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The Dynamics of Domestic Violence: Learning about the Match*

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Abstract

We present a dynamic lifecycle model of women's choices with respect to partnership status, labour supply and fertility when a male partner's true tendency for abusive behaviour is unobserved. 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.

Keywords: Domestic violence, Learning, Fertility, ALSPAC

JEL Classification: J12, J13

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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 7 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, 2017), culture and social norms (Alesina et al., 2016; Tur-Prats, 2016), health and health innovations (Papageorge et al. 2016), 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, Witte and Long, 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-Bo, 2009), and welfare and cash-transfers policy (Angelucci, 2008; Bobonis et al, 2013; Hidrobo and Fernald, 2013; Ramos, 2016, and Hsu, 2017).

However, even with this flurry of contributions, a number of core questions – particularly of 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; Tolman and Wang, 2005; and 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 explore predicted responses to changes in the economic environment, including through policy.

A key question is whether women, upon entering partnerships, know their partner's abusive nature or if this is something they learn over time through experience? In our model we incorporate 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. A woman does not directly observe her partner's type, but holds beliefs 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. Moreover, a woman may strategically delay fertility within a relationship until she is reasonably certain about the partner's nature.

To estimate the model, we use data from the Avon Longitudinal Study of Parents and Children (ALSPAC), a local survey that has followed a set of children from birth along with their parents. 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 measures of intimate partner abuse, and we observe partnership, labour supply and subsequent fertility choices.

Our model is exclusively focused on the behaviour of women. The behaviour of their male partners with respect to abuse is modelled in a highly "reduced form" by assuming a semi-endogenous stochastic process where the likelihood that a man engages in abuse depends on his nature and age, and on the wife's chosen labour supply. Our model thus assumes that men's behaviour is non-strategic. This modeling choice is done in part for simplicity, but also in part as response to lack of consensus in the literature regarding the drivers behind male abuse.

We model women's choice of partnership status, labour supply, and child-bearing from the moment they enter the "marriage market" until the end of their fertile period. As such, our model builds on an established literature developing lifecycle models of family decisions.[1] The relationship between our work and two contributions to this literature are worth noting in more detail. The first is Brian, Lillard, and Stern (2006). Their key focus is on the choice between marriage and cohabitation, and they treat labour supply and fertility as exogenous. In their model, a couple jointly learn 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. The second is Bowlus and Seitz (2006) which is the only contribution to date that estimates 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 partner – creating a strong incentive to delay fertility within marriage by one or more years. The uncertainty and the need to learn 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 violent men are less likely to be abusive towards women who participate in the labour market. Among working women, the model however suggests that the relatively lower observed frequency of abuse experienced by part time working women is due to selection.

Our counterfactual simulations highlight that higher female wages would reduce abuse towards women (Aizer, 2010). 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

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

relationships and as they are financially better placed to leave any bad relationship.

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 pre-marital fertility and the latter particularly encouraging fertility early in marriages. However, whereas subsidized childcare also encourages labour supply, income support for single mothers leads to lower labour supply. As a result, more generous income support to single mothers perhaps somewhat surprisingly leads to higher exposure to abuse overall. In contrast, subsidized childcare encourages labour supply 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 higher incidence of abuse among 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 we present a set of linear regressions to highlight some key dynamic relationships in the data. Section III describes the model, starting with a simple illustrative version highlighting in particular how key parameters will be identified from the onset rate, persistence and overall level of abuse before outlining the full empirical model. 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 Data and Illustrative Dynamics

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.[2] The initial recruits were pregnant women with estimated dates of delivery between April 1991 and

[2]For a detailed description of the ALSPAC cohort, see Boyd et al. (2013).

December 1992.[3] While first and foremost a child development survey, ALSPAC also repeatedly surveyed the mothers of the study children (and their partners), and it is from these mothers' surveys that our data are constructed. Our female sample population is hence the mothers of the ALSPAC children who were repeatedly surveyed as part of the ALSPAC design. In particular 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.[4]

A particular feature of our data is that, per construction, each woman in the sample has a birth between the first and the second wave. A potential issue with this is that many of the women in the data can be expected to already have learned their partners' nature before entering the survey. While many of the women in our sample will indeed have lived with their partners for several years about half of the sample women have been living with their current partners for no more than three years at the start of the survey. Also on the positive side, 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.

A second key data consideration 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 as findings could otherwise be confounded by reporting and other composition effects. 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 will make use of a relatively subjective self-reported measure of physical and emotional abuse: whether the respondent reports that the partner has been physically

[3]Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees.

[4]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.

or emotionally "cruel" to her since the last survey. Though these questions are much less specific than ones typically used in many dedicated domestic violence survey modules, we will nevertheless show that the estimated incidence of abuse in our sample is very similar – both in terms of level and in terms of demographic correlates – to the best available evidence from the UK drawn from the Crime Survey for England and Wales.

Sample Population

ALSPAC recruited 14,541 pregnant women who returned at least one questionnaire or attended a "Children in Focus" clinic by 19/07/99.[5] In order to conduct our analysis, 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 which eliminates 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.

We start by characterizing the demographic characteristics of the sample population at baseline.[6] Note that at this stage, all the women in the sample are mid-pregnancy. Table

[5]Of these initial pregnancies, there was a total of 14,676 fetuses, resulting in 14,062 live births and 13,988 children who were alive at 1 year of age. When the oldest children were approximately 7 years of age, an attempt was made to bolster the initial sample with eligible cases who had failed to join the study originally. As our study only makes use of data up until the age of 6, we do not use these additional study women – known as the "Phase I enrolment" sample – in our analysis.

[6]The ALSPAC study website contains details of all the data that is available through a fully searchable data dictionary. See http://www.bristol.ac.uk/alspac/researchers/access/

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 1: Demographic characteristics of the ALSPAC sample at baseline.

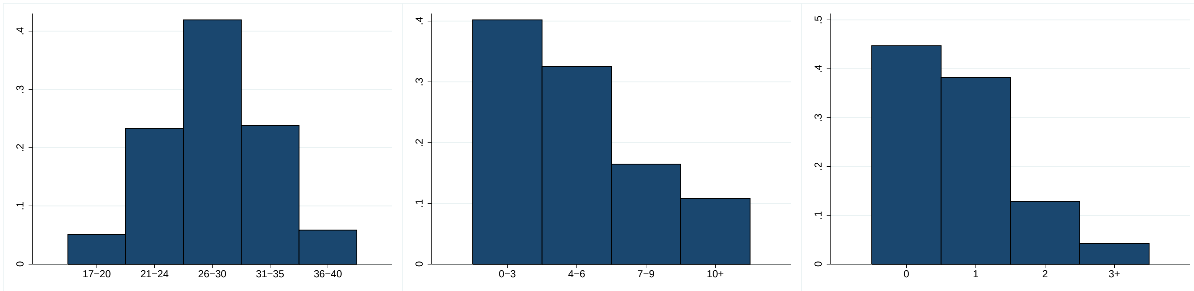
1 gives basic information about the population at this stage. The sample women were, on average, 28 years old at the start of the survey..

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.

Primarily for estimation purposes, we delineate only a limited number of qualification groups of roughly equal size. The "low" qualification group include women without any formal qualification or with a qualification at NVQ1 level, most notably a CSE or a "low" GCSE.[7] The "medium" qualification group holds a qualification at NVQ2 level, most notably an O-level degree or "high" GCSE. The "high" qualified group holds a qualification at NVQ3 level or beyond, which includes A-level degree, university undergraduate degree and beyond.

