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Fertility expectations and residential mobility in Britain

Article (Published version)
(Refereed)

Original citation: Ermisch, John and Steele, Fiona (2016) *Fertility expectations and residential mobility in Britain.* Demographic Research, 35. pp. 1561-1584. ISSN 1435-9871
DOI: 10.4054/DemRes.2016.35.54

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DEMOGRAPHIC RESEARCH
A peer-reviewed, open-access journal of population sciences

DEMOGRAPHIC RESEARCH

VOLUME 35, ARTICLE 54, PAGES 1561–1584
PUBLISHED 21 DECEMBER 2016
http://www.demographic-research.org/Volumes/Vol35/54/
DOI: 10.4054/DemRes.2016.35.54

Research Article

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Demographic Research: Volume 35, Article 54
Research Article

Fertility expectations and residential mobility in Britain

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Abstract

BACKGROUND
It is plausible that people take into account anticipated changes in family size in choosing where to live. But estimation of the impact of anticipated events on current transitions in an event history framework is challenging because expectations must be measured in some way and, like indicators of past childbearing, expected future childbearing may be endogenous with respect to housing decisions.

OBJECTIVE
The objective of the study is to estimate how expected changes in family size affect residential movement in Great Britain in a way which addresses these challenges.

METHODS
We use longitudinal data from a mature 18-wave panel survey, the British Household Panel Survey, which incorporates a direct measure of fertility expectations. The statistical methods allow for the potential endogeneity of expectations in our estimation and testing framework.

RESULTS
We produce evidence consistent with the idea that past childbearing mainly affects residential mobility through expectations of future childbearing, not directly through the number of children in the household. But there is heterogeneity in response. In particular, fertility expectations have a much greater effect on mobility among women who face lower costs of mobility, such as private tenants.

CONCLUSIONS
Our estimates indicate that expecting to have a(nother) child in the future increases the probability of moving by about 0.036 on average, relative to an average mobility rate of 0.14 per annum in our sample.

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CONTRIBUTION
Our contribution is to incorporate anticipation of future events into an empirical model of residential mobility. We also shed light on how childbearing affects mobility.

1. Introduction

It is plausible that people take into account anticipated changes in family size in choosing where to live. The objective of the study is to estimate how expected future fertility affects residential movement in Great Britain using a mature 18-wave panel survey, the British Household Panel Survey (BHPS), which began in 1991 and collected data annually until 2008. Previous research has found strong associations between the number and age of children and residential mobility. Typically the probability of a residential move declines with the number of children and the age of the youngest child (e.g., Böheim and Taylor 2002; Steele, Clarke, and Washbrook 2013), which is generally argued to be due to higher economic and social costs of moving for large families and older children (e.g., Sandefur and Scott 1981). Mobility tends to be highest during pregnancy and shortly after a birth (Clark and Davies Withers 2007; Kulu 2008; Steele, Clarke, and Washbrook 2013), a pattern which is commonly explained by adjustment moves whereby changes in housing are made in response to an imminent or recent birth: for example, to acquire more space. On the other hand, it is widely acknowledged that couples' childbearing decisions may be influenced by their current housing situation, with changes to housing made in anticipation of childbearing and difficulty in securing housing suitable for a family leading to delayed fertility (Clark 2012; Feijten and Mulder 2002; Mulder and Wagner 2001).

The close interrelationship between fertility and housing decisions and uncertainty in the causal direction have led to joint modelling of birth and housing histories, allowing for bidirectional effects and unmeasured influences common to both processes (Enström Öst 2012; Kulu and Steele 2013). However, a limitation of previous research is that it is based on the relative timing of births (or conceptions) and housing transitions, that is, observed fertility and housing events. In particular, evidence for anticipatory moves comes from analyses of mobility during and shortly after pregnancy. This ignores the lag between the decision to have a child and conception, and the fact that couples' housing choices may take account of long-term family plans. Furthermore, the impact of existing children or the arrival of a new child on mobility might operate through their impact on expected future childbearing (e.g., the more children a woman has the less likely she is to expect more).

Estimation of the impact of anticipated events on current transitions in an event history framework is challenging. The main problems are that there are a potentially infinite number of anticipation terms in the transition rate equation and expectations about them are unobserved. One way to circumvent both of these issues is to make the 'rational expectations assumption' (that people hold unbiased expectations given the information available), but it is not appealing because of the a priori parameter restrictions which must be imposed in order to structure estimation, such as exponential discounting or 'quasi-myopia' (see Malani and Reif 2015). Another, even less appealing, approach to address unobserved expectations is to use indicators of future events as proxies for anticipated behaviour (see Hoem and Kreyenfeld 2006 for a critique of this 'conditioning on the future' approach). It is preferable to measure expectations directly, and there is considerable research in this area (e.g., see the survey in Manski 2004). In the current study we use measures of fertility expectations in the BHPS.

Another challenge in estimating the effect of anticipated fertility on mobility is that, like indicators of past childbearing, expected future childbearing may be endogenous with respect to housing decisions. Suppose, for example, that an unmeasured variable 'taste for stability,' which may be time-invariant or time-varying, is associated with a preference towards having (more) children and also a lower propensity to move house. If the true effect of anticipating a(nother) child is to increase the probability of a move, failure to account for shared unmeasured influences on fertility expectations and mobility will lead to an estimated effect that is biased downward. We consider various joint models of mobility and expected fertility to address this issue.

