Qualification	8.46	2.88
Obs.			56,790		
Panel B: Male Wages by Age and Qualification					
Age Group	**Mean**	**Std. Dev.**	**Qualification**	**Mean**	**Std. Dev.**
Aged 17-24	7.15	2.24	Low Qualification	7.22	2.26
Aged 25-31	8.68	3.15	Medium Qualification	8.94	3.25
Aged 32-65	9.95	3.63	High Qualification	10.78	3.52
Obs.			53,326		

Table A.3: Summary statistics of hourly wages.

Abuse

As noted above, our indicators of abuse are based on self-reported measures. At each wave the mother was asked to complete a 42-item recent-events inventory, with "recent" specified to the respondent as the period since the previous survey. Two recurrent items were "Your partner was physically cruel to you" and "Your partner was emotionally cruel to you" and we take the responses at face value. For the majority of the analysis we will combine the two into a single indicator of abuse of "any kind". There are good reasons for doing so. First, as will be seen below, the two types of abuse have similar persistence and demographic patterns and have similar relationships to women's observed partnership and fertility choices. This suggests that the two forms of reported partner abuse are equivalent in terms of how they reflect males' underlying types and the women's learning about these. Second, even in surveys that use detailed itemized categories of abusive behaviour the distinction between physical and emotional/verbal abuse is often somewhat ad hoc. Hence we combine any form of reported partner cruelty into a single measure of abuse.

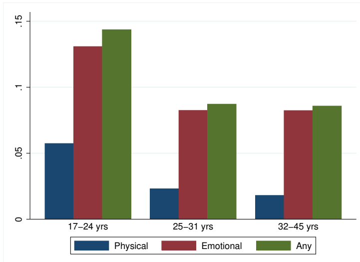
Table A.4 provides summary statistics on the incidence and dynamics of abuse. Overall, 9.2 percent of women report some form of abuse in any given year, with nearly all those reporting some abuse also reporting emotional abuse. The fraction of women reporting physical abuse is significantly lower at 2.4 percent. A striking feature of the abuse variables is their persistence: close to half (49.5 percent) of those reporting some abuse in a given period also report abuse in the following period.

		Time $t+1$	
Time t	**Mean**	**Not Abused**	**Abused (any)**
Not Abused	0.908	0.943	0.057
Abused (any)	0.092	0.505	0.495
		Time $t+1$	
Time t	**Mean**	**Not Physically Abused**	**Physically Abused**
Not Physically Abused	0.976	0.982	0.018
Physically Abused	0.024	0.647	0.353
		Time $t+1$	
Time t	**Mean**	**Not Emotionally Abused**	**Emotionally Abused**
Not Emotionally Abused	0.913	0.945	0.055
Emotionally Abused	0.087	0.511	0.489
Obs.		56,926	

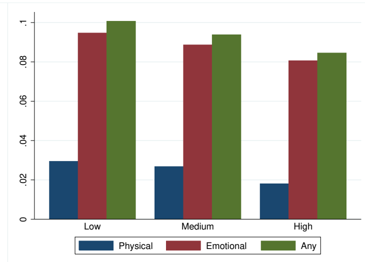
Table A.4: Abuse levels and transition rates.

Panels (a) and (b) of Figure A.2 show how the reported incidence of abuse varies across age groups and qualification levels. The finding that the rate of abuse is highest towards young women is in line with both UK and international evidence.[28] The reported incidence of abuse is also monotonically decreasing with qualification. Panels (c) and (d) show how the reported incidence of abuse varies with two further personal characteristics that are of an endogenous nature: partnership duration and labour supply status. Panel (c) shows the incidence of abuse by partnership duration. Hence longer partnership duration is associated with a lower current level of abuse. For labour supply we observe, in panel (d), a U-shaped relationship, with the lowest incidence of abuse occurring for women working part-time. Even though the ALSPAC measures are self-reported and subjective it can be shown that they agree well, both in terms of level and demographic pattern, with the best available measures of physical and emotional abuse in the UK, obtained from the interpersonal violence modules of the Crime Survey for England and Wales.