Figure 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

[7]The sample population were potentially affected by two major UK educational reforms. First, the raising of the school leaving age from 15 to 16 in 1973 affecting those born after September 1957. This reform is well-known to have significantly raised the academic qualification rate (Dickson and Smith, 2011). Second, the introduction of the General Certificate for Secondary Education (GCSE) in 1986, affecting those born after September 1970. This reform, which replaced the previous age 16 qualifications known as the Certificate for Secondary Education (CSE) and the General Certificate of Education Ordinary Level (O-level), further increased the academic qualification rate. In our sample, only about ten percent of the women were born early enough to face the lower school leaving age, and also only about ten percent of the women were born late enough to face the new GCSE system. Hence the sample women overwhelmingly faced a school-leaving age of 16 with the CSE/O-level qualification system. The O-level qualification in particular acted a pathway to the A-level (Advanced Level) and the A-level qualification in turn is the standard requirement for university entrance.



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

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

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.

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.[8] 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", but Table 2 presents a breakdown also by type 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: half of those reporting some abuse in a given period also report abuse in the following period.

Panels (a) and (b) of Figure 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.[9] The reported incidence of abuse

[8]Each questionnaire specifies to the respondent what time period is meant by "recent"; in particular these periods are specified so as to measure events since the last survey.

[9]For a recent US report highlighting the age-gradient in the incidence of intimate partner violence based on

		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	

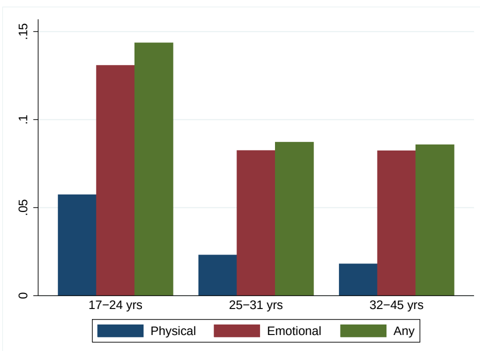
Table 2: Abuse levels and transition rates.

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 more direct endogenous nature: partnership duration and labour supply status. Panel (c) shows the incidence of abuse by partnership duration (at the beginning of the 12-month period). 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 (at the beginning of the 12-month period). Even though the ALSPAC measures are self-reported and subjective we show in Appendix A that, both in terms of level and demographic pattern, they agree well 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.

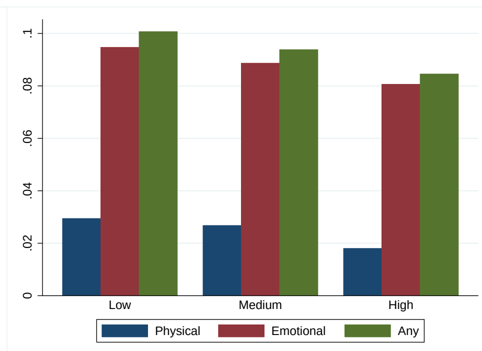
Partnership Status, Children and Labour Supply

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. We will correspondingly refer to the event of a woman leaving her

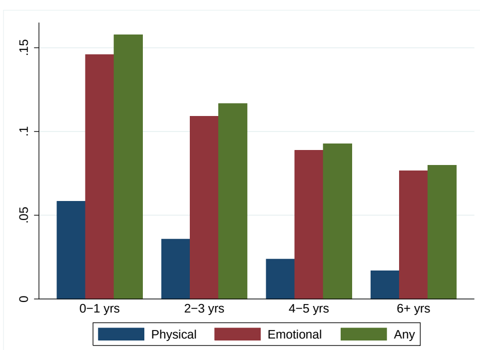
the National Crime Victimization Survey, see Truman and Morgan (2014). For evidence based on the National Intimate Partner and Sexual Violence Survey, see Breiding, Chen and Black (2014).



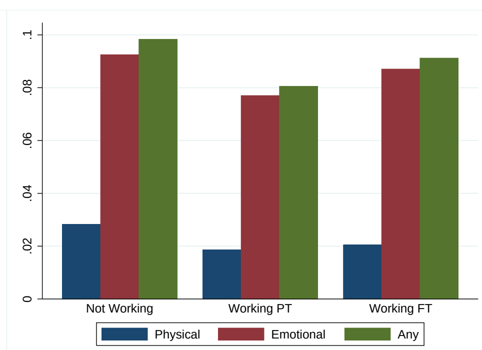
(a) Age Category at $t-1$



(b) Qualification Category



(c) Partnership Duration at $t-1$



(d) Labour Supply Status at $t-1$

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

partner as “divorcing” and the event of forming a new partnership as “marrying”.

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. In a small number of cases, a woman is observed to switch partners from one period to the next.[10] For estimation purposes we want to avoid direct partner-to-partner transitions; in such cases we therefore ignore the initial months of the new partnership and effectively assume that the woman was single for one intervening period. Panel A of Table 3 notes that, across all person-year observations, only some 94 percent of women are married. This is obviously lower than at baseline; indeed, the proportion married drops monotonically 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 at an annual rate of 12 percent.

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 3 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 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.[11]

[10] Direct partner to partner transitions can be detected in the data from information provided by the mother on the duration of her current relationship and on the status of the male partner being the biological father of the ALSPAC child or not.

[11] 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: 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 3: Marriage, births and labour supply.

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 3. 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.[12] 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, thus imputing annual earnings to be 1,000 and 2,000 times the hourly wage respectively.

While the ALSPAC data unfortunately only contain information about total household income (including benefit income), they do contain detailed occupational information in the form of 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 wage among all women aged 18-59 observed in the UK Labour Force Survey between 1993 and 1999. Panel B in Table 1 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 C of Table 1.

[12] Conditioning on no child birth between t and $t+1$, the rate of remaining in full time employment is 83 percent.

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 4: Summary statistics of hourly wages.

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.[13] The results are presented in Table

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

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

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 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 $t-2$. The lower estimated coefficients in the FE model suggest potential selection both into partnerships and partnership responses to abuse.

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 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 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 1), 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 looks at how a woman's labour supply status at time t is affected by the experience of abuse between $t-1$ and t. The evidence here is rather mixed, but if anything the results suggest that women respond to experiencing abuse by less frequently remaining out of 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.

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. We assume that there are two types of males: (i) men who have a "violent nature" and who are abusive with a high frequency, and (ii) men who have a "non-violent nature" and who are abusive much more rarely. The abuse behaviour of males is modelled, in a "reduced form", as non-strategic and stochastic with the probability of abuse depending on his type and age, and on the wife's chosen level of labour supply.

While men differ in their nature, a woman who meets a new prospective partner does not directly observe his nature; instead she forms beliefs which she updates based on her observations of his behaviour. In particular, when experiencing abuse, her belief that he has a violent nature increases, which in turn lowers her expected future utility from remaining married. 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 her husband once children are present and as a consequence she will be more prone to stay even if that means suffering abuse. In order to steer clear of this potential “trap” she can delay fertility until she knows her husband’s type better and hence the true propensity to divorce, 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 policy that empowers her 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 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, $m_t \in \{0, 1\}$. In this simple version we normalize the utility of being single to zero and let ψ^m denote the per-period utility of being married. In addition, each woman obtains, in each period t, a random utility ε_t^m from being married which we take to be i.i.d. normally distributed with zero mean and variance σ_m^2.

A woman who enters a period as married can choose to either remain married or to divorce. Single women randomly receive marriage offers at rate ς from a new prospective partner. Any new prospective male partner is of one of two possible types, $r \in \{0, 1\}$: he is either of the “non-violent type” ($r = 1$) or he is of the “violent type” ($r = 0$). The husband’s type is a fixed personal characteristic. However, the woman receiving the marriage offer does not observe the proposing male’s type. The probability that a new prospective male partner is of the non-violent type is denoted by

$$\phi_b = E[r] \in (0, 1), \tag{1}$$

and thus also represents the woman's initial beliefs about the type of any new partner.