Our theoretical framework is based on the transaction costs approach pioneered by Weinberg, Friedman, and Mayo (1981) and Venti and Wise (1984). From this perspective, changes in housing needs, such as the expectation of an additional child, give rise to disequilibrium in people's housing consumption, and adjustments in response to it often require moving house. Because residential mobility is a costly process, moves are made only when desired housing consumption deviates from actual consumption by a sufficiently large amount, with the threshold being a function of the costs of moving. If moving costs are relatively high, changes in housing need may have little impact on residential movement compared to variation in moving costs. These transaction costs may be financial or social. The importance of social ties outside the household for geographical mobility has long been recognized (e.g., McGinnis 1968). More recently the term 'local social capital' (Kan 2007) has been used to refer to household resources that arise from social ties or networks, for example, the number of close friends living locally (Belot and Ermisch 2009), having someone nearby to turn to in an emergency (Kan 2007), contact with neighbours, and membership of local clubs

(David, Janiak, and Wasmer 2010). The existence of such local networks has been found to deter moves, especially longer-distance moves (Kan 2007; Belot and Ermisch 2009; David, Janiak, and Wasmer 2010).

The expected benefits and costs of moving, and their relative weights in the decision to move, vary according to household circumstances. For example, the desire to move in anticipation of having (more) children in the future may be offset by the associated transaction costs among those households facing the highest financial or social costs. We therefore investigate the extent to which the effect of fertility expectations on mobility is moderated by household characteristics. We focus on two factors identified from previous research in Britain and elsewhere to be strongly associated with both mobility and the level of financial or social costs of mobility: housing tenure and having children. Legal fees and stamp duty land tax raise the cost of a move for owner-occupiers relative to renters, while the social costs may be higher for homeowners because of a greater investment in forming local ties (DiPasquale and Glaeser 1999; Kan 2007). The social costs of a move tend to be higher among parents than among individuals without children. In Britain parents report having more friends living nearby than their childless counterparts (Belot and Ermisch 2009), while in the United States parents are more likely to have someone close by to call upon in an emergency (Kan 2007). Social costs for parents may also include the upheaval of changes in school and childcare arrangements, and disruption to their children's social networks.

Our contribution is twofold. First, we incorporate anticipation of future events into an empirical model of residential mobility and allow for the potential endogeneity of expectations in our estimation and testing framework. Second, we shed light on how childbearing affects mobility. In particular, we produce evidence consistent with the idea that past childbearing mainly affects residential mobility through expectations of future childbearing, not directly through the number of children in the household. Our parameter estimates indicate that expecting to have a(nother) child in the future increases the probability of moving by about 0.036 on average (relative to an average annual mobility rate of 0.14 in our sample), but there is heterogeneity in response. The impact of fertility expectations is much greater among women who face lower transaction costs in changing residence (e.g., private tenants, in contrast to social tenants or owner-occupiers) and among childless women.

2. Methods

2.1 Fertility expectation measure

We use data from the BHPS (Institute for Social and Economic Research 2010), a long-running panel study that began with a nationally representative sample of about 5,500 private households in 1991. Approximately 10,000 original sample members were followed up annually until 2008. Mobility is measured by a change in residence between waves $t-1$ and t. In waves 2, 8, 12, 13, and 17, the BHPS asked the question "Do you think you will have any (more) children?" The response is taken as the measure of fertility expectations ($\mathrm{E}_t[d_{f,i}]$ below). It is not an ideal expectations variable as it does not specify when the children are expected to arrive, nor does it allow for the uncertainty of response, say by indicating the chances of having another child.

The measure is in the long tradition of fertility intentions/expectations data going back at least 75 years. Similar questions have been successfully asked, for example, in the US Current Population Survey and the series of National Fertility Studies in the United States (e.g., Westoff and Ryder 1977). Twenty-six years ago Manski (1990) examined the behavioural content of responses to these types of questions and found that people's responses to yes/no fertility expectations questions do not identify the probability that a person will have another child, but they can provide bounds on it. Under the maintained "hypothesis that individuals have rational expectations and that their responses to intentions questions are best predictions of their future behavior" (Manski 1990: 934), it is possible to estimate these bounds and to test whether the BHPS data is consistent with them. Although this 'best-case' response is unrealistic, it provides an upper bound on the information contained in the BHPS fertility expectation question.

The analytical sample is composed of women aged under 45 who were not living with their parents in the previous year and who have a valid expectations variable. In Appendix 1 we show that the expectations data is indeed consistent with Manski's bounds, indicating that the responses have behavioural content in terms of future childbearing. To illustrate, among women reporting that they expect another child in year t, 56% have a child in the next five years. In contrast, among women who do not report expecting another child in year t, 14% have one in the following five years. The Manski bounds suggest that the probability of having another child implied by the expectations data lies between 0.17 and 0.67 (see Appendix 1).

It might be argued that the percentage having a child in the subsequent years after reporting that they expect to have another child is rather low. To provide perspective, among those who expect to move house in the next year, 52% do so and 71% do so within two years, in contrast to 6% who move within a year and 14% within two years among those not expecting to move in the next year. Thus, even when the time frame is specified, only about half act on their expectations in the specified time frame. In both cases, expectations and behaviour can diverge because new information becomes available to respondents after the time of the survey, leading to changes in their behaviour. Furthermore, it is harder to have a child exactly when you want than to move house when you want. We argue, therefore, that although imperfect the measure of expectations has considerable value. Note that 30% of women who expect another child also expect to move in the next year, compared to 12% of those who do not expect another child.