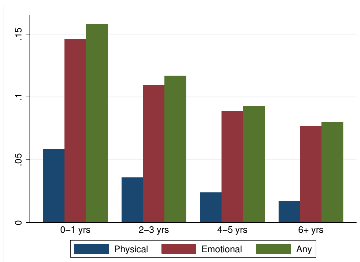
[28]For a recent US report highlighting the age-gradient in the incidence of intimate partner violence based on the National Crime Victimization Survey, see Truman and Morgan (2014).



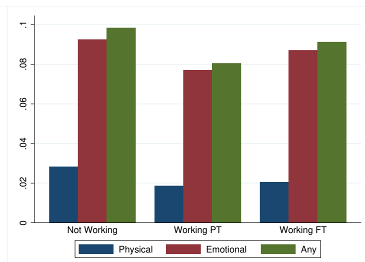
(a) Age Category at $t-1$



(b) Qualification Category



(c) Partnership Duration at $t-1$



(d) Labour Supply at $t-1$

Figure A.2: Incidence of abuse by age, qualification, partnership duration and labour supply status.

Illustrative Dynamics

In order to guide our modelling of women's responses to abuse, we will start with a preliminary analysis of the dynamic patterns in the data. Noting however that all women in the sample, per construction, report a birth between the first and the second sample period, the below illustrative analysis will be entirely based on person-year observations from the third sample period onwards when the ALSPAC child would have been aged between 20 months and 7 years. As noted above, this is a time when many of the women in the sample made key choices in terms of either returning to work or having a further child, and also a period when a number of them chose to break up their current partnerships. We will use a set of simple linear regressions – estimated both by pooled OLS and with individual fixed effects – to explore the association between these choices and abuse. In doing so it is important to pay attention to the timing of the variables involved as some variables – most notably marital and labour supply status – measure the state of a variable *at a given point in time*, whereas other variables – including abuse, births and divorce – measure events occurring *over the 12 months*.

For ease of interpretation all models are estimated as simple linear probability models. All models estimated by OLS include dummies for qualification level, and all regressions include controls for the female respondent's age and age squared.[29] The results are presented in Table A.5.

Consider first how current marital status at time t relates to the experience of abuse. Since the abuse reported at t indicates events over the past 12 months, we can relate the respondent's current marital status to her currently reported abuse experience. However, for comparison, we further include abuse reported at $t-1$ (thus measuring exposure to abuse 13-24 months prior the currently observed marital status). The first columns of Panel A of Table A.5 reports the results from a simple linear OLS regression whereas the second column gives the results from a corresponding individual fixed effects (within) regression. Both regressions indicate that a woman is markedly more likely to be single at time t if she also reports having experienced abuse at some point between time $t-1$ and t or between $t-1$ and $t-2$.

In order to focus on the choice of separating from a partner as a response to abuse, the remaining columns in Panel A use only observations for which the respondent was married at $t-1$ and we use as a dependent variable whether she divorced her partner between $t-1$ and t. In order to ensure that we only relate this to abuse that predates the potential divorce decision, we only include lagged abuse, that is abuse occurring between $t-2$ and $t-1$. Hence the regression considers whether, among all women who were married at $t-1$, those who were abused between $t-2$ and $t-1$ were more more likely to subsequently divorce between $t-1$ and t. Columns (iii) and (iv) report the results from OLS and FE regressions respectively, with both indicating a positive effect of abuse on divorce risk. The final two columns in Panel A look separately at physical and emotional abuse, again estimated with fixed effects. Both indicate a positive impact on divorce risk, though the impact of lagged physical abuse is imprecisely measured.