What distinguishes male types is their propensity to engage in abuse. Let $z_t \in \{0,1\}$ indicate a woman's exposure to abuse at time t and let χ_r denote the per period probability that a male of type r engages in abuse; we then assume that $0 < \chi_1 < \chi_0 < 1$. This difference in abuse behaviour means that a woman updates her beliefs based on the husband's observed actions. 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

$$\phi_{t|z_{t-1}=0} = \frac{\phi_{t-1}\left(1-\chi_1\right)}{\phi_{t-1}\left(1-\chi_1\right) + \left(1-\phi_{t-1}\right)\left(1-\chi_0\right)}, \tag{2}$$

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

$$\phi_{t|z_{t-1}=1} = \frac{\phi_{t-1}\chi_1}{\phi_{t-1}\chi_1 + \left(1-\phi_{t-1}\right)\chi_0}. \tag{3}$$

Experiencing abuse is associated with the instantaneous disutility $\psi^z > 0$. Hence the expected disutility from abuse in period t for a married woman with current beliefs ϕ_t are $\pi\left(\phi_t\right)\psi^z$, where

$$\pi\left(\phi_t\right) = \phi_t\chi_1 + \left(1-\phi_t\right)\chi_0, \tag{4}$$

captures her perceived likelihood of experiencing abuse.

Consider then a woman who is either married or who has met a new potential partner. Based on her current beliefs, $\phi_t \in [0,1]$, about her available partner and also on her marriage utility shock ε_t^m she decides on her marital status, $m_t \in \{0,1\}$, for the current period. Letting δ denote the discount rate, the model can then be solved using standard dynamic programming. In particular, there will be a present discounted value $V^m\left(\phi_t\right)$ associated with entering a period as married with belief ϕ_t and a value V^s associated with entering a period as single.[14]

Consider then divorce behaviour. A woman who enters a period as married with beliefs ϕ_t will divorce if

$$\psi^m + \varepsilon_t^m - \pi\left(\phi_t\right)\psi^z + \delta\left[\pi\left(\phi_t\right)V^m\left(\phi_{t+1|z_t=1}\right) + \left(1-\pi\left(\phi_t\right)\right)V^m\left(\phi_{t+1|z_t=0}\right)\right] < \delta V_s, \tag{5}$$

[14] Formally, $V^m\left(\phi_t\right)$ and V^s satisfy
$$V^m\left(\phi_t\right) = E_{\varepsilon_t^m}\left[\max\left\{\psi^m + \varepsilon_t^m - \pi\left(\phi_t\right)\psi^z + \delta\left[\pi\left(\phi_t\right)V^m\left(\phi_{t+1|z_t=1}\right) + \left(1-\pi\left(\phi_t\right)\right)V^m\left(\phi_{t+1|z_t=0}\right)\right], \delta V_s\right\}\right]$$
and $V^s = \varsigma V^m\left(\phi_b\right) + \delta\left(1-\varsigma\right)V^s$ respectively.

which means that there will be a threshold ε_t^m below which she will divorce. Moreover, this threshold value will be a function of her current beliefs ϕ_t: women with more pessimistic beliefs about their husbands' types will set a higher threshold value for ε_t^m and will hence be more prone to divorce. As experiencing abuse will worsen a woman's beliefs about her husbands nature, divorce will be more likely after incidents of abuse.

For a given set of parameters, the model can be solved numerically and then forward-simulated to generate a steady state distribution of marital status, abuse incidence and beliefs. Doing so allows us to highlight how key parameters of the model relate to moments in the data. In this simple model we normalize ψ^m to unity and set the discount parameter to $\delta = 0.95$. A woman's rate of accepting a new marriage offer will be the same as the rate at which a married woman with belief ϕ_b continues her marriage. Since this rate can be expected to be high (see below), the rate at which single women enter new partnerships is largely determined by the partner meeting rate ς. E.g. at $\varsigma = 0.14$, the expected duration of singlehood will, empirically plausibly, be around seven years.

We now turn to the more specific parameters, σ_m^2, ψ^z, ϕ_b, χ_0 and χ_1, and discuss how these can be related to divorce behaviour and abuse incidence. The regressions in Table 5 showed that women who reported experiencing abuse were more likely to divorce: the raw divorce rates in the data are 0.075 and 0.014 (see Table 7 below) which we match here. These stylized facts help pin down the variance σ_m^2 and the disutility ψ^z. As the utility shock ε_t^m is temporary, it needs to be sufficiently large to make even some women who hold very positive beliefs about their husbands occasionally choose to divorce. Moreover, even women who were exposed to abuse are distinctly more likely to remain with their partners than divorce which effectively limits ψ^z. Setting $\psi^z = 0.32$ and $\sigma_m^2 = 2.72$ generates steady state divorce rates that match the empirical moments. More generally it implies that the probability of divorce as a function of beliefs ϕ_t goes from around a low rate of little over one percent for women who firmly believe that their partners are of the non-violent type up to close to ten percent for women who firmly believe that their partners are of the violent type.

This suggests that the systematic instantaneous utility of marriage is substantially reduced by abuse, but remains positive, $\psi^m - \psi^z > 0$. Women who, through experience, firmly believe that their partners are of the violent type do not necessarily immediately leave their husbands; however, compared to women who hold more positive beliefs, the abused women are less willing to accept temporary negative marriage utility shocks.

The three remaining parameters are the baseline beliefs (or, equivalently, the frequency of non-violent males among prospective partners), and the abuse rates of non-violent and violent male types respectively. These are closely related to the overall abuse rate and the abuse "transition" rates in Panel D of Table 3. Setting $\phi_b = 0.64$, $\chi_1 = 0.03$ and $\chi_0 = 0.71$ generates an overall abuse rate of 0.092, an abuse onset rate of 0.057 and a persistence rate of 0.495.

In order to generate a level of abuse persistence corresponding to that observed in the data it must be that some men are high-repeat offenders. However, it cannot be that all abuse is perpetrated by such violent men. In particular, the higher divorce rate after abuse implies that the prevalence of violent men in the steady state pool of husbands is much lower – less than 10 percent in the current example – than the prevalence of such men among the new potential partners encountered by single women ($1 - \phi_b = 0.36$). In order to still predict a substantial overall rate of abuse, the calibrated model suggests a low rate of abuse also by men with a non-violent nature.

The empirical model presented below will expand on the current simple one by also incorporating labour supply and fertility decisions. As such it will have a different cardinalization and will also have a finite time horizon. Nevertheless, it will retain some of the key qualitative features from this very simple framework. In particular, it will have a similar size of the temporary marriage utility shocks relative to the systematic utility of marriage, a similar disutility of abuse relative to the baseline utility of marriage, and similar estimated frequencies of male types and their abuse propensities.

Bearing in mind that the core learning mechanism will be practically the same in the full model as in the current illustrative version, we will use the current simplified version to highlight the implied "speed of learning" and the associated distribution of beliefs. To do so, consider a population of women who get married at time $t = 0$ and who, for simplicity, remain married for

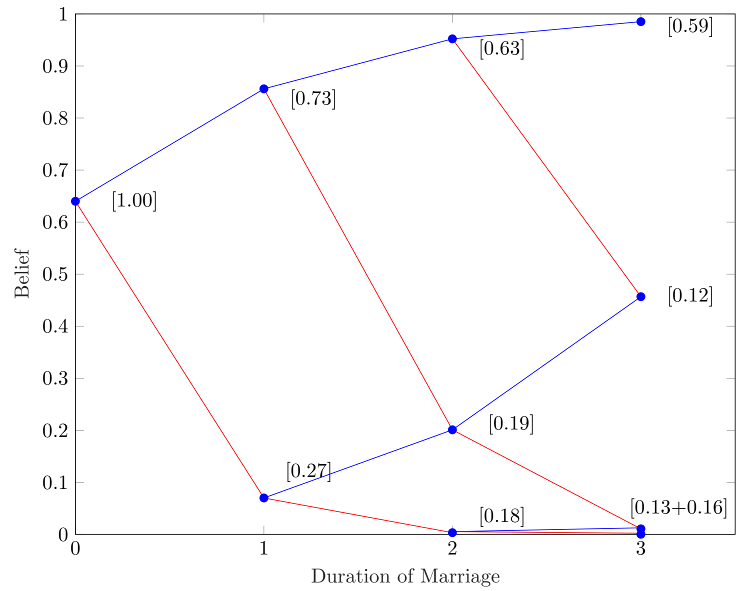


Figure 3: The evolution of the belief distribution.

at least three periods.