2.2 Model specification

Following Malani and Reif (2015), a basic model of anticipation effects of events d on outcome y takes the form:

$$y_{ti} = \lambda_0 d_{ti} + \sum_{j=1}^{\infty} \lambda_j \mathrm{E}_t\left[d_{t+j,i}\right] + e_{ti} \tag{1}$$

where y_{ti} is some continuous outcome variable (a latent variable for a binary response) for person i at time t; d_{ti} is an indicator of events at time t; $\{d_{t+j,i}: j = 1,\ldots,\infty\}$ is a sequence of future events after t; E_t indicates expectations based on information at time t; and e_{ti} captures other influences on the outcome (including events that occurred prior to t). In this study d_{ti} is current fertility and the future sequence of events refers to future fertility.

In our application to the anticipatory effects of fertility on residential mobility, we have a direct, albeit imperfect measure of $\sum_{j=1}^{\infty} \lambda_j \mathrm{E}_t\left[d_{t+j,i}\right]$, denoted as $\mathrm{E}_t[d_{f,i}]$, which is derived from the survey question about expected fertility discussed in the preceding subsection. The main equation of interest is:

$$y_{ti}^{*} = \alpha_i + \delta \mathrm{E}_t[d_{f,i}] + \boldsymbol{\pi}' \boldsymbol{X}_{ti} + u_{ti} \tag{2}$$

y_{ti}^{*} is the latent mobility propensity between $t-1$ and t, where movement takes place when $y_{ti}^{*} > 0$. The parameter δ, which measures the impact of expected future childbearing on mobility, is the parameter of primary interest. Other predictors of mobility, including d_{ti}, are represented by the vector $\boldsymbol{X}_{ti}$ with coefficients $\boldsymbol{\pi}$. The effects of time-invariant unobservables are captured by α_i, which may be treated as random or fixed, and u_{ti} are time-varying residuals. Our main hypothesis is that $\delta > 0$: expecting a(nother) child encourages movement in anticipation of its arrival.

An important issue in the estimation of Equation 2 is that there may be unmeasured factors influencing both mobility and expectations, leading to correlation between $\mathrm{E}_t[d_{f,i}]$ and u_{ti} and, in a random effects model, α_i. We therefore specify a simultaneous equations model in which Equation 2 is jointly estimated with an equation for expectations:

$$\mathrm{E}_t[d_{f,i}] = \mu_i + \boldsymbol{\beta}'\boldsymbol{Z}_{ti} + \epsilon_{ti} \tag{3}$$

where $\boldsymbol{Z}_{ti}$ is a vector of covariates (including d_{ti}) with coefficients $\boldsymbol{\beta}$ and, in general, $\mathrm{E}[\alpha_i\mu_i] \neq 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] \neq 0$.

2.3 Estimation and testing

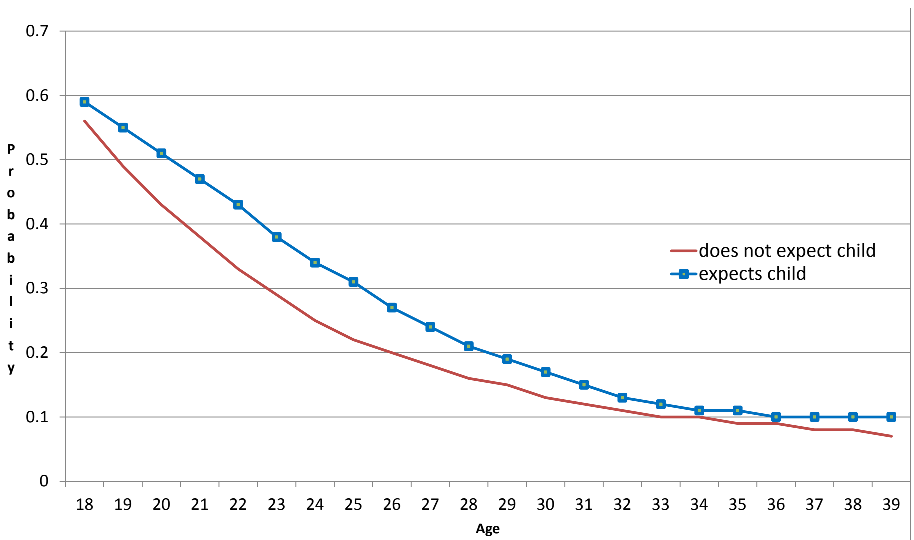
All causal identification is conditional. We estimate a number of models, which differ in the identification assumptions made, in order to examine the sensitivity of the estimate of δ to different assumptions. The variables of $\boldsymbol{X}_{ti}$ will typically be a subset of those in $\boldsymbol{Z}_{ti}$ for identification of δ. Such covariate exclusion restrictions are not strictly necessary under the assumption that shared unmeasured influences of mobility and fertility expectations are time-invariant, that is, $\mathrm{E}[\alpha_i\mu_i] \neq 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$. In that case, within-individual variation across repeated measures of mobility and expectations may be used to identify δ (see Lillard, Brien, and Waite 1995; Steele et al. 2005). However, it is plausible that some of the shared unmeasured influences will be time-varying, in which case it is preferable for $\boldsymbol{Z}_{ti}$ to include one or more time-varying variables that are not contained in $\boldsymbol{X}_{ti}$, rather than rely on functional form for identification. Throughout we assume that $\boldsymbol{X}_{ti}$ and $\boldsymbol{Z}_{ti}$ are uncorrelated with the residual error terms, u_{ti} and ϵ_{ti}, and the residual error terms are uncorrelated over time.