The FE regression in specification (iv) suggests a clear divorce response to abuse: using the estimated coefficients, the model predicts that the divorce hazard increases from 1.8 percent to 4.8 percent. The fact that the regression focuses only on *non-immediate* separation responses to abuse – that is, it does not account for abuse followed by a separation *within* the same time period – implies that this is, on the one hand, almost certainly an underestimate of the divorce response to abuse. On the other hand, the rate of divorce between $t-1$ and t among women who also report abuse over that same period is about 13 percent (not in table), and is almost

[29]The regressions for births reported in panel (B) further control for the lagged number of children.

certainly an overestimate of the divorce response to abuse. The data therefore clearly indicate that the vast majority of women who experience abuse do not, at least in the short-run, leave their partners.

Consider next how the experience of abuse affects the decision to have a (further) child. Since the birth variable indicates a birth event over the last year we lag the abuse variables by one period. The regressions reported in Panel B of Table A.5 thus relate a birth occurring between $t-1$ and t to whether the woman experienced abuse between $t-2$ and $t-1$. Recalling that the average probability of a further birth in the periods included in the regressions is 0.12 (see Table A.2), the first two columns suggest that experience of abuse reduces the fertility hazard by 20 - 40 percent. The final four columns report negative coefficients both for physical and emotional abuse, though the coefficient on the former is small and not very precisely estimated in the FE specification. A consistent pattern is again that the estimated effects of abuse are smaller in the FE specifications than in the pooled OLS specification, suggesting selection effects based on unobserved heterogeneity.

Panel C of Table A.5 looks at how a woman's labour supply status at time t relates to her experience of abuse between $t-1$ and t. This relationship is weak, if anything showing a positive association between abuse and currently labour supply. Combined with the observation above that not working at $t-1$ was positively associated with reporting abuse between $t-1$ and t (Figure A.2, panel d) this that some women respond to abuse by entering the labour force. The results in panels A-C thus suggest that women who experience abuse respond by more frequently leaving their partner, reducing their fertility, and possibly also increasing their labour supply. However, the overall response to abuse may well involve a combination of these dimensions, which will be accounted for in the structural model estimated below.

Panel A: Partnership Status						
Dep. Var.	**Married at t**		**Divorced since $t-1$**			
Specification	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Any Abuse (t)	-0.097**	-0.065**				
	(0.008)	(0.008)				
Any Abuse ($t-1$)	-0.133**	-0.062**	0.063**	0.030**		
	(0.008)	(0.007)	(0.005)	(0.006)		
Physical Abuse ($t-1$)					0.022	
					(0.012)	
Emotional Abuse ($t-1$)						0.031**
						(0.006)
Obs.	36,641	36,641	34,482	34,482	34,482	34,482
Method	OLS	FE	OLS	FE	FE	FE

Panel B: Birth						
Dep. Var.			**Birth since $t-1$**			
Specification	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Any Abuse ($t-1$)	-0.046**	-0.027**				
	(0.005)	(0.007)				
Physical Abuse ($t-1$)			-0.035**	-0.011		
			(0.010)	(0.012)		
Emotional Abuse ($t-1$)					-0.047**	-0.027**
					(0.005)	(0.007)
Obs.	35,033	35,033	35,033	35,033	35,033	35,033
Method	OLS	FE	OLS	FE	OLS	FE

Panel C: Labour Supply Status						
Dep. Var.	**Not Working at t**		**Working PT at t**		**Working FT at t**	
Specification	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Any Abuse (t)	-0.005	-0.018	-0.013	0.015	0.018**	0.003
	(0.008)	(0.010)	(0.008)	(0.010)	(0.006)	(0.007)
Obs.	31,485	31,485	31,485	31,485	31,485	31,485
Method	OLS	FE	OLS	FE	OLS	FE

Table A.5: Illustrations of the dynamic pattern in the data using pooled OLS and fixed-effects regressions.

Online Appendix B: Unreported Matched Moments

This appendix reports moments matched in the full model but not reported in the text, along with a set of moments that were not matched in the estimation but used post-estimation for checking fit. Tables B.1 - B.3 report moments relating to marriage and fertility, employment and wages respectively. Table B.4 reports fit to additional unmatched moments.