Figure 3 illustrates how the distribution of beliefs develops in this population. In the figure, a blue line represents a period without abuse and a red line a period with abuse. At the time of marriage all women hold the baseline beliefs. In the first period of marriage 73 percent of the women experience no abuse and update their beliefs to $\phi_1 = 0.86$; in contrast, 27 percent of women do experience abuse and update their beliefs to $\phi_1 = 0.07$. After two periods of marriage, each woman will either have experienced 0 (63 percent), 1 (19 percent) or 2 (18 percent) episodes of abuse, leading to beliefs ϕ_2 that are 0.95, 0.20 and 0.003 respectively. After one further period, 88 percent of the women have beliefs ϕ_3 that are either above 0.98 or below 0.02. Hence within just a few periods, the vast majority of women will have very firm beliefs about the nature of their partners. This high speed of learning also means women can expect not to have to wait long if they choose to delay fertility until they are more confident about their partner's nature. For that we now turn to the full empirical model.

The Full Empirical Model

The full version of the model 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 is 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

$$U_t = \frac{\mu^{k_t} C_t^{1-\lambda}}{1-\lambda} + \left(\Psi_t^m - \bar{\Psi}_t^z\right) m_t + \Psi_t^n, \tag{6}$$

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 captures the direct utility of children, Ψ_t^n. 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

$$C_t = \begin{cases} \tau\left(w_t + w_t^h - c_t\right) & \text{if } m_t = 1 \\ w_t - c_t & \text{if } m_t = 0 \end{cases}, \tag{7}$$

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).

Wage Offers

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

$$w_t^k = \exp\left(\beta_0^k + \beta_1^k a + \beta_2^k x_t - \beta_3^k x_t^2 + \varepsilon_t^k\right), \text{ for } k = 1, 2, \tag{8}$$

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 earnings factor 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,

$$\frac{\Pr(a=1|q)}{\Pr(a=0|q)} = \exp\left(\beta_0^a + \beta_1^a d_{q=1} + \beta_2^a d_{q=2}\right), \tag{9}$$

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

$$x_{t+1} = x_t + k_t, \tag{10}$$

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 (7) is specified in a similar way as

$$w_t^h = \exp\left(\beta_0^h + \beta_1^h a + \beta_2^h t + \beta_3^h t^2 + \varepsilon_t^h\right), \tag{11}$$

where ε_t^h is also a temporary productivity shock. The presence of the woman's permanent productivity type a in the husband's wage offer equation (11) 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

$$A = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{h1} & 0 & a_{hh} \end{bmatrix}. \tag{12}$$

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.[15] 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 estimation.

Hence we specify the two components of c_t as follows

$$c_t = \rho^{k_t} \left(\beta_1^{cc} n_t + \beta_2^{cc} n_t^2\right) - \left(\beta_1^{ci} n_t + \beta_2^{ci} n_t^2\right)(1 - m_t), \tag{13}$$

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

Marriage, Learning and Conception

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, $r \in \{0, 1\}$.[16] 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 in period t is indicated by $z_t \in \{0, 1\}$. z_t is realized after the woman has decided on her level of labour supply k_t and conception f_t. Hence a married woman makes these decisions under uncertainty about potential exposure to abuse. A non-violent husband type is, in any given period, abusive with probability χ_1. A violent husband type is abusive with probability

[15] 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.

[16] 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.

$\chi_0(k_t, t)$ which we specify as a logistic function of her chosen labour supply and of time t,

$$\chi_0(k_t, t) = \frac{\exp\left(\chi_0^{k_t} + \chi_0^t t\right)}{1 + \exp\left(\chi_0^{k_t} + \chi_0^t t\right)} \text{ for } k_t = 0, 1, 2. \tag{14}$$

The dependence of the abuse probability on the wife's labour supply k_t, while there to help capture key patterns in the data, also generates incentive effects. For instance a woman who experiences abuse may choose to increase her labour supply in order to build up her work experience and future earnings capacity, anticipating that she is now more likely to leave her partner. The incentives for doing so while still married will depend on whether increasing her labour supply will increase or decrease the risk of further abuse. The inclusion of t as an argument of $\chi_0(k_t, t)$ captures that the tendency for a violent man to engage in abuse may decrease with age. One interpretation of this is that abuse occurs as men lose control and that young men may be particularly susceptible to do so. A woman's beliefs are updated exactly as in (2) and (3) while also taking into account that the abuse rate by violent men depends on her chosen labour supply and on age.

The expected disutility from abuse for a married woman in (6) with current belief ϕ_t and chosen labour supply k_t is given by $\bar{\Psi}_t^z = \pi(\phi_t, k_t)\psi^z$ where

$$\pi(\phi_t, k_t) = \phi_t \chi_1 + (1 - \phi_t)\chi_0^{k_t}, \tag{15}$$

is her perceived probability of experiencing abuse and where ψ^z is the direct disutility of abuse.

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 (6) 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.

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 particular 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.[17] This places us as close as possible to the timing of the ALSPAC sampling frame, where women are first observed a few months into a pregnancy.[18]

[17]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.

[18]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

Identification

Overall 45 parameters are estimated using 92 empirical moments. The set of moments included in the estimation, which contain both static and dynamic ones and ones that link choice dimensions, can be broadly split into three main groups by what they help identify. The first group contains moments related to employment – employment status by age, qualification level and marital status, and employment transitions – and wages – wages by labour supply status and qualification, and of husbands. These moments strongly identify the parameters associated with the wage offer functions, unobserved ability structure, the disutility of work effort, income associated with non-employment, and the correlation between per-period earnings shocks.

The second group of moments include those used for the simple illustrative model above: the marriage- and marriage transition rates, the abuse- and abuse transition rates, and the divorce response to abuse. We further add abuse by qualification level, age, labour supply status, and partnership duration, the count distribution of abuse over the seven observed periods, the divorce response to abuse and the *average partnership duration at divorce*. These moments identify the disutility of abuse, the size of match quality shocks, the arrival rate of partners, and the type-specific abuse frequencies. Combined with the identified earnings structure, the observed marriage rate further identifies the sharing parameter. Interestingly, observed rates of abuse help identify the marital utility shock, which has been difficult to identify in discrete choice dynamic programming (DCDP) models that do not incorporate domestic abuse data (see e.g., Keane and Wolpin (2010) and Sauer (2015)).

The third main group of empirical moments relates to children and contains fertility measures – average age- and partnership duration at first birth, the arrival rate of siblings, the distribution of completed fertility, proportion of out-of-wedlock birth for younger and older mothers. These moments help identify the utility of children, conception utility shocks, child-related costs, and the level of child-support.[19]

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.

[19] As an auxiliary moment we include the fraction of women who remain childless. As this empirical moment,

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 DCDP models.[20]

From the simple model above, we expect that the speed of learning is quite high. Hence it is important from an identification perspective that we observe a large number of women making decisions in the early stages of partnerships. Defining an "early-stage" partnership as one with duration of no more than four years, the proportion of observations from the ALSPAC sample that pertain to early-stage partnerships is about 20 percent, or close to 12,000 observations. Moreover, these observations account for 30 percent of all observed births and 36 percent of all observed divorces.

V Estimation Results

In this section, we report estimates of the structural model presented in Section III. In assessing the model, we consider the within-sample fit and the reasonableness of the parameter values.

Moments and Model Fit

Tables 6 to 9 present the moments included in the estimation, comparing the empirical and simulated values. Table 6 presents abuse-related moments while Table 7 reports the moments related to marital status and fertility. Table 9 presents the employment-related moments – labour supply status by age, qualification level and marital status, and employment transitions while, finally, Table 9 reports hourly wages by labour supply status, of husbands, and by qualification

per construction, cannot be computed in the ALSPAC data, we obtain it from the Office for National Statistics (2013), Table 3.