As both mobility and fertility expectations are measured by binary variables, the simultaneous equations model defined by Equation 2 and Equation 3 is specified as a multilevel bivariate probit model. We assume normally distributed individual random effects (α_i, μ_i) and time-varying errors (u_{ti}, ϵ_{ti}). The restriction $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$ is relaxed by assuming (u_{ti}, ϵ_{ti}) follow a bivariate normal distribution, with variances of 1 (as standard identification constraints) and correlation parameter ρ. We consider two ways of relaxing the restriction $\mathrm{E}[\alpha_i\mu_i] = 0$, or equivalently that expectations $\mathrm{E}_t[d_{f,i}]$ are uncorrelated with α_i. The first approach is a multilevel extension of the bivariate probit model, with both (α_i, μ_i) and (u_{ti}, ϵ_{ti}) assumed to follow bivariate normal distributions. The second approach is a form of the Mundlak–Chamberlain correlated random effects model, where the individual mean of $\mathrm{E}_t[d_{f,i}]$ is included among the covariates (Mundlak 1978; Chamberlain 1980). The inclusion of the individual mean removes the correlation between $\mathrm{E}_t[d_{f,i}]$ and α_i (see Skrondal and Rabe-Hesketh 2004). Individual means of the other time-varying predictors in Equation 2 and Equation 3 are also included to allow for correlation between $\boldsymbol{X}_{ti}$ and α_i and between $\boldsymbol{Z}_{ti}$ and μ_i. As an additional robustness check, we consider a conditional logit model which treats α_i as fixed effects and therefore does not require the assumption that fertility expectations are uncorrelated with α_i.

2.4 Other factors affecting mobility

Younger women are more likely both to move and to expect another child. Thus, it is important to control for age. Figure 1 shows that the difference in the annual mobility rate between those expecting another child and others is larger for women in their twenties. Residential mobility is usually local. The mean distance moved is 32 kilometres, but the median is only 3 kilometres, and three-quarters move less than 15 kilometres. The distances decline with age.

Figure 1: Probability of moving house and expectation of another child



Housing tenure affects the costs of moving house. Owner-occupiers face high transactions costs, including taxes on the purchase as well as legal and moving costs. While social tenants (tenants of local authorities and housing associations) face lower transaction costs than owners, their movement is hindered by administrative impediments which make it difficult to change residence within the social sector, particularly if they move across local authority boundaries. These features are consistent with the percentages of women who move each year: 45% of private tenants, 9% of owners, and 13% of social tenants. Having a partner may also impede mobility over longer distances where there are dual earners in the couple (Böheim and Taylor 2002).

Overcrowding or room stress (e.g., Clark and Huang 2003) can encourage a move. Here we take the number of rooms per household member as an indicator of the absence of room stress. Thus, we expect a larger value to reduce residential mobility.

In principle family resources could affect both fertility expectations and residential mobility. In nearly 80% of the woman-year observations in our sample, the woman has a partner, making household income most relevant. It needs to be measured in the previous year because movement could affect income. Using our second estimation approach (the 'correlated random effects model') it turns out that the previous year's real household income, either raw or an equivalized version (divided by the square root of household size), has an impact on mobility which is only a fraction of its standard error, and this is also true for the estimated impact of household income on the expectation of having another child. Note that the lack of impacts of income in our models is after controlling for its individual mean. It is indeed the case that higher-income women are more likely to move and more likely to expect another child, but this reflects heterogeneity in the sample (i.e., variation in α_i and μ_i), not the impacts of income.

Thus, the vector $\boldsymbol{X}_{ti}$ contains age and its square, presence of a live-in partner, and housing tenure – homeowners (including those with a mortgage), private tenants, and 'social tenants' (the reference group) – and rooms per household member, all measured in the previous year. As in most transition rate models, it also contains a residential duration variable: years in the current residence.

The sample size and number of moves in the full analytical sample are shown in the first column of Table 1. The second column provides the same information for the sample used for estimation in the next section; missing information on other explanatory variables produces a small reduction in the sample size relative to the first column. Note that because many women were not present at all five waves in which the expectations information was collected (for various reasons, including moving out of and into the panel), women are observed on average for 2.4 years.

Table 1: Sample sizes and number of moves in different samples

	Full sample	Main sample	'Within' sample
Number of moves per woman			
0	1,952	1,921	0
1	608	571	460
2	121	115	101
3	19	18	8
Number of women	2,700	2,625	569
Number of observations	6,493	6,173	2,017
Women ever observed moving (%)	27.7	26.8	100
Women moving per annum (%)	14	13.8	34

Any fixed effect estimation uses within-woman variation, and so identification is based on women who were observed with at least one year in which they moved and one year in which they did not. There are 569 such women, and their movement patterns are shown in the third column of Table 1. As to the expectation variable, $\mathrm{E}_t[d_{f,i}]$, there are 585 women who are observed expecting additional children in at least one year and not expecting more children in at least one year. Among this group 410 expected a child once, 120 twice, 44 three times, and 11 four times.

3. Results

3.1 Model comparisons

We present results from three models which differ according to the assumptions made about the correlation between the covariates in the mobility equation and the unmeasured influences represented by α_i and u_{ti} in Equation 2. We define the vector $\boldsymbol{W}_{ti} = \left(\mathrm{E}_t[d_{f,i}],\ \boldsymbol{X}_{ti}\right)$. The most restrictive model (Model 1 of Table 2) is the mobility equation of Equation 2, estimated as a standard random effects probit model with the assumptions $\mathrm{E}(\alpha_i \boldsymbol{W}_{ti}) = 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$. Model 2 maintains the assumption that $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$ but allows for correlation between $\boldsymbol{W}_{ti}$ and α_i. The latter is accommodated by assuming that α_i is a linear function of the individual (across waves) means of the time-varying explanatory variables (expecting a child, housing tenure, length of residence, age, rooms per household member, and presence of a live-in partner) plus an error term, v_i, where v_i is assumed to be orthogonal to these means.

