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Fertility, economic incentives and individual heterogeneity: Register data-based evidence from France and Germany

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Abstract

This study demonstrates the importance of accounting for correlated unobserved heterogeneity to correctly identify the relevance of career and education for fertility decisions. By exploiting individual-level life-cycle information on fertility, career and education from large administrative longitudinal datasets, this paper shows that non-linear panel models produce substantially different results than the cross-sectional approaches widely used in previous studies. Higher opportunity costs of having children are found to be associated with lower fertility within a country, while the magnitude of the adjustment differs strongly across countries. In Germany, fertility decisions are found to depend more on individual circumstances than in France, where better public childcare support enhances the compatibility between family and professional life.

KEYWORDS

correlated random effects, family policy, Poisson panel regression, unobserved heterogeneity

1 | INTRODUCTION

In most developed countries, the decline in fertility is widely considered one of the greatest societal challenges. Reproduction numbers below the replacement rate lead to population ageing

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with all the undesirable consequences such as increasing financial obligations for health, pension and social insurances. The key to shape fertility must be to better understand the factors that determine fertility. There is extensive literature on fertility in the social sciences, economics and demography. Much of this work has focused on the relationship between fertility and education. Some work is descriptive (e.g. Rendall et al., 2005, Skirbekk et al., 2006, Isen & Stevenson, 2010, Oppermann, 2017) and some work uses regression analysis (e.g. Naz et al., 2006, Jones & Tertilt, 2008, McCrary & Royer, 2011, Cygan-Rehm & Maeder, 2013, Fort et al., 2016). Although not all studies reach the same conclusion, there is some consensus, in particular among demographers, that there is both a negative relationship between education and fertility, and a postponing behaviour among higher educated females (e.g. Gustafsson, 2001, Ní Bhrolcháin & Beaujouan, 2012, Schaeper et al., 2017, Tropf & Mandemakers, 2017).

Figure 1 displays the average number of children per female by education and wage for France and Germany. In addition to the fact that the average number of children is higher in France than in Germany, the figure suggests that wages and education are negatively related to fertility, and apparently more so in Germany than in France. The point of departure of this paper is that the problem is more complex. Fertility depends on many other factors confounding the relationship of interest, especially the woman's professional career, and factors that are usually unobserved, such as the preference for children. Females with relatively weaker preferences for children may sort into higher education and jobs with higher wages, introducing a correlation between observed and unobserved factors and fertility. In addition, there may be a simultaneity problem as the number of children also plays a role for education and wages. In most economic and social decision problems, there is a wealth of relationships between the relevant variables, making the direction of causality unclear. Omitted variables, simultaneity, and related issues violate the assumptions of standard regression models which yield inconsistent estimates if not appropriately adapted or if more comprehensive data are unavailable.

Many existing studies on fertility rely on data from one period only, such as censuses or surveys, and use regression methodology for cross-sectional data (e.g. Naz et al., 2006, O'Donoghue & O'Shea, 2006, Cygan-Rehm & Maeder, 2013, Fort et al., 2016). Others rely on household survey data that are rather small (Hotz & Miller, 1988, Francesconi, 2002, Keane & Wolpin, 2010) or suffer from non-response and recall errors in important variables (Francesconi, 2002). Others lack individual level information about employment and fertility (Fort et al., 2016, Heckman & Walker, 1990, Del Boca, 2002, Keane & Wolpin, 2010, Adda et al., 2017). To sum up,

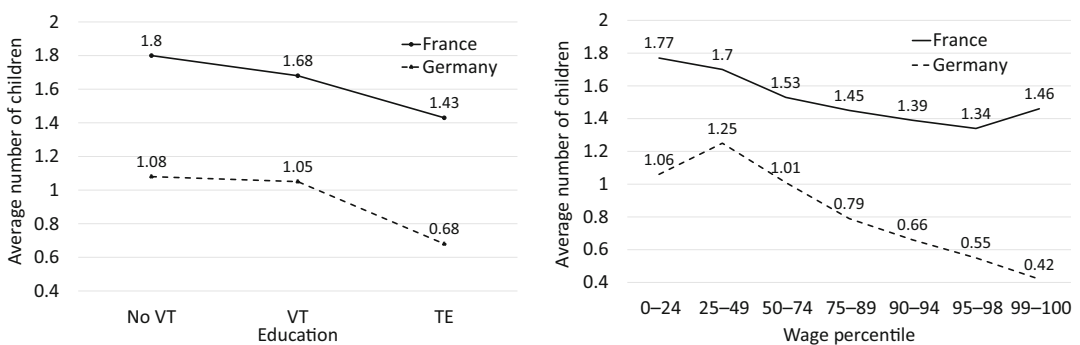


FIGURE 1 Average number of children by education and wage. Completed fertility at age 45 or, if not available, at last observed age. Excluding females from the last birth cohort (born after 1978). TE, tertiary education; VT, vocational training. Based on the BASiD/DADS-EDP, own calculations.

the data sets employed in previous studies do not contain information about both fertility and employment situation (especially wages) at the individual level over the entire life-cycle of the female.

Much of the existing analysis on the interaction between fertility and career has focused on employment outcomes such as wages. Although there is consensus that mothers experience a wage penalty compared to childless females (Budig & England, 2001, Anderson et al., 2002, Gangl & Ziefle, 2009, Picchio et al., 2021), additional research is required to analyse the role of the interplay of career and education for fertility.