[20] A woman's beliefs are a key state variable and the belief space, $\Phi \in [0, 1]$, is in principle continuous. For computational purposes we use a 74-point grid. The grid used is not equi-spaced, but rather denser towards the ends of the unit interval. This feature is chosen to reflect the natural properties of the learning process in which belief changes implied by the Bayesian updating process tend to be smaller when the prior is closer to either zero or unity.

level.

Looking first at abuse, Table 6 show that, in line with the simple 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 over the seven periods.[21]

It also slightly 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 non-violent men at a particularly higher rate (see below). Instead, their lower exposure reflects differences in behaviour which in turn reflect differences in economic opportunities. The high qualified women are less financially dependent on their partners in general and particularly so at the relatively early ages as they delay their fertility more: high-qualified women have an age at first birth that is close to three years higher than that of the low- or medium-qualified women. As a result, they are less likely to have children during the critical early stages of relationships and are less likely to become trapped with abusive partners.

The model somewhat under-predicts the particularly high abuse incidence among young women, however, perhaps more importantly from a learning perspective, it quite closely predicts the relationship between partnership duration and exposure to abuse. This pattern in abuse is driven by endogenous divorces: the baseline model predicts that the proportion of married women who have violent husbands drops from around 34 percent among newlyweds to 24 percent among women who have been married for 10 years. In contrast, the estimated parameters do not suggest that violent men become markedly less abusive with age (see below).

The model further replicates the U-shaped relationship between the level of labour supply

[21]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.

and exposure to abuse, implying that PT work is the labour supply status least associated with abuse. The difference between PT and FT in particular is due to endogenous choice of labour supply mode as the estimated parameters do not suggest any marked difference in the rates at which violent men are abusive towards PT and FT working women (see below).

Instead, the difference stems from who chooses which mode of labour supply: in the baseline model, PT work tends be chosen by women with more positive (rational) beliefs about their partners' nature, with longer partnership duration, and with a larger number of children. In contrast, FT work is more relatively more commonly chosen by women with more negative expectations about their partners' nature, with shorter marriage duration and with fewer children. This also means that FT work is associated with a higher future divorce risk than is PT work.

Finally, the model predicts well that women who experience abuse at time t are substantially more likely to divorce in the following period, and also substantially less likely to conceive a further child.

Turning to Table 7 we see that the model fits the marital transitions well, though the overall divorce rate is slightly under-predicted. The model also predicts an age-pattern in the proportion of births that are out of wedlock, though not quite as sharp as observed in the data. 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. Again, the model slightly over-predicts births to single women. The model also predicts well the proportion of women who remain childless and the distribution of number of children among those who do have children.[22] Importantly, the model predicts the timing of first births very well, both in terms of the mother's age and partnership duration. It also replicates fairly accurately the average duration at divorce.

The model fits the labour supply pattern quite well as can be seen in Table 8. In terms of employment transitions, of those who enter employment, the model somewhat overpredicts the rate at which women enter full-time employment. Also, among those leaving part-time employment, the model slightly overpredicts the rate of moving out of employment rather than

[22]This also implies that the distribution of birth order in our simulated sample matches that among the ALSPAC sample children.

Panel A: Abuse Rate and Abuse Transitions			
	Mean	No Abuse at $t+1$	Abuse at $t+1$
No abuse at t	0.908	0.943	0.057
	0.911	*0.945*	*0.055*
Abuse at t	0.092	0.505	0.495
	0.089	*0.554*	*0.446*
Panel B: Count Distribution of Abuse Incidents			
0	1-2	3-4	5+
0.748	0.169	0.057	0.026
0.704	*0.195*	*0.068*	*0.033*
Panel C: Abuse Rate By Qualification Level			
Low Qual.	Medium Qual.	High Qual.	
0.101	0.094	0.085	
0.109	*0.104*	*0.054*	
Panel D: Abuse Rate By Age Group			
Age 17-24	Age 25-32	Age 33-40	
0.144	0.087	0.085	
0.100	*0.084*	*0.089*	
Panel E: Abuse Rate by Partnership Duration in Years			
0-1	2-3	4-5	7+
0.158	0.117	0.093	0.079
0.190	*0.153*	*0.120*	*0.064*
Panel F: Abuse Rate By Labour Supply at $t-1$			
Not Working	Part-Time	Full-Time	
0.101	0.084	0.106	
0.092	*0.081*	*0.099*	
Panel G: 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	*0.052*	*0.098*	*0.072*

Table 6: Matched moments: abuse.

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
	0.100	*0.865*	*0.135*
Married at t	0.937	0.019	0.981
	0.900	*0.016*	*0.984*
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
0.133	*0.063*	*0.098*	*0.069*
Panel C: Distribution of Nr Children			
Childless	1 Child	2 Children	3+ Children
0.190	0.102	0.409	0.299
0.182	*0.103*	*0.428*	*0.287*
Panel D: Average Age and Partnership Duration at Key Events			
Average Age at 1st Birth		Av. Partnership Duration: At 1st Birth	At Divorce
26.95		3.64	6.78
27.02		*3.61*	*7.13*

Table 7: Matched moments: marriage and fertility.

moving to full-time employment. For the labour supply by marital status, the model captures the lower rate of employment by single mothers and the relatively high frequency of part-time work by married mothers. In terms of hourly wages (Table 9), 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, though the variation in wages is overpredicted for low- and medium-qualified women but underpredicted for high-qualified women.

Parameter Estimates

The estimated parameters are reported in Tables 10 and 11, with Table 10 presenting the β-coefficients from equations (8), (9) (11), (13) and (17), and Table 11 reporting all remaining parameters.

Consider first the earnings regressions in Panel A of Table 10. 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

Panel A: Employment Status			
	Not Working	Working Part-Time	Working Full-Time
All	0.471	0.345	0.184
	0.468	*0.346*	*0.186*

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
	0.779	*0.165*	*0.056*
Part-Time at t	0.183	0.703	0.114
	0.266	*0.684*	*0.050*
Full-time at t	0.229	0.302	0.469
	0.277	*0.310*	*0.413*

Panel C: Employment Status by Age Group			
	Not Working	Working Part-Time	Working Full-Time
Aged 17-24	0.585	0.207	0.208
	0.626	*0.209*	*0.165*
Aged 25-31	0.486	0.344	0.170
	0.430	*0.351*	*0.220*
Aged 32-40	0.438	0.374	0.188
	0.395	*0.449*	*0.156*

Panel D: Employment Status by Marital Status			
	Not Working	Working Part-Time	Working Full-Time
Single	0.590	0.240	0.171
	0.683	*0.192*	*0.126*
Married	0.463	0.352	0.185
	0.444	*0.363*	*0.193*

Panel E: Employment Status by Qualification Level			
	Not Working	Working Part-Time	Working Full-Time
Low Qual.	0.575	0.307	0.118
	0.606	*0.275*	*0.118*
Medium Qual.	0.490	0.349	0.160
	0.555	*0.300*	*0.146*
High Qual.	0.396	0.362	0.242
	0.230	*0.470*	*0.300*

Table 8: 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
	6.64	*7.87*	*9.28*
St. Dev	2.70	2.90	3.51
	2.79	*2.79*	*3.02*
Panel B: Accepted Hourly Wages by Qualification Level			
	Low Qual.	Medium Qual.	High Qual.
Mean	5.35	6.07	8.78
	5.58	*6.44*	*8.25*
St. Dev	1.64	1.92	2.89
	2.91	*3.02*	*2.12*

Table 9: Matched moments: wages.

Panel A: Wage Offer Functions				
	Non-Emp. $log(w^0)$	PT Emp. $log(w_t^1)$	FT Emp. $log(w_t^2)$	Husband $log(w_t^h)$
Constant	7.266	7.19	7.751	9.525
	(0.439)	(0.002)	(0.002)	(0.002)
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	0.762	5,168.91	3,020.92	
	(0.001)	(9.412)	(1.413)	
n_t^2	-0.004	-212.95	-664.28	
	(0.000)	(1.396)	(0.622)	
Panel C: Ability Probability Function				
Constant	0.255			
	(0.005)			
$q = 1$	0.418			
	(0.005)			
$q = 2$	0.996			
	(0.002)			

Table 10: Parameter estimates: linear equations.