We include this linear function in the mobility equation Equation 2 and use random effects probit estimation. Model 2 is denoted the 'correlated random effects probit' model.

Table 2: Model comparisons (N = 6,106)

Model[a]	1	2	2-joint	3
	$\mathrm{E}(\alpha_i \boldsymbol{W}_{ti}) = 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$	$\mathrm{E}(\alpha_i \boldsymbol{W}_{ti}) \neq 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$	$\mathrm{E}(\alpha_i \boldsymbol{W}_{ti}) \neq 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$	$\mathrm{E}(\alpha_i \boldsymbol{W}_{ti}) \neq 0$ and $\mathrm{E}[u_{ti}\epsilon_{ti}] \neq 0$
–Log-likelihood	2,061.27	1,844.52	3,557.07	3,556.16
Number of parameters	10	17	49	50
Chi-sq. Model 1 vs. Model 2[b] (d.f.; p-value)	433.49 (7; <0.001)			
Chi-sq. Model 2-joint vs. Model 3[b] (d.f.; p-value)			1.81 (1; 0.178)	
$\mathrm{cor}[u_{ti}\epsilon_{ti}]$ (SE)	0[c]	0[c]	0[c]	–0.158 (0.117)
$\mathrm{SD}(\mu_i)$ (SE)			1.035 (0.074)	1.033 (0.075)
Expect another child δ (SE)	0.122 (0.058)	0.187 (0.094)	0.187 (0.094)	0.393 (0.181)

[a] Model 1 is a standard random effects probit model for mobility. Model 2 is the correlated random effects probit model which extends Model 1 to include individual means of all time-varying covariates. Model 3 is a bivariate probit model for mobility and fertility expectations; it extends Model 2 to include an equation for expectations with correlated error terms between the mobility and expectations equations. Model 2-joint is a simultaneous equations specification of Model 2, that is, Model 3 with the residual error constrained to zero. It is fitted to allow a test of $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$.
[b] Likelihood-ratio test.
[c] Parameter constraint.

The most general model considered is an extension of Model 2 that allows $\mathrm{E}[u_{ti}\epsilon_{ti}] \neq 0$. As in Model 2, $\boldsymbol{W}_{ti}$ is permitted to be correlated with α_i and, in addition, $\boldsymbol{Z}_{ti}$ may be correlated with μ_i. This model is a random effects simultaneous equations model where the mobility and fertility expectations equations must be jointly estimated because of the non-zero correlation between their error terms. We cannot in fact estimate the full specification of this model, with correlated individual random effects across the equations, because $\mathrm{var}(v_i)$ is estimated to be close to zero after inclusion of the individual means of $\boldsymbol{W}_{ti}$. A simplification was therefore fitted with $\mathrm{var}(v_i) = 0$ but including μ_i and allowing for $\mathrm{E}[u_{ti}\epsilon_{ti}] \neq 0$; this is our least restrictive model (referred to as Model 3). In addition to the variables in $\boldsymbol{X}_{ti}, \boldsymbol{Z}_{ti}$ in Equation 3 contains the woman's educational qualifications (four dummy variables), number of children aged 0–2, 3–4, 5–11, 12–15, and 16–18 years, and an indicator of a birth in the current year. In contrast to Model 2, this model requires covariate exclusion restrictions to identify δ, and the omission of the education and past childbearing variables from the mobility equation represents the exclusion restrictions used to identify the impact of fertility expectations on mobility, when $\mathrm{E}[u_{ti}\epsilon_{ti}] \neq 0$. Note that their exclusion does not mean that we are assuming that these variables are unrelated to between-person variation in levels of mobility, because our estimation approach does not use between-person variation to estimate the parameters. Instead we are assuming that they are uncorrelated with u_{ti}, that is, previous childbearing is not correlated with shocks to mobility. The child-related variables are very strong predictors of expecting to have another child, with past childbearing reducing the chances of expecting to have more children. Analogous to α_i, μ_i is assumed to be a linear function of the individual (across waves) means of the time-varying explanatory variables in $\boldsymbol{Z}_{ti}$. Model 3 is a simultaneous equations extension of the correlated random effect probit model. For the purposes of comparing Model 2 with Model 3, we estimate Model 2 as a restricted form of the simultaneous equations Model 3 with the constraint $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$; this model is referred to as 'Model 2-joint.'

Before discussing the results, two preliminary remarks are in order. First, the woman's educational qualifications have virtually no effect on residential mobility when added to the $\boldsymbol{X}_{ti}$ variables in a model analogous to Model 2 in Table 2. In addition, there is no evidence that current and past childbearing affect mobility after controlling for expected fertility (the p-value for a Wald test that the coefficients of the five child variables are all zero is 0.80). Thus, in what follows we omit women's educational qualifications, current childbearing, and past childbearing from the mobility equation. Second, for the model comparisons we restrict the sample to observations for which there is no missing data on predictors of fertility expectations in $\boldsymbol{Z}_{ti}$, which reduces the sample by 67 woman-year observations compared to the sample in Table 1.