In this paper, we study the importance of economic factors and unobserved heterogeneity on fertility outcomes in France and Germany. By using large-scale linked administrative data sets with daily information for several decades, our analysis benefits in two dimensions: first, we can model the employment situation of women during their life cycle in great detail, including wages, tenure and occupation. Second, by exploiting the longitudinal structure of the data, we can apply econometric panel techniques which give consistent estimates even if included variables are confounded with unobserved factors such as preferences. We can, therefore, separate the effect of education from the effect of the employment situation while allowing both to be related with unobserved factors. To deal with so-called endogeneities stemming from omitted variables and simultaneity, the panel data approach is preferred over a cross-sectional analysis with instrumental variables. The latter is plagued by inefficiencies and easily suffers from sizable estimation biases when instruments are invalid. By analysing the role of the number of children for labour supply, Jakubson (1988) has demonstrated that a correlated random effects (CRE) panel model gives substantially different results than a cross-sectional model.

This analysis also adopts a panel methodology that allows unobservables to be correlated with covariates. It is the first study to look at fertility that applies a nonlinear Poisson panel methodology. Regarding the methodology and the subject matter, our analysis makes two main contributions to the literature. First, by using panel data with detailed information about the professional career and by estimating a panel model, we purge the relationship between education and employment characteristics and fertility from individual unobserved factors. These unobservables, such as preferences, bias estimates in previous studies not using panel data. We compare our results with hypothetical results based on inferior data sets and models to assess the direction and magnitude of potential differences. By doing so, we highlight the importance of making large administrative panel data available for these types of analyses. We suggest a decomposition of the estimated partial covariate effects on the expected number of children that decouples the role of unobserved confounders, such as preferences, from the actual role of the covariate. We hereby show that education and wages of females are substantially related with unobserved factors, rendering cross-sectional models invalid. Second, we exploit comprehensive longitudinal employment information over a period of several decades to perform a detailed analysis of the relationship between various career-related factors and fertility outcomes in France and Germany. France and Germany are of particular interest, as these countries are characterised by substantial differences in fertility, female labour force participation, family policies and approaches to childcare. We can therefore analyse whether education and career play a different role for fertility decisions in different institutional setups.

The structure of this paper is as follows: Section 2 introduces the relevant statistical methodology. Section 3 describes the data and sample. Section 4 compares the contextual settings of France and Germany and states the main hypotheses. The estimation results are given in Section 5. Section 6 concludes.

2 | STATISTICAL METHODOLOGY

This section outlines the statistical frameworks for our data analysis. In the first subsection, we formally present several statistical panel models that are used in the application. The second subsection focuses on the interpretation of marginal effects (ME) and a decomposition analysis of them. In the last subsection, we describe the problem of unobserved heterogeneity for consistently estimating the effects of individual characteristics, such as education or wage, on fertility when the analysis is based on cross-sectional data. We report directly comparable results for the models outlined before in one overview table (Table 1). These results point to the importance of using appropriate panel data methods by showing that estimates partly change substantially when doing so.

2.1 | Count data regression models

In this subsection, we present the Poisson count data regression model and relevant panel data variants that are used in the application to estimate the partial relationship between various observable factors and the number of children.

Let y_{it} denote the number of children for female $i = 1, \dots, N$ and period $t = 1, \dots, T_i$. y_{it} can only take on non-negative integer values $m = 0, 1, 2, \dots$. The non-negative expected number of children conditional on individual characteristics \mathbf{x}_{it} ($1 \times K$) and an unobserved time-invariant individual effect $a_i \geq 0$ is

$$E[y_{it} | \mathbf{x}_{it}, a_i] = a_i \lambda_{it} = a_i \exp(\mathbf{x}_{it} \boldsymbol{\beta}), \quad (1)$$

where $\boldsymbol{\beta}$ is a $(K \times 1)$ vector of unknown parameters. It is common for count data to assume a Poisson distribution, for example, $y_{it} | \mathbf{x}_{it}, a_i \sim \mathcal{P}(a_i \lambda_{it})$. We follow Cameron and Trivedi's (2013, chapter 9) convention and for the sake of identification, we exclude the constant term from \mathbf{x}_{it} . A first approach to estimate this model is to use a pooled maximum likelihood estimator. An important advantage of Poisson estimates is that they are consistent as long as the conditional mean is correctly specified (Gouriéroux et al., 1984). This holds even with misspecified higher moments, although at the expense of efficiency. Models with other count distributions may be more efficiently estimated but have the disadvantage of being more complex and time intensive. Given the size of our data sets we give a lower priority to efficiency. The conditional mean function is misspecified, however, in presence of confounded or endogenous covariates.

The availability of panel data allows to model unobserved individual heterogeneity and to mitigate biases of cross sectional or pooled models. The conditional joint density for individual i is obtained by integrating out the unobserved individual-specific effect:

$$\Pr(y_{i1}, \dots, y_{iT_i} | \mathbf{x}_i) = \int_0^\infty \Pr(y_{i1}, \dots, y_{iT_i} | \mathbf{x}_i, a) f(a | \mathbf{x}_i) da. \quad (2)$$

We consider models which are assumed to satisfy

$$E[y_{it} | \mathbf{x}_{i1}, \dots, \mathbf{x}_{iT_i}, a_i] = E[y_{it} | \mathbf{x}_{it}, a_i], \quad t = 1, \dots, T_i \quad (3)$$

$$\Pr(y_{i1}, \dots, y_{iT_i} | \mathbf{x}_i, a_i) = \prod_{t=1}^{T_i} \Pr(y_{it} | \mathbf{x}_i, a_i). \quad (4)$$

with $\mathbf{x}_i = (x_{i1}, \dots, x_{iT_i})$. Equation (3) defines strict exogeneity of \mathbf{x}_{it} conditional on a_i , while Equation (4) defines independence of the dependent variable over time conditional on \mathbf{x}_i and a_i . The strict exogeneity assumption rules out lagged values of y_{it} as explanatory variables but it does not restrict the relationship between \mathbf{x}_{it} and a_i .