Panel A: Preference Parameters					
Marriage		Abuse	Fertility	Work Effort Cost	
ψ^m	σ_m^2	ψ^z	σ_f^2	μ_1	μ_2
338.68	773.95	177.41	1.703	0.9998	0.958
(0.460)	(1.235)	(0.599)	(0.013)	(0.001)	(0.000)
Panel B: Abuse Parameters - Type Freq.					
$\phi_b^{q=0}$	$\phi_b^{q=1}$	$\phi_b^{q=2}$			
0.636	0.645	0.6751			
(0.001)	(0.002)	(0.003)			
Panel C: Abuse Parameters - Abuse Freq.					
χ_1	χ_0^0	χ_0^1	χ_0^2	χ_0^t	
0.029	0.969	0.242	0.208	-0.006	
(0.000)	(0.001)	(0.000)	(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	0.142		
(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 11: Parameter estimates continued: remaining parameters.

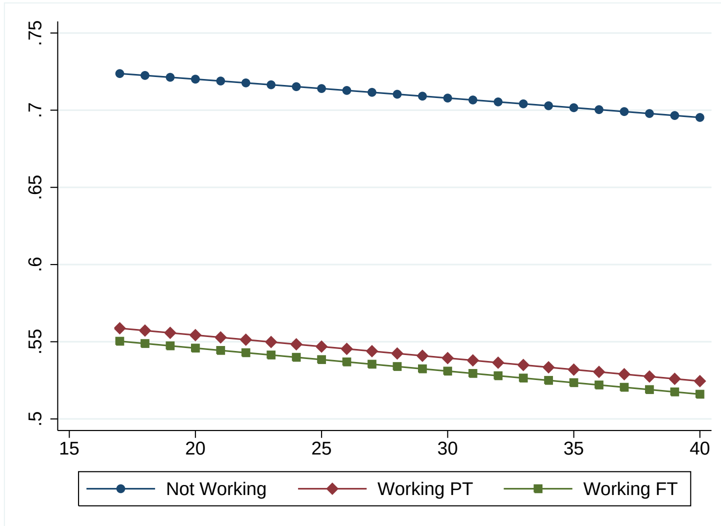


Figure 4: Abuse frequency for violent male type by age and wife's labour supply status.

down to zero for women who have worked FT for fifteen years.

The estimated maximum childcare costs (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 2-3 children.

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.

Consider now the parameters presented in Table 11. Similar to the simple model above, the estimated ψ^z indicates that exposure to abuse substantially reduces the utility from marriage, and the estimated σ_m^2 indicates that there are sizeable temporary match quality shocks.

The estimates of ϕ_b^q indicate that there is no substantial difference across qualification groups in the rate of encountering violent men. In line with the simple model, the estimated abuse probability for a non-violent male χ_1 is low. Figure 4 plots $\chi_0\left(k_t, t\right)$ by the wife's level of labour supply and by age. The estimates thus suggest that the rate of abuse by violent men towards non-working women is substantially higher than towards working women. There is however little difference between PT and FT work status. Also, the estimated functions do not suggest that the observed age gradient in abuse incidence is significantly driven by age-dependent abuse behaviour by violent men.

The estimated meeting rate ς is also effectively unchanged from the simple model. 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.[23]

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 change the information structure in the model so as to assume that 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.[24] The corresponding literature on

[23]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.

[24]Key contributions include Dicker-Conlin and Houser (2002), Eissa and Hoynes (2000, 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 Dicker-Conlin and Houser (2002) find little or no effect of the EITC on marriage.

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.[25] 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 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.[26]

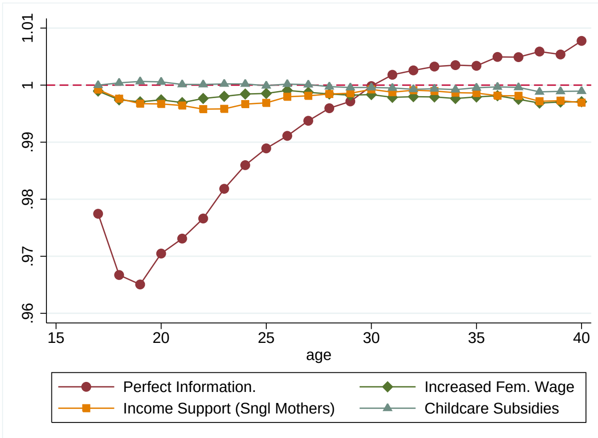
The results from the counterfactual simulations are presented in Table 12 and Figures 5 - 7. Table 12 presents results for a set of statistics computed across the women's lifetimes. Figure 5 highlights some more details of the dynamics of the responses by presenting various outcomes – relative to the baseline model – by age. Figure 6 focuses in particular on the timing of conceptions relative to first marriage. Figure 7 focuses specifically on labour supply responses by qualification group.

The Effect of Uncertainty

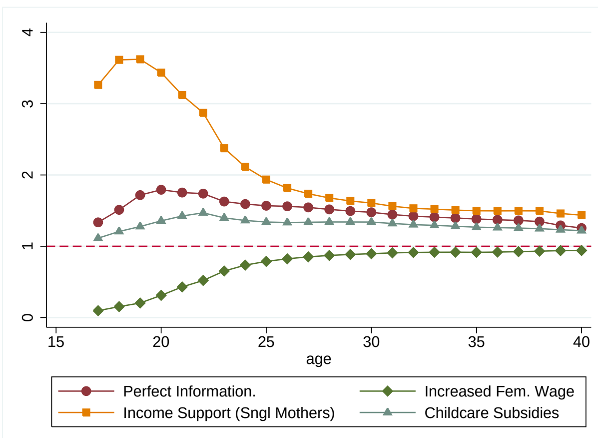
In the first counterfactual simulation we explore how uncertainty about males' types affects women's choices and outcomes. We focus here on the extreme opposite scenario relative to the baseline case, namely the case where any woman can immediately observe the type of any

[25] Baughman and Dickert-Conlin (2009) studies the effect of the US Earned Income Tax Credit, Brewer, Ratcliff, and Smith (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, Hener and Rainer (2016) study the effect of public childcare in Germany. A leading example of an analysis of pro-natalist policies is Milligan's (2005) study of the Allowance for Newborn Children introduced in Quebec in 1998.

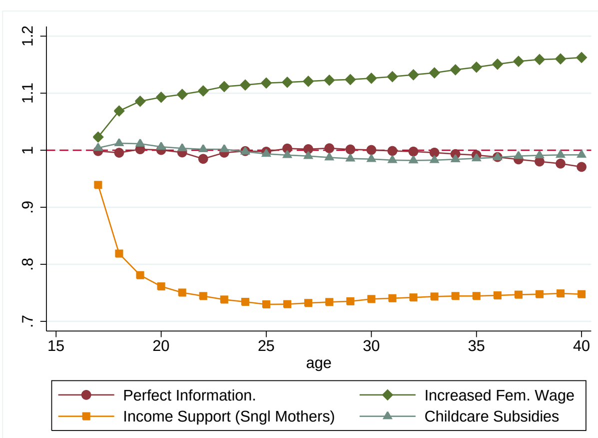
[26] A recent review of the literature is provided by McTavish et al. (2016).



(a) Relative Married Rate



(b) Relative Nr of Children



(c) Relative Experience

Figure 5: Proportion married, number of children, and labour market experience relative to the baseline economy.

	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	27.018	25.384	28.329	24.474	25.596
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	0.115	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 12: Counterfactual simulations: lifetime outcomes.