A likelihood ratio test comparing Model 2 with Model 1 soundly rejects Model 1. There is strong evidence of correlation between the time-varying predictors of mobility, including fertility expectations, and unmeasured time-invariant influences. Having next compared Model 3 with Model 2 (or Model 2-joint), we find that we cannot reject the simpler Model 2. The estimate of $\mathrm{cor}[u_{ti}\epsilon_{ti}]$ in Model 3 is negative, from which it follows that a positive shock increasing the probability of moving is associated with a reduction in the chances of expecting another child, but it is smaller than its standard error. For all three models the estimate of δ is in the anticipated direction: planning to have more children is associated with an increased probability of a move. However, the magnitude of δ increases as assumptions about the correlation between unmeasured influences on mobility and fertility expectations (and potentially correlated explanatory variables in $\boldsymbol{X}_{ti}$) are weakened. The increase in the estimate of δ after allowing for a correlation between α_i and $\boldsymbol{W}_{ti}$ suggests a disproportionate representation of women with a lower than average propensity to move among those with a tendency to expect future childbearing. Failure to allow for this selection effect in Model 1 leads to downward bias in the estimate of δ. Similarly, allowing for the negative (albeit nonsignificant) correlation between time-varying errors u_{ti} and ϵ_{ti} leads to a further increase in the estimate of δ.

As Model 2 has been not been rejected, we use the full estimation sample (Table 1) to estimate it. Recall that this model imposes no covariate exclusion restrictions for identification. The parameter estimates are shown in Table 3. The impact of expecting a(nother) child in the future is statistically significant at the 0.05 level (p-value = 0.027). The coefficients of the individual means suggest the following correlations with a woman's personal mobility propensity, or 'random effect' (α_i): women with a higher mobility propensity have shorter lengths of residence, tend to live in less crowded housing, and are more likely to be owners and older. Also, women who are more likely to expect future childbearing have lower mobility propensities. Regarding other effects on mobility, it increases with length of time in the residence and with the degree of overcrowding, declines with age, and is higher for private tenants and lower for owner-occupiers (relative to social tenants).

The impact of expecting to have another child could vary with the pre-existing degree of crowding in the household. Thus, we also estimated a model with an interaction between rooms per household member and expecting to have another a child. Although the coefficient on the interaction term is significant at the 0.10 level, the average marginal effect at the mean level of rooms per household member is very similar to that in the model of Table 3.

Table 3: Correlated random effects probit (Model 2) for residential mobility

Variable (mean; SD*)	Probit coefficient (SE)	Average marginal effect (SE)
Expect another child (0.253)	0.205 (0.093)	0.036 (0.017)
Age–20 (14.2; SD = 6.7)	–0.114 (0.014)	–0.019 (0.002)
Age–20 sq. (248; SD = 180)	0.0021 (0.0005)	0.0004 (0.0001)
Partner (0.78)	–0.125 (0.083)	–0.022 (0.015)
Owner (0.71)	–0.324 (0.130)	–0.059 (0.025)
Private tenant (0.12)	0.654 (0.126)	0.139 (0.032)
Length of residence (5.75 years; SD = 5.3)	0.126 (0.010)	0.021 (0.002)
Number rooms per person (1.6; SD = 1.1)	–0.140 (0.041)	–0.024 (0.007)
Mean expect child (0.25)	–0.234 (0.118)	–0.039 (0.020)
Mean age (14.0; SD = 5.6)	0.044 (0.009)	0.007 (0.001)
Mean partner (0.77)	–0.007 (0.113)	–0.001 (0.019)
Mean owner (0.70)	0.297 (0.151)	0.050 (0.025)
Mean private tenant (0.12)	–0.028 (0.162)	–0.005 (0.027)
Mean length of residence (5.7 years; SD = 4.5)	–0.280 (0.016)	–0.047 (0.003)
Mean rooms per person (1.6; SD = 0.7)	0.155 (0.055)	0.026 (0.009)
constant	–0.056	

Mean dependent variable (mobility) = 0.138; N = 6,173 (2,625 women); Log likelihood = –1,869.47.
*SD presented only for continuous variables.

3.2 Past childbearing versus expected fertility

The more conventional residential mobility model is similar to Model 1 (i.e., it uses between-person variation to estimate its parameters) but with indicators of the number of children of different ages and current childbirth substituted for the fertility expectation variable. We use a much larger sample to estimate that model (2,901 women; 22,926 person-year observations) and find that the number of children aged 3–

15 significantly reduces mobility, and it continues to do so if we estimate the equivalent of Model 2. On average, an additional child aged 3–15, irrespective of exact age, reduces the probability of moving by 0.016 (SE = 0.004).

The impact of past childbearing is less clear when we confine the sample to the waves of data in which we have the fertility expectations measure. In the equivalent of Model 1, the number of children aged 3–15 has a statistically significant negative effect at the 0.05 level (average marginal effect of –0.012; p-value = 0.015), but in the equivalent of Model 2 its effect is similar but not signifiant (p-value = 0.11).

Adding the number of children aged 3–15 and its individual mean to Model 2, we find that an additional child aged 3–15 does not have a significant impact on the probability of moving (p-value = 0.19), while expecting an additional child increases the probability by an average marginal effect (SE) of 0.032 (0.016), which is close to the estimate in Table 3. Thus, it appears that the significant negative impact of school-age children on mobility often found in previous work could be a result of an absence of measures of expected childbearing.

4. Heterogeneous response

The broad impression from Tables 2 and 3 is that the impact of expected childbearing on residential mobility is positive. In the most parsimonious model accepted by the data, the probit coefficient is 0.21 (Table 3) and the conventional conditional logit FE estimator produces a similar coefficient (see Appendix 2). The estimates imply an average marginal effect of about 0.036. Although significantly larger than zero, the confidence intervals are relatively wide, which may indicate heterogeneity in response. Figure 1 indeed suggests that younger women's mobility may respond more positively to the expectation of another child.