Panel A: Marriage Rate and Marital Transitions			
	Mean	Single at $t+1$	Married at $t+1$
Single at t	0.063	0.880	0.120
	0.101	*0.866*	*0.134*
Married at t	0.937	0.019	0.981
	0.899	*0.015*	*0.985*
Panel B: Out-of-Wedlock Births and Birth Rate by Marital Status			
Pr. Birth is Out of Wedlock if:		Birth Rate of:	
Aged 17-24	Aged 25-40	Married	Single
0.123	0.028	0.125	0.037
0.136	*0.067*	*0.099*	*0.070*
Panel C: Distribution of Nr Children			
Childless	1 Child	2 Children	3+ Children
0.190	0.102	0.409	0.299
0.181	*0.109*	*0.415*	*0.303*
Panel D: Average Age and Partnership Duration at Key Events			
Average Age		Av. Partnership Duration:	
at 1st Birth		At 1st Birth	At Divorce
26.95		3.64	6.78
26.44		*3.67*	*7.41*

Table B.1: Matched moments: marriage and fertility.

Panel A: Employment Status			
	Not Working	Working Part-Time	Working Full-Time
All	0.471	0.345	0.184
	0.465	*0.355*	*0.180*

Panel B: Employment Transitions			
	Not Working at $t+1$	Part-Time at $t+1$	Full-Time at $t+1$
Not Working at t	0.801	0.166	0.033
	0.769	*0.175*	*0.056*
Part-Time at t	0.183	0.703	0.114
	0.271	*0.686*	*0.044*
Full-time at t	0.229	0.302	0.469
	0.275	*0.317*	*0.409*

Panel C: Employment Status by Age Group			
	Not Working	Working Part-Time	Working Full-Time
Aged 17-24	0.585	0.207	0.208
	0.636	*0.207*	*0.157*
Aged 25-31	0.486	0.344	0.170
	0.427	*0.359*	*0.214*
Aged 32-40	0.438	0.374	0.188
	0.383	*0.467*	*0.151*

Panel D: Employment Status by Marital Status			
	Not Working	Working Part-Time	Working Full-Time
Single	0.590	0.240	0.171
	0.658	*0.217*	*0.125*
Married	0.463	0.352	0.185
	0.443	*0.370*	*0.187*

Panel E: Employment Status by Qualification Level			
	Not Working	Working Part-Time	Working Full-Time
Low Qual.	0.575	0.307	0.118
	0.601	*0.287*	*0.112*
Medium Qual.	0.490	0.349	0.160
	0.551	*0.309*	*0.140*
High Qual.	0.396	0.362	0.242
	0.225	*0.478*	*0.297*

Table B.2: Matched moments: employment.

Panel A: Accepted Hourly Wages by Labour Supply Status and of Husbands			
	Part-Time	Full-Time	Husband
Mean	6.86	7.90	9.40
	6.71	*7.97*	*9.28*
St. Dev	2.70	2.90	3.51
	2.80	*2.74*	*3.03*
Panel B: Accepted Hourly Wages by Qualification Level			
	Low Qual.	Medium Qual.	High Qual.
Mean	5.35	6.07	8.78
	5.65	*6.48*	*8.36*
St. Dev	1.64	1.92	2.89
	2.87	*3.01*	*2.10*

Table B.3: Matched moments: wages.

Panel A: Abuse Incidence by Number of Children			
	1 Child	2 Children	3 Children
Abuse rate	0.093	0.090	0.097
	0.102	*0.081*	*0.108*

Panel B: Marriage and Divorce by Qualification Level			
	Low Qual.	Medium Qual.	High Qual.
Prop. married	0.897	0.939	0.957
	0.856	*0.874*	*0.972*
Divorce rate	0.018	0.015	0.011
if no abuse	*0.013*	*0.012*	*0.011*
Divorce rate	0.059	0.065	0.056
if abuse	*0.050*	*0.054*	*0.047*

Table B.4: Model fit to additional moments.