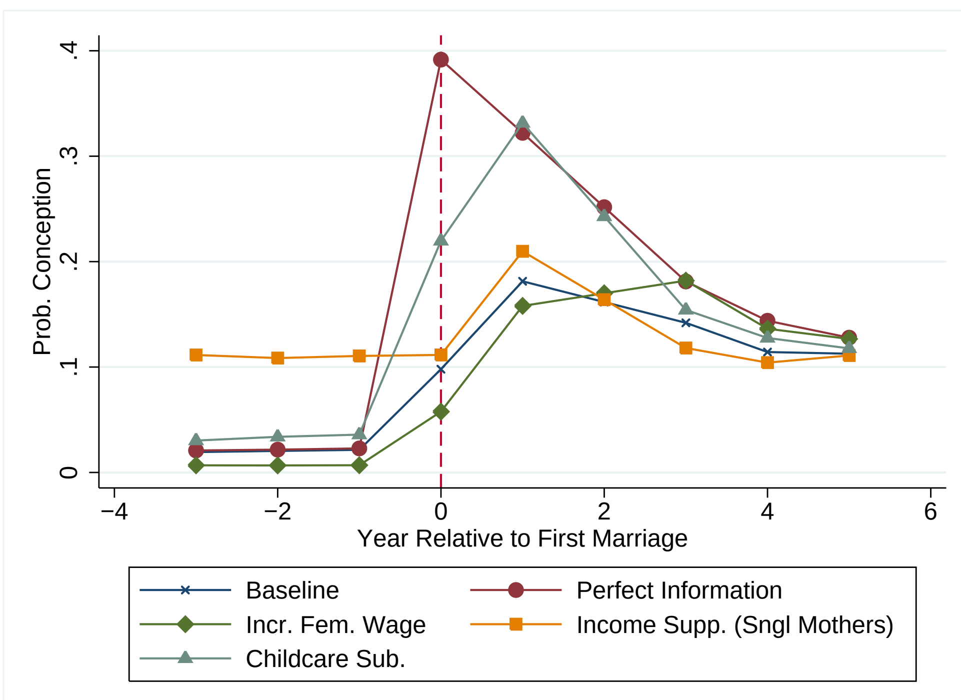


Figure 6: Conception rate in years around year of first marriage.

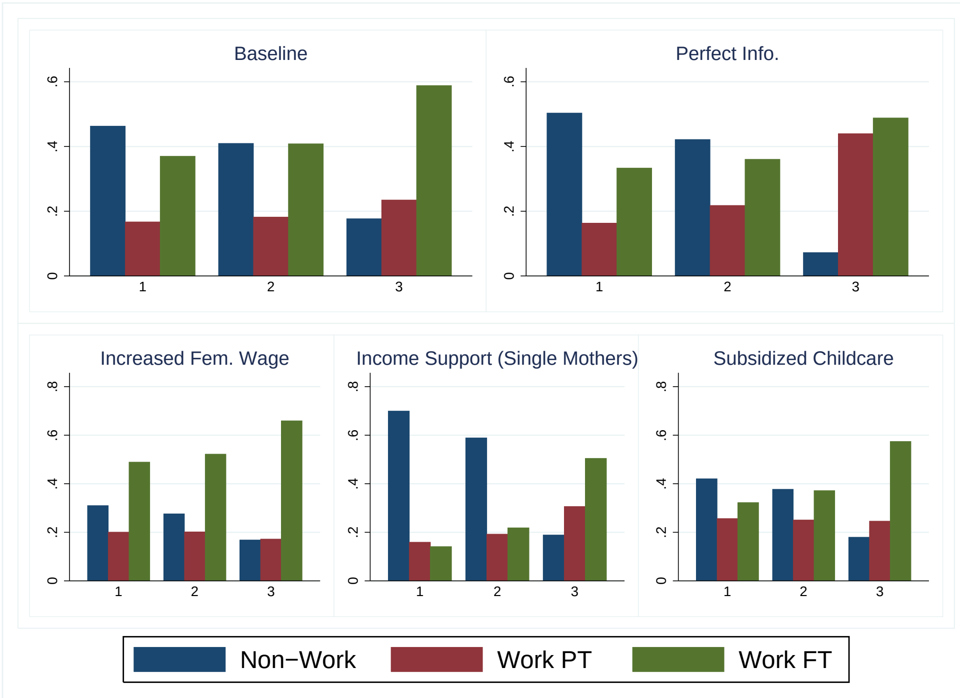


Figure 7: Counterfactual simulations: labour supply by qualification group.

potential new partner.[27]

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, uncertainty increases the proportion of women who are married in early adulthood. As shown in Figure 5, the proportion of women who are married is higher under uncertainty below the age of 30.[28]

[27]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 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.

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

However, divorces are also higher when types are not directly observable; as a 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 6 which plots the conception rate in years around first marriage (where $year = 0$ indicates the year of first marriage). With uncertainty, conceptions are higher in the years following marriage than in the actual 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 12), 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 7 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 in the perfect information scenario (Table 12). For women with children, 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 5 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 6). 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 5). Figure 7 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 12 we also see that the average age at first birth increases by over a year and Figure 5 shows that below the age of 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 6). 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, about, 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 relative wages for women reduces exposure to abuse is in line with the findings in Aizer (2010), though somewhat smaller.[29]

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.

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, $m_t = 0$, 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, marriages can also be bad in terms of match quality, which would tend increase the attractiveness of single-motherhood more generally. Furthermore, generous income support generates an (expected) income effect and provides consumption smoothing over marital states. These latter effects will boost fertility incentives and lower labour supply. Taking such broader responses into account, it is less clear that a generous child support policy would indeed reduce the incidence of abuse. To explore this, we increase 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 12). Age at first birth reduces by about two and a half years on average and, as can be seen from Figure 6, 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

[29] 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.

– women work less, with low- and medium qualified women in particular being more likely to be out of the labour force (Figure 7). 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 12 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 0.3, see Table 11) 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 the mother participating in the labour market and hence encourages labour supply. Second, it reduces the overall expected cost associated with children which encourages fertility. Consider first fertility. As can be seen from Table 12, 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 (Figure 6). Despite the higher fertility, the overall labour force participation rate increases, with low- and medium-qualified women in particular working more frequently part-time (Figure 7).

While higher labour supply should, given the estimated parameters, reduce exposure to abuse, the increased fertility may increase it, leaving the net effect on abuse incidence ambiguous. Indeed, Table 12 suggests that the opposing effects effectively cancel out, leaving no discernable net overall effect. 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 12 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 6 that fertility in the first three years of marriage increases quite sharply relative to the baseline case. Hence, with subsidized childcare, women choose more frequently to conceive early in their marriages whilst they are still learning about the partner's nature. Moreover, their increased work experience does not seem to offer enough empowerment to raise the divorce rate (as in the case of higher income to single mothers), thereby more frequently leaving women and their children exposed to abuse.

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 partner "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: an experience of abuse today increases the expectation of future abuse, thereby reducing the expected value of continued marriage and increasing the likelihood of divorce. 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 effect on 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. Such a policy could, in principle, make mothers more financially independent and hence more able to walk away from abusive partners. However, we found that it also encourages fertility – premarital fertility in particular – and decreases labour supply. This meant that when women do enter marriage they more frequently do so with children and with less accumulated labour market experience. As a result, once married, they tend to work less and to find it more difficult to leave abusive partners due to having lower wages. Hence, we found that increased income support for mothers would actually increase the incidence of abuse towards women in general and particularly strongly so for mothers.

A policy of subsidized childcare available to households where the mother is working naturally encourages mothers to work. But it was found to also encourage fertility, particularly early within marriage while the woman is still learning about the partner's type, making it more difficult to subsequently leave a relationship. While the higher labour supply tends to reduce exposure to abuse, the increased fertility tends to have the opposite effect. Indeed, overall we found no significant net effect of subsidized childcare on women's exposure to abuse. However, it was found to, somewhat paradoxically, increase the incidence of abuse among mothers raising the concern that it also increases children's exposure.