Variation in the impact of expected childbearing with age could be related to their costs of moving, which may in turn be related to their housing situation. As discussed earlier, women with high costs of moving may be less responsive to factors, such as expecting to have more children, which increase the benefits of a different residence, because the additional benefits must exceed a very high threshold to offset the costs. Also, older women and women who have children may have already made the move required to add further to their family, reducing the effect of future anticipated fertility for them as opposed to young and/or childless women. We therefore consider extensions to the correlated random effects model of Table 3 to include interactions between expected future fertility and a) housing tenure (private renters vs. homeowners or social tenants) and b) past fertility (childless vs. one or more child).

Table 4 presents calculations of the average of individual marginal effects of expecting a(nother) child on the probability of residential mobility from these interaction models, averaged over the entire estimation sample (all variables other than fertility expectations and private tenancy/childless are set at each woman's observed values in calculating each woman's effect). The average marginal effect is much larger for private tenants than for homeowners or social tenants, presumably reflecting the lower costs of moving among private tenants. The 95% confidence intervals for the effects for the two tenure groups do, however, overlap.

Table 4: Extensions of correlated random effects probit Model 2 to include interactions between fertility expectations and housing tenure and having children*

	Marginal effect of expecting a child	SE
Private tenant	0.094	0.037
Not private tenant	0.029	0.017
Overall	0.037	0.017
Childless	0.046	0.022
Has child	0.021	0.018
Overall	0.031	0.017
Overall, Model 2 (i.e., no interactions)	0.036	0.017

* Marginal effect of expecting another child is calculated as the discrete difference between the mobility probability if everyone were expecting another child and the mobility probability if everyone were not expecting one. It is calculated first as if everyone were a private tenant (childless) and then as if everyone were a social tenant or homeowner (had a child), and the residual woman-specific random effect is set to zero. Standard errors are calculated by the delta method.

As noted earlier, childless women may perceive their costs of moving to be lower than women with children, or they are more likely to need to adjust their housing in anticipation of the arrival of a child than women who have started their family. On average, childless women (women who were pregnant were not designated as childless) are more likely to move in any year than women with children (22% vs. 10%), and they are more likely to expect to have a child (52% vs. 12%). Their higher mobility is, however, mainly confined to those who expect to have a(nother) child; among childless women who do not have this expectation, mobility is only marginally higher on average (12% vs. 9%). It is interesting to note that women who expect to have their first child are much more likely to actually move in the next two years than women with children who expect another child (43% vs. 27%), suggesting that the fertility expectations window of childless women is shorter than that of women with children.

Table 4 indicates that the average marginal effect of expecting to have one's first child is twice as large as the effect of expecting another child among women who already have one. Whether we should attribute the difference to the lower mobility costs of the childless, or their greater need to make a housing adjustment for the arrival of the child, or a 'parity effect' is difficult to say, and indeed the last may be due to the former two reasons. Correspondingly, being childless only increases the probability of moving among those who expect to have a child in the future (a marginal effect of 0.031 vs. 0.006).

5. Conclusions

The objective of the study was to estimate how expected changes in family size affect residential movement in Great Britain. Our first contribution has been to incorporate anticipation of future events into an empirical model of residential mobility and allow for the potential endogeneity of expectations in our estimation and testing framework. We estimated the model using a mature 18-wave panel survey, the BHPS. Our second contribution has been to shed light on how childbearing affects mobility. In particular, we have produced evidence consistent with the idea that past childbearing mainly affects residential mobility through expectations of future childbearing, not directly through the number of children in the household. This suggests that the significant negative impact of school-age children on mobility often found in previous work could be a result of an absence of measures of expected childbearing.

Our estimates indicate that expecting to have a(nother) child in the future increases the probability of moving by about 0.036 on average (relative to an average mobility rate of 0.14 per annum in our sample), but there is heterogeneity in response. Fertility expectations have a much greater effect on mobility among women who face lower costs of mobility, such as private tenants, compared with homeowners or social tenants, and among childless women.

The analysis can be extended in a number of directions. For instance, high-fertility ethnic groups (e.g., Pakistani, Bangladeshi) tend to be less mobile and low-fertility ethnic groups (e.g., Chinese) are more mobile (Stillwell, Hussain, and Norman 2008). To what extent might this be because people with larger families are less likely to expect to have more children or have other attributes relevant to residential mobility?

We have done some preliminary work in this direction using Understanding Society,[3] the successor to the BHPS, which has completed five annual waves. It oversampled ethnic groups. The same fertility expectations question that was used in this paper was asked in the first (2009–2010) and fifth (2013–2014) waves, and we can observe annual residential mobility from the second wave forward. As with the BHPS data, the expectations responses satisfy the Manski bounds (see Appendix 1). We confirm from these data that, compared to white British women, Pakistani and Bangladeshi women have larger family sizes and lower residential mobility over the first five waves and Chinese women have lower family sizes and higher residential mobility. Chinese women are also more likely to expect another child than white British women. We are unable to use the same statistical techniques as used above because the expectations questions were asked only in the first and fifth waves, but in a conventional cross-sectional probit model for residential movement between the fourth and fifth waves with similar covariates to the models above we find that neither Pakistani nor Chinese women have mobility propensities significantly different from British whites, but Bangladeshis are much less likely to move. In this model, expecting to have another child increases the probability of moving by 0.033 on average, which is similar to what we found with the BHPS data.

To summarize, the traditional fertility intentions/expectations measure has behavioural content in terms of future fertility. Using a range of identification assumptions and two independent sources of data, we find evidence that expecting a(nother) child increases the probability of residential mobility in Britain substantially. The external validity of the finding depends on the attributes of the housing market in the given context: for instance, we found that the impact is much greater for private tenants, for whom mobility costs are much lower. This suggests that in countries/regions in which the private rental housing market dominates the effect can be larger in the population than it is in Britain. Finally, the expectations measure can most likely be improved in terms of behavioural content by having the question specify when the next child is expected to arrive and by indicating the chances of having another child in terms of a probability.