A well-known model that allows for arbitrary correlations between \mathbf{x}_{it} and a_i is the fixed effects (FE) Poisson model, see Cameron and Trivedi (2013). We estimate the FE model for comparison but do not focus on it because it neither identifies the parameters of time-invariant covariates nor produces interpretable marginal effects.

Instead, we focus on the CRE model, which allows a_i to be conditionally correlated with \mathbf{x}_{it} . Based on the ideas of Mundlak (1978) and Chamberlain (1980, 1982) for the linear model, the individual effect is specified as

$$a_i = \exp(\bar{\mathbf{x}}_i \boldsymbol{\xi} + \varepsilon_i), \quad (5)$$

where $\bar{\mathbf{x}}_i$ denotes the vector of time averages of the time-varying covariates. ε_i is an i.i.d. error term independent of \mathbf{x}_{it} . The term $\bar{\mathbf{x}}_i \boldsymbol{\xi}$ in Equation (5) establishes a direct relationship between a_i and \mathbf{x}_{it} . In contrast, any correlation between time-constant variables and a_i is only modelled indirectly via the correlation between the (mean of the) time-varying and the time-constant variables. The model therefore only allows for restrictive endogeneity patterns for the time-constant covariates, which may affect the consistency of estimated coefficients on these variables. Plugging (5) into (1) yields

$$E[y_{it} | \mathbf{x}_{it}, a_i] = \exp(\mathbf{x}_{it} \boldsymbol{\beta} + \bar{\mathbf{x}}_i \boldsymbol{\xi} + \varepsilon_i). \quad (6)$$

Under the common assumption that $\exp(\varepsilon_i)$ follows a gamma distribution $\mathcal{G}(\gamma, \gamma/\alpha)$, it turns out that conditionally on observables $\bar{\mathbf{x}}_i$, the random term a_i is also characterised by a Gamma distribution: $\mathcal{G}(\gamma, \exp(-\bar{\mathbf{x}}_i \boldsymbol{\xi}) \gamma / \alpha)$ with $E[a_i | \bar{\mathbf{x}}_i] = \alpha \exp(\bar{\mathbf{x}}_i \boldsymbol{\xi})$, and $V[a_i | \bar{\mathbf{x}}_i] = \alpha^2 \exp(2\bar{\mathbf{x}}_i \boldsymbol{\xi}) / \gamma$. The conditional density of unobserved heterogeneity is then given by:

$$f(a | \bar{\mathbf{x}}_i) = \frac{1}{\Gamma(\gamma)} \left(\frac{\gamma}{\alpha} \exp(-\bar{\mathbf{x}}_i \boldsymbol{\xi}) \right)^\gamma a^{\gamma-1} \exp\left(-\frac{\gamma}{\alpha} \exp(-\bar{\mathbf{x}}_i \boldsymbol{\xi}) a\right).$$

This conditional density can be plotted for different values of α , γ and $\bar{\mathbf{x}}_i \boldsymbol{\xi}$ as it is done in Figure A1 in the Appendix.

When we condition the expected number of children and its variance on observables only, it turns out that $E[y_{it} | \mathbf{x}_{it}, \bar{\mathbf{x}}_i] \leq V[y_{it} | \mathbf{x}_{it}, \bar{\mathbf{x}}_i]$ when $\alpha, \gamma > 0$. In the case where $\boldsymbol{\xi} = 0$, the density of unobserved heterogeneity is independent of $\bar{\mathbf{x}}_i$ which corresponds to an unconditional Gamma marginal density, and characterises the random effects (RE) model. We do not report results for the RE Poisson model, because it is plagued by the same sources of inconsistencies as the pooled model.

The cross-sectional or pooled model requires independence between unobserved heterogeneity and covariates and neglects heterogeneity by requiring $a_i = \alpha$, and hence $V[a_i] = 0$. This implies equidispersion: $V[y_{it} | \mathbf{x}_{it}] = E[y_{it} | \mathbf{x}_{it}]$, which does not fit the data in many applications. Violation of equidispersion alone does not affect the consistency of the estimator, but its efficiency, and it invalidates inference. For this reason, robust standard errors (SE) and statistics are reported for the pooled model.

We have reasoned that FE and CRE models are more adequate in the context of our application than RE or pooled models without unobserved effects, because FE and CRE models

permit for correlation between observables and unobservables. A disadvantage of the CRE model is that it is expected to mainly address correlation between time-constant unobservables and time-varying covariates. One of the reviewers pointed to other interesting approaches to tackle endogeneities. Picchio et al. (2021) consider a system of two labour market outcome equations to study the effect of fertility on these outcomes. They address the endogeneity of fertility related variables by estimating selection equations and by incorporating unobserved time-varying RE. Fernandez-Val (2009) studies bias correction techniques for coefficients and average partial effects for the FE probit model to mitigate the incidental parameter problem. However, Martin (2017) shows that with panel Poisson FE models, the average partial effects of time-varying covariates can be consistently estimated despite the incidental parameters problem. Regarding the CRE approach, Hsu and Shiu (2021) show that (under reasonable assumptions) the density of the unobserved heterogeneity is identified for nonlinear CRE models. These two results are useful for the estimation of the density of unobserved heterogeneity pursued here.

In the application we estimate pooled, CRE and FE variants of the Poisson model. For comparison, we also estimate linear regression models such as pooled OLS and FE, which do not restrict the count variable to be non-negative and integer valued.

Serial correlation between observations for the same female requires further adjustments of SEs and inference statistics. Therefore, we report cluster-robust SEs, which are implemented using block bootstrap, where clustering is done at the individual level. For more details, and related references for the Poisson count models for panel data, see the textbooks by Cameron and Trivedi (2013) and Wooldridge (2010).

2.2 | Marginal effects and decomposition analysis

2.2.1 | Marginal effects

Given the limited interpretability of the parameters in non-linear models, we report ME in the application. The ME of the j th (continuous) covariate on the expected number of children in the Poisson model with unobserved effects is

$$ME_j(\mathbf{x}_{it}, a_i) = \frac{\partial E[y_{it} | \mathbf{x}_{it}, a_i]}{\partial x_{itj}} = a_i \exp(\mathbf{x}_{it}\boldsymbol{\beta})\beta_j = \beta_j E[y_{it} | \mathbf{x}_{it}, a_i], \quad (7)$$

with x_{itj} the j th component of \mathbf{x}_{it} . Computing the ME is not possible without knowing a_i . One advantage of the CRE model (over FE) is that it yields an estimate for $\exp(\bar{\mathbf{x}}_i\xi)$ which is consistent for $E[a_i | \bar{\mathbf{x}}_i]$ and this allows to compute ME_j . In our empirical analysis, we compute the average ME_j which is the sample average of $ME_j(\mathbf{x}_{it}, a_i)$. In the case of discrete covariates, we take the sample average of differences in estimated conditional expectations of y_{it} given \mathbf{x}_{it} and a_i , when the covariate increases by one unit.

2.2.2 | Decomposition analysis: the role of observables and unobservables

We illustrate the dilemma of confounded observables and unobservables with the help of a simple decomposition. The number of children y is determined by observed covariates (\mathbf{x}) and by

individual heterogeneity (a). Given that a is not observable, our empirical model cannot directly base on both but only on \mathbf{x} :

$$E[y|\mathbf{x}] = \int E[y|\mathbf{x}, a] f(a|\mathbf{x}) da,$$

where $f(a|\mathbf{x})$ denotes again the conditional density of the unobserved heterogeneity. The difference in the expected number of children between two females can be decomposed into two parts. One is due to different observables such as different educational degrees or different wages, the other is due to different unobservables such as relative preferences. Put formally, the difference in the expected number of children between a woman A with covariates \mathbf{x}_A and a woman B with covariates \mathbf{x}_B can be written as:

$$\begin{aligned} E[y|\mathbf{x}_A] - E[y|\mathbf{x}_B] &= \int E[y|\mathbf{x}_A, a] f(a|\mathbf{x}_A) - E[y|\mathbf{x}_B, a] f(a|\mathbf{x}_B) da \\ &= \underbrace{\int (E[y|\mathbf{x}_A, a] - E[y|\mathbf{x}_B, a]) f(a|\mathbf{x}_B) da}_{\text{Difference holding "preferences" constant}} \\ &\quad + \underbrace{\int E[y|\mathbf{x}_A, a] (f(a|\mathbf{x}_A) - f(a|\mathbf{x}_B)) da.}_{\text{Difference holding observed characteristics constant}} \end{aligned} \quad (8)$$

We estimate both contributions to this simple decomposition: the part due to changing covariates holding ‘preferences’ constant (first difference, upper term) and the part due to different preferences if both women had the same covariates (second difference, lower term). In the special case where the individual unobserved heterogeneity is independent of the covariates, the second difference vanishes and empirical results obtained from cross-sectional data and panel data become similar, provided that the data are large enough. The decomposition in Equation (8) is applicable when A and B differ in all, some, or only one covariate. The last case is the most prevalent as it corresponds to the ME of changing one covariate, holding all others constant. For the CRE model, unobserved heterogeneity a_i is assumed to be independent of \mathbf{x}_i conditionally to $\bar{\mathbf{x}}_i, \xi$, where the dimension of $\bar{\mathbf{x}}_i$ equals the number of time varying covariates in the model. It follows that $f(a|\mathbf{x}_i) = f(a|\mathbf{x}_i, \bar{\mathbf{x}}_i, \xi) = f(a|\bar{\mathbf{x}}_i, \xi)$, where the first equality is valid because $\bar{\mathbf{x}}_i := T_i^{-1} \sum_t \mathbf{x}_{it}$. The second equality results from the conditional independence which reduces the conditioning set to the scalar $\bar{\mathbf{x}}_i, \xi$. The decomposition in (8) then simplifies to:

$$\begin{aligned} E[y|\mathbf{x}_A] - E[y|\mathbf{x}_B] &= \int (E[y|\mathbf{x}_A, a] - E[y|\mathbf{x}_B, a]) f(a|\bar{\mathbf{x}}_B, \xi) da \\ &\quad + \int E[y|\mathbf{x}_A, a] (f(a|\bar{\mathbf{x}}_A, \xi) - f(a|\bar{\mathbf{x}}_B, \xi)) da. \end{aligned} \quad (9)$$

The second (lower) term is not identified with cross-sectional data. Despite our focus on the expected value, the analogue of the decomposition can also be applied to the conditional probability of having a certain number of children. In this case, the expectation operator in Equations (8) and (9) simply needs to be replaced by a probability. When combining the Poisson model with Gamma densities for a_i , the resulting negative binomial model allows to simplify Equation (9)

further, and to decompose the overall expected number of children into a part due to changes in the explanatory variables and a part due to the shift in the unobserved heterogeneity:

$$E[y|\mathbf{x}_A] - E[y|\mathbf{x}_B] = (E[y|\mathbf{x}_A, \bar{\mathbf{x}}_B\xi] - E[y|\mathbf{x}_B, \bar{\mathbf{x}}_B\xi]) + (E[y|\mathbf{x}_A, \bar{\mathbf{x}}_A\xi] - E[y|\mathbf{x}_A, \bar{\mathbf{x}}_B\xi]). \quad (10)$$

If \mathbf{x}_A differs from \mathbf{x}_B in one variable only, it corresponds to the ME. Estimates for this are reported for Model D in Table 1. We also use this expression to study changing fertility patterns over cohorts (see Appendix A.2).

2.2.3 | Decomposition of cross-country differences

The public debate often focuses on differences between countries in estimated population means, such as the average number of children. To understand better the origin of the difference in the unconditional expected number of children between France (F) and Germany (D), we use our regression results to decompose it into three components (see Section 5.3):

$$\begin{aligned} E_F[y] - E_D[y] &= \int (E_F[y|\mathbf{x}, a] - E_D[y|\mathbf{x}, a]) f_F(a|\mathbf{x}) da dF_F(\mathbf{x}) \\ &+ \int E_D[y|\mathbf{x}, a] (f_F(a|\mathbf{x}) - f_D(a|\mathbf{x})) da dF_F(\mathbf{x}) \\ &+ \int E_D[y|\mathbf{x}, a] (dF_F(\mathbf{x}) - dF_D(\mathbf{x})) f_D(a|\mathbf{x}) da. \end{aligned} \quad (11)$$

The first term of the RHS in Equation (11) shows how much is due to different β s in the two countries. These are the differences in responses that are due to different strengths of the ME. The second term shows how much is due to differences in the distribution of unobservables, in particular different ξ s. The third term expresses the part due to differences in the distribution of the observed characteristics.

2.3 | Fertility choices and unobserved heterogeneity

The expected number of children is typically computed within a country, for individuals with different characteristics and preferences. Because education, income and fertility are to some extent chosen by individuals, there is likely endogenous sorting: women with stronger relative preferences for career may choose longer educational tracks and fewer children. In contrast, females with stronger relative preferences for children may choose shorter educational tracks, refrain from climbing the career ladder and have more children. Naturally, unobserved individual preferences are related with both fertility and career outcomes. Hence, it is crucial to account for these preferences to avoid mistakenly attributing differences in fertility caused by preferences to education or income.

Although some surveys include questions related to individual preferences such as personality traits, family status, desired number of children etc., the full set of individual preferences can unfortunately never be observed. While the presence of unobservables in the fertility equation does not in itself invalidate results, the problem arises from correlations with the included observable variables. This correlation between the explanatory variables and the error term makes the

observables endogenous. In addition to the omission of correlated variables, the problem may also arise from simultaneity of the outcome and the covariates. Whatever is the origin of endogeneity, it invalidates estimation results if not appropriately taken into account. Our approach is to use longitudinal information which allows us to take care of individual specific unobservables in the model. For time series of independent surveys (repeated cross sections), specific methods first proposed by Deaton (1985) have been developed to control for individual unobserved effects. However, when there is panel data available, it is preferable to rely on panel models as they have better statistical properties.

To illustrate the relevance of using a panel methodology in the context of our analysis, we present a selection of results from our application. The full set of results are presented and interpreted in detail in Section 5, including inference about some hypotheses. Table 1 compares ME for a selection of variables for four different models: a cross-sectional model of *completed* fertility with commonly used covariates (A); a pooled cross-sectional model for *current* fertility with commonly used covariates (B); a pooled cross-sectional model for current fertility with the full set of covariates (C) and a CRE panel model with the full set of variables (D). All models are Poisson count models. Reported statistics for Model A, B and C are estimated ME on the expected number of children when changing the respective covariate, while holding all others constant. For Model D, we report the terms of our decomposition in Equation (9), plus the overall effect given on the left hand side (LHS).

The results in Table 1 reveal that it is important to include information about the employment situation of the female and to use panel data methods to allow observables to be correlated with unobserved heterogeneity. Model A, which consider women with completed fertility, have been routinely studied in the context of fertility (e.g. Naz et al., 2006, Cygan-Rehm & Maeder, 2013, Fort et al., 2016). Model A is based on one observation for each female at the end of her reproductive cycle. Going from Model A to Model B shows that the restriction to completed fertility in Model A leads to selectivity in the sample such that some of the estimated effects change considerably. For example, the estimated effects of the cohort variables decrease strongly in magnitude when going from Model B to Model A. While the restriction to one year only decreases the precision of the estimate, the selection of observations for which the dependent variable attains its maximum causes the estimates for Model A to be different. Without reporting these results, we confirmed this by estimating Model B with data restricted to one calendar year (i.e. one observation per female), which only led to less precision compared to Model B.

Regression analysis for fertility that is based on census information or a survey at one time point is expected to give results similar to Model B or C (although based on a much smaller sample). The addition of covariates that describe the current situation of the female (Model C) is expected to reduce the omitted variable bias. For both countries, the effect of higher education reduces further in magnitude. The cohort effects for Germany also decrease further in size, while they increase slightly for France.

Our preferred approach corresponds to Model D. It exploits the panel data structure and allows unobserved heterogeneity to be correlated with included covariates. In contrast to the other models, the estimates are compatible with selection into, for example, education and jobs with high wages based on individual preferences. When comparing two females with the same unobserved heterogeneity (first difference of Equation 9, column 5), the effect of wages on fertility decreases further. The non-zero second difference terms in Equation (9) for the wage categories (column 6) provide evidence for wages to be correlated with unobserved heterogeneity (since the conditional density of the unobserved effect changes with wage). The larger the size of the second difference term, the more biased are the results for the time varying variables in Model C. Therefore, by

TABLE 1 Estimated marginal effects for different model specifications

	A	B	C	D		
	Compl. fertility Basic variables Pooled	Full data Basic variables Pooled	Full data Full set of variables Pooled	Full data		
				Full set of variables		
				Panel - CRE		
(1)	(2)	(3)	LHS	First term	Second term	
(1)	(2)	(3)	(4)	(5)	(6)	
France						
<i>Education - Reference category: No VT</i>						
VT	-0.125	-0.057	-0.030	-0.077	-0.077	
TE	-0.308	-0.273	-0.217	-0.190	-0.190	
<i>Wage - Reference category: No wage or in first wage quartile</i>						
25-49 wage pct.			-0.028	-0.048	-0.043	-0.005
50-74 wage pct.			-0.079	-0.069	-0.051	-0.018
75-89 wage pct.			-0.120	-0.075	-0.048	-0.027
90-94 wage pct.			-0.172	-0.088	-0.049	-0.039
95-98 wage pct.			-0.178	-0.060	-0.018	-0.043
99-100 wage pct.			-0.147	-0.025	0.013	-0.038
<i>Cohort - Reference category: Born 1949-1958</i>						
1959-1968	-0.154	-0.080	-0.137	0.013	0.013	
1969-1978	-0.265	-0.239	-0.314	-0.085	-0.085	
1979-1989	—	-0.456	-0.535	-0.081	-0.081	
Germany						
<i>Education - Reference category: No VT</i>						
VT	-0.067	-0.073	-0.026	-0.099	-0.099	
TE	-0.377	-0.330	-0.235	-0.327	-0.327	
<i>Wage - Reference category: No wage or in first wage quartile</i>						
25-49 wage pct.			-0.050	-0.059	-0.028	-0.031
50-74 wage pct.			-0.156	-0.115	-0.081	-0.034
75-89 wage pct.			-0.246	-0.161	-0.128	-0.033
90-94 wage pct.			-0.303	-0.179	-0.147	-0.032
95-98 wage pct.			-0.375	-0.206	-0.166	-0.040
99-100 wage pct.			-0.444	-0.214	-0.161	-0.053
<i>Cohort - Reference category: Born 1949-1958</i>						
1959-1968	-0.276	-0.128	-0.071	-0.011	-0.011	
1969-1978	-0.488	-0.351	-0.225	0.060	0.060	
1979-1989	—	-0.683	-0.559	-0.048	-0.048	

Notes: Dependent variable: number of children. Basic variables (A, B): education, age, interaction age × education, cohort. Full set of variables (C, D): basic variables plus wage, tenure, wage increase, employment, past employment, having twins/multiples and year categories. First and second term correspond to the estimated decomposition terms in Equation (8). Abbreviations: CRE, correlated random effects; TE, Tertiary education; VT, vocational training.

not allowing for unobserved heterogeneity to be correlated with observables, a pooled model (C) produces inconsistent results. Hence, the overall ME of Model D (column 4), which combines the effect of changing the covariate and the effect of the correlation between the covariate and the unobserved heterogeneity, is quite off the estimated effects of the pooled Model C. For example, the ME of tertiary education is 1.5 times as large in Model D as in Model C for Germany. To sum up, the pooled model is neither informative for the joint effect (LHS of Equation 9), nor for the partial effect (first difference term).

3 | DATA

We construct comparable samples from two administrative data sources for France and Germany. This is a non-trivial exercise given that these data sources differ substantially in shape and content as they are collected through different processes. In this section we provide a brief overview of how this comparability is achieved and present first stylised facts. More details on the data preparation and harmonisation and descriptive statistics are given in Appendix A.1.

3.1 | France: Déclaration Annuelle des Données Sociales - Echantillon Démographique Permanent, 2010 (DADS-EDP 2010)

The French panel contains socio-demographic information of individuals observed in the EDP combined with administrative employment data from the DADS since 1976. Drawing its information from civil registers and the census, the EDP contains details on education, marriage and fertility. Only persons born from 1 to 4 October of each year are followed. Since 2004 the dataset is enriched by individuals born from 1 to 4 of April and July. The information in the DADS stems from mandatory declarations completed by all businesses with dependently employed staff. It comprises data on start and end dates of employment, wages, hours worked, types of contract and occupation. Self-employed, civil servants and individuals that have never been employed do not appear in this data. Since 2004, persons living in French overseas territories have been included, whereas before 2004 only continental France was considered.

3.2 | Germany: Biographical data of selected social security agencies in Germany (BASiD)

The Biographical data of selected social security agencies in Germany (BASiD) links administrative individual-level data from the Federal Employment Agency and the Institute for Employment Research to data from the German Pension Insurance. Detailed information on the dataset can be found in Hochfellner et al. (2011). The pension insurance covers 96% of the German population, from which a 1% random sample is made available via the BASiD. The dataset encompasses individuals up to the age of 67 who held an insurance account at the end of 2007, provided that they had at least one entry and that they were still alive. Periods of employment, training measures, registered unemployment and certain types of inactivity are reported with exact dates. Furthermore, the database provides information on average daily salary, occupation, type of employment (full-time vs. part-time), characteristics of the employing firm and demographic information such as gender, age, educational achievements and dates of birth for any child.

3.3 | Constructing comparable data samples

The French dataset is more selective than the German dataset in terms of individuals included and periods recorded: the DADS-EDP exclusively encompasses persons with at least one record of non-self-employed work, whereas the BASiD also covers individuals that have never been dependently employed but were observed by the Federal Employment Agency or the Pension Insurance for a different reason, for example due to voluntarily insured self-employment or the eligibility for minimum income support. Selection into these data sets is therefore not entirely random and might hereby induce biases for our country-specific estimates. Individual employment histories are less complete in the French data than in the German data because the former exclusively contain periods of dependent employment. This restriction affects the set of explanatory variables included in the comparative two-country analysis as the current and past labour market states likely affect fertility behaviour. Unfortunately, no information on marital status and hence on a potential partner is recorded in the BASiD. The French dataset contains the date of marriage but neither has current updates on marital status nor information on the spouse. Information on personal preferences, religion or social conventions is not provided in any of the data sources. Instead, we exploit the longitudinal dimension of the data to address the omission of important variables. The precision of our analysis benefits from the large cross-sectional and longitudinal data dimensions that are not available with survey data. Furthermore, errors due to misstatements in the birth and employment variables are unlikely since they are key variables of administrative records.

We construct comparable annual panel data sets for the period 1994 to 2007 for the two countries. The panels are based on employment records of women aged between 18 and 45 in the respective years, where the variables are constructed from any daily information that is available in the raw data since the 1970s. We group education information into three categories: having no vocational training or higher education (no VT), having completed a vocational training (VT) and holding a tertiary education diploma (TE). In both panels, a woman is observed for at least one and at most 14 years. The French panel contains 102,574 females, the German panel 175,353. When we construct aggregate birth rates from the BASiD and the DADS-EDP, they are somewhat lower than the birth rates reported by the national statistical institutes. This pattern is observed with and without the restrictions on our sample and could be due to general selectivity of the underlying data sources or by births which occurred after the last observed record in our data. Descriptive statistics of the independent variables and the estimation samples are given in Table A1.

4 | BACKGROUND, MECHANISMS AND HYPOTHESES

Systematic differences in fertility behaviour and female labour force participation between women in France and Germany are likely due to different historical and cultural backgrounds, social conventions and family policies. While there was still a strong historical attachment to the male breadwinner model in Germany, the French state provided incentives for young mothers to return to the labour market quickly. In addition to the goal of reconciling work and family life, the French system promoted families of three or more children. In contrast, Germany neither encourage young mothers to return to work nor favoured large families but supported child-rearing at home with cash benefits. In the following, we briefly compare the different national child-care arrangements, child-rearing benefits and aggregated transfers during the period 1994–2007.

This is followed by hypotheses to be tested in the empirical analysis. A more detailed presentation of the family policies in France and Germany can be found in Section S.II of the Supplementary Material S1.

Unlike in France, the German approach to childcare was characterised by a shortage of childcare places for children below the age of 6, a late entry into daycare and an incompatibility between the regular working hours of parents and the opening hours of day care institutions. For more details on the childcare policies see Brewster and Rindfuss (2000), Plantenga et al. (2005), Fagnani and Math (2010) and Salles et al. (2010). Due to the restricted supply of childcare places in conjunction with traditional gender roles, it was more difficult for mothers in Germany to return to paid work. OECD data confirm these patterns: while both countries spent similar percentages of GDP on family cash benefits between 1994 and 2007, government expenditure on family services was approximately twice as high in France as in Germany. In addition, expenditure on childcare and education was between 1.8 and 3.6 times higher in France than in Germany (OECD, 2019). Due to the better possibilities to work for mothers in France compared to mothers in Germany, there are less pronounced opportunity costs of having children in terms of forgone career opportunities and lost wages in France. Therefore, we expect weaker responses in fertility to employment and education in France than in Germany.

Towards the end of our analysis period, Germany began to promote female employment and to invest in public childcare. For example, the percentage of children aged under three attending childcare facilities or being cared for by child minders increased from 6.3 in 1994 to 15.5 in 2007 in Germany (Fagnani & Math, 2010). We therefore anticipate a *ceteris paribus* increase in fertility in later years.

In the macro literature, a positive relationship between female labour force participation and fertility has been found repeatedly (e.g. Brewster and Rindfuss, 2000, Ahn & Mira, 2002, Billari & Kohler, 2004, Adsera, 2004), even though it may look at a glance counter-intuitive on the individual level. By hypothesising individual fertility in France to be weaker affected by education and wages than in Germany, we expect individual level behaviour to be consistent with macro outcomes.

The two countries also differ in their tax breaks and social benefits in relation to having children, which are the (*Allocations familiales*), the (*Complément familial*) and the (*Quotient familial*) in France and the (*Kinderfreibetrag*) and the (*Kindergeld*) in Germany. Baclet et al. (2005) create a so-called effective tax rate for the two countries, which combines the incentives set by the income tax, the child cash benefits and the child tax reductions. For both countries they find that the effective tax rate decreases with the number of children. The evolution of the effective tax rate with income differs between both countries: for households earning below a certain threshold, the effective tax rate is lower in Germany than in France. For pre-tax incomes greater than 36.000–45.000 Euros (depending on the marital status and the number of children), however, the German effective tax rate is higher than the French. For a more complete picture, social assistance and housing benefits also need to be taken into account. The resulting aggregate transfers in France are U-shaped in family income: on the one hand, low-income families gain relative to median earners. On the other hand, high-income families benefit from the *quotient familial* (Bechtel et al., 2005). We therefore expect a relative increase in fertility at high levels of income in both countries. Since aggregate transfers for high wages are higher in France than in Germany, we expect this increase in fertility with high incomes to be stronger in France than in Germany. However, negative opportunity costs of having children, which are higher in Germany than in France, will reduce this effect.

In both countries females are expected to sort into employment according to their preferences for children and career (Adda et al., 2017). Females with relatively high career ambitions

compared to preferences for children likely sort into higher educational tracks and jobs with higher wages. We therefore expect a non-trivial correlation between unobserved and observed employment related factors in both countries.

5 | EMPIRICAL RESULTS

5.1 | Main results

As outlined in Section 2 we focus on the CRE model and the estimation of the average ME on the expected number of children. These are reported in Figure 2 along with their 95% block bootstrap confidence intervals. Although we mainly focus on the effects on the expected value, we sometimes also refer to the estimated ME on the probabilities of having a certain number of children (both estimates are readily obtained with the Poisson model). These results are given in Table A4.

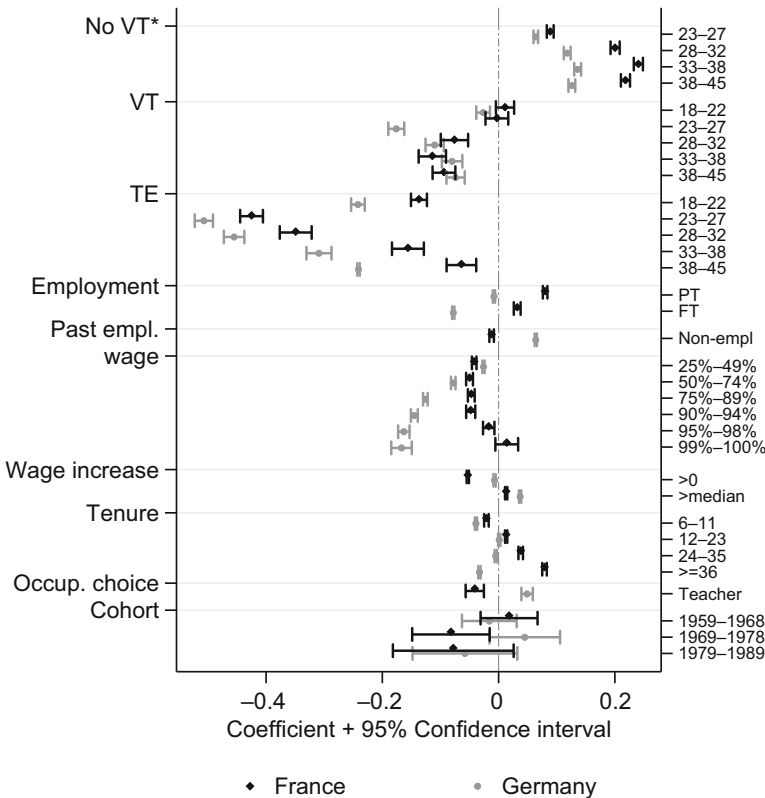


FIGURE 2 Average marginal effects of the Poisson correlated random effects model. Dependent variable: number of children. Based on Tables A2 and A3. Confidence intervals based on 100 bootstrap replications (this value was chosen due to very long computing times). FT, Full-time; PT, Part-time; TE, Tertiary Education; VT, Vocational Training. *Reference Categories*: No VT: aged 18–22; VT and TE: having No VT and being of the same age, Employment: not employed, Past Employment: Employed, Wage: 0 or in the 1st to 24th wage percentile, Wage Increase: 0 or negative, Tenure: 0–5 months, Occupational Choice: not teacher, Cohort: 1949–1958. *Marginal effects of no VT are divided by 5 for better visibility.

5.1.1 | Cohorts

Estimated cohort effects are mostly insignificant for both countries, which is in contrast to when one uses data on completed fertility or cross-sectional data (compare Table 1). When not appropriately controlling for correlated unobserved heterogeneity, the estimated cohort effects of cross-sectional analyses are largely inconsistent. Our results appear to contradict the well-known strong decline in unconditional fertility by cohort. To shed light on this puzzle and to understand better why unconditional fertility declines, we apply the decomposition approach of Section 2.3. The results in Appendix A.2 show that the decline in average fertility across cohorts is due to changes in unobservables such as preferences but also due to changes in the distribution of observables such as education, age and wage (compare Table A5). We also confirm that the distribution of unobserved heterogeneity shifts to the left across cohorts.

5.1.2 | Education and age

While for both countries higher educational attainment is associated with a significantly lower expected number of children at most ages, the estimated ME are up to twice as large in magnitude for Germany than for France. In Germany, having a tertiary education degree compared to having no vocational training is estimated to reduce the expected number of children by 0.24 to 0.51, in France by 0.06 to 0.43. The decline in the expected number is mainly due to a hike in the probability of remaining childless of +14 percentage points in Germany and +8 percentage points