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.

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Appendix A: Comparison with the British Crime Survey

In this appendix we provide a comparison between the measured incidence of domestic abuse in the ALSPAC data and that in the British Crime Survey. In 1996 the British Crime Survey introduced a dedicated computerised self-completion intimate partner violence (IPV) module. The IPV module was further developed and used again in 2001, and then annually from 2005 onwards. Due to the assured anonymity and privacy when completing the module, and the detailed set of questions, the BCS IPV modules are considered to be one of the best quality large-scale evidence on the incidence of domestic abuse internationally.

The 1996 survey, while overlapping in time with the ALSPAC data, suffers two main drawbacks. First, it does not measure emotional abuse but instead focuses on threat of harm. Second, for physical abuse, it only gives details of the "most recent occasion". In contrast, the later surveys contained an itemized list of abusive behaviours (see below), including verbal abuse and non-physical controlling behaviour, where the respondent was asked about any incidence of each type of behaviour over the past 12 months. We focus here on the 2001 BCS IPV survey as it offers a sufficient degree of detail while still being close in time to later years of the ALSPAC data. Including also surveys from 2005 onwards would substantially increase observation numbers, but would involve using survey data obtained on average over a decade after the ALSPAC sample.[30] Hence we compare our ALSPAC sample to all women aged 17-45 in BCS 2001. This of course creates a key difference in that many of the women in the BCS sample are neither mothers nor pregnant. For this reason, we will present some comparisons that focus on the subsample of BCS women who have at least one child ("mothers").

As part of the BCS IPV module, the respondents are asked if they have experienced any of the abusive behaviours listed in Table A.1 by an existing or past intimate partner over the past 12 months. We classify each recoded behaviour as either physical or non-physical abuse as indicated and create dummy variables to indicate the experience of one or more of the listed behaviours within each group. In addition to the IPV module questions, the BCS respondents are also queried about intimate partner abuse as part of the main BCS survey. The abuse

[30] An extended comparison that includes also BCS 2005 - 2007 is available on request from the authors.

Behavior	**Physical Abuse**	**Non-Physical Abuse**
Prevented from fair share of h-hold money		x
Stopped from seeing friends and relatives		x
Repeatedly belittled you		x
Frightened you, by threatening to hurt you		x
Pushed you, held you down or slapped you	x	
Kicked, bit, or hit you	x	
Choked or tried to strangle you	x	
Threatened you with a weapon	x	
Threatened to kill you	x	
Used a weapon against you	x	
Used other force against you	x	

Table A.1: Itemized abusive behaviours in the BCS IPV module.

reporting in the main survey is known to be substantially lower than in the dedicated IPV module, thus indicating under-reporting in the open survey. We include it here to compare the under-reported BCS measure to the ALSPAC measure.

Table A.2 provides summary statistics for the ALSPAC and the BCS data. The women in the data are similar in age and in the distribution of qualifications. However, all women in the ALSPAC data are either already mothers (or they are pregnant) whereby they naturally have a higher average number of children. The number of children become more similar when conditioning on having at least one child ("mothers"). As labour supply is strongly related to motherhood, the women in the ALSPAC data are significantly less likely to be working full time than the BCS women.

Turning to the measures of abuse, we see that average reported incidence of physical abuse is lower in the ALSPAC data than in the BCS. This is consistent with a degree of under-reporting. Nevertheless, the reported frequency of physical abuse in the ALSPAC is still noticeably higher than that in the BCS main survey, suggesting that the level of under-reporting in the ALSPAC is not severe.

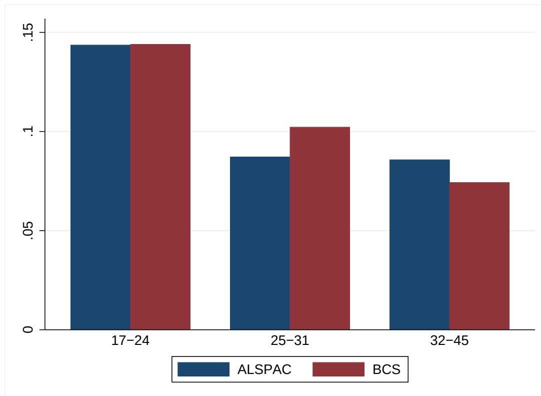
In contrast, the reported rate of emotional abuse in the ALSPAC data is higher than the reported non-physical abuse in the BCS. This is consistent with the underlying questions in the ALSPAC survey being more open to interpretations by the respondent than the precisely

	ALSPAC	**BCS 2001**
Age	31.1	32.8
	(4.98)	(7.41)
Qualification: Low	0.244	0.294
	(0.430)	(0.456)
Qualification: Medium	0.381	0.301
	(0.486)	(0.459)
Qualification: High	0.374	0.405
	(0.486)	(0.491)
Nr of Children	1.85	1.15
	(1.03)	(1.09)
Nr of Children (Mothers)	2.01	1.80
	(0.92)	(0.83)
Not Working	0.471	0.319
	(0.499)	(0.466)
Working PT	0.345	0.271
	(0.475)	(0.445)
Working FT	0.184	0.410
	(0.388)	(0.492)
Abuse Any	0.092	0.084
	(0.289)	(0.277)
Physical Abuse	0.024	0.043
	(0.153)	(0.203)
Emotional Abuse	0.087	0.062
	(0.282)	(0.241)
Ph. Abuse: Main Survey		0.011
		(0.103)
Nr. Obs.	56,926	2,142

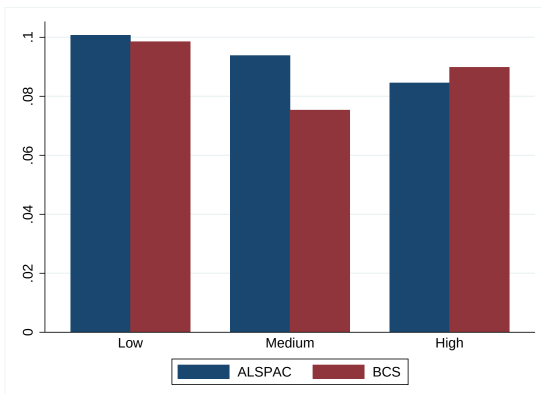
Table A.2: Summary statistics for the ALSPAC sample and the BCS 2001 sample.

itemized questions in the BCS IPV module. Nevertheless, the physical and the emotional abuse variables are highly overlapping in both datasets: the correlation between physical and emotional abuse is 0.40 in ALSPAC and 0.38 in the BCS. Combining physical and emotional abuse into any abuse, gives a similar overall rate in the two data sets.

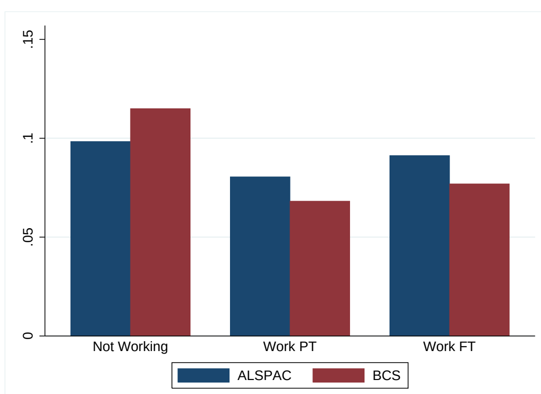
Figure A.1 highlights how the incidence of any abuse varies with the respondent's demographic characteristics in each data set. For comparability, we restrict the BCS sample to include only mothers. Panel (a) shows that the abuse incidence decreases with age in both data sets, while panel (b) shows that the rate of abuse is highest among low qualified women in both data sets. Finally, panel (c) highlights how there is a U-shaped relationship between labour supply and reported abuse in both data sets.



(a) Age group



(b) Qualification level



(c) Level of labour supply

Figure A.1: Incidence of any intimate partner abuse in the ALSPAC sample and in BCS 2001.