[3] See http://www.understandingsociety.ac.uk.

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Appendix 1

Testing the consistency of expectations data with a best-case response

As Manski (1990) demonstrated a quarter of a century ago, responses to intentions or yes/no expectations questions do not identify the probability that a person will behave in a particular way but they can provide bounds on it. Furthermore, we can test whether responses to the fertility expectations question are consistent with the idealized assumption of a best-case response. Let $E = 1$ indicate a woman's response that she expects to have a(nother) child (0 otherwise) and $C = 1$ indicate actually having another child. The data does not identify the probability of having another child, conditional on expecting one: $P(C = 1 \mid E)$; but it does imply bounds on it under certain assumptions (all results carry over to conditioning on covariates, which have been omitted here for simplicity).

The first part of the best-case hypothesis is to assume rational expectations. Such a woman would recognize that her future behaviour will depend in part on conditions known to her at the time of the survey and in part on events that have not yet occurred. For the rational expectations hypothesis to hold it does not suffice that she has a subjective distribution for the unknown events. Rational expectations assume knowledge of the actual probability distribution generating these unknown events.

The second part of the best-case hypothesis concerns how the respondent maps her expectations into a response to the yes/no question. Her best-prediction response depends on the losses she associates with the two possible prediction errors ($E = 0$, $C = 1$) and ($E = 1$, $C = 0$). As Manski (1990: 936) points out, "These losses may be influenced by the wording of the intentions question; for example, the respondent may interpret differently questions that ask what she 'expects,' 'intends,' or 'is likely' to do." Whatever the loss function, she responds that she expects to have another child when the probability of having one (conditional on the information available) is greater than some threshold probability, π. Manski (1990: Equation 4) shows that given this best-case response there are the following bounds:

$$P(C = 1 \mid E=0) \leq \pi \leq P(C = 1 \mid E=1)$$

Note that $\pi = 0.5$ if the loss function is symmetric.

These bounds on the threshold probability express all of the information about expectations contained in the data. Taking a five-year fertility window (i.e., all future fertility occurs in that window) and a sample of BHPS women of childbearing age for whom we can observe the window ($n = 3{,}381$), $0.138 \leq \pi \leq 0.563$. Taking a four-year fertility window (n = 3,768), $0.107 \leq \pi \leq 0.500$. If, for instance, $\pi = 0.5$, the BHPS fertility expectations data is consistent with the best-case response hypothesis. It appears, therefore, that the responses to the BHPS fertility expectations question have considerable behavioural content.

We can also obtain bounds (Manski 1990: Equation 8) for the probability of having another child, $P(C = 1)$:

$$\pi P(E = 1) \leq P(C = 1) \leq \pi P(E = 0) + P(E = 1)$$

For the BHPS data: $\pi\, 0.339 \leq P(C = 1) \leq \pi\, 0.661 + 0.339$. The observed value of $P(C = 1)$ for the five-year fertility window is 0.282, which indeed lies between the bounds of 0.17 and 0.67 when $\pi = 0.5$.

Finally, for comparison, we can test the consistency of the BHPS data on expecting to move in the next year with the best-case response hypothesis. The proportions moving in the next year are 0.055 and 0.518 for those not expecting to move and those expecting to move in the next year, making the data consistent with the best-case response hypothesis when $\pi = 0.5$. The probability of moving in the next year implied by the mobility expectations variable is between 0.08 and 0.58. The actual movement in the next year was 0.129.

Appendix 2: Conditional logit fixed effect estimates

An alternative approach to allow $\boldsymbol{W}_{ti}$ to be correlated with α_i is to fit a conditional logit fixed effects model. Consistent with our findings in Table 2, we assume that $\mathrm{E}[u_{ti}\epsilon_{ti}] = 0$, that is, we assume that $\mathrm{E}_t[d_{f,i}]$ is exogenous. We shift from the normality assumption for u_{ti} to the assumption that u_{ti} has a standard logistic distribution in order to carry out conditional logit estimation. Here the parameters are identified fully by within-woman variation in mobility. The parameter estimates, along with random effect estimates of the same parameters, are shown in Table A-1. A Hausman test soundly rejects the hypothesis that $\boldsymbol{W}_{ti}$ is not correlated with α_i. Note that the coefficient of fertility expectations here is not directly comparable to the probit coefficients in Tables 2 and 3 because of the different distributional assumption; it is roughly comparable by dividing by the residual standard deviation in the logit model: about 1.8. This conversion produces a probit coefficient of about 0.187, which is equal to the correlated random effects probit estimate presented in Table 2.

Table A-1: Conditional ('fixed effects') and random effect logit estimates*

	FE	RE	Diff. FE-RE
Expect another child	0.336	0.227	0.109
	(0.176)	(0.103)	(0.143)
Age–20	–0.185	–0.130	–0.055
	(0.037)	(0.022)	(0.029)
Age–20 sq./100	0.304	0.278	0.026
	(0.133)	(0.087)	(0.102)
Partner	–0.205	–0.383	0.177
	(0.184)	(0.099)	(0.155)
Owner	–0.469	–0.095	–0.374
	(0.280)	(0.119)	(0.251)
Private tenant	1.261	1.328	–0.067
	(0.270)	(0.127)	(0.239)
Length of residence	0.207	–0.042	0.250
	(0.026)	(0.012)	(0.023)
Number of rooms per person	–0.283	–0.095	–0.188
	(0.102)	(0.053)	(0.086)

* Standard errors in parentheses.
Hausman test: chi-square (8 df) = 138.66 (p-value < 0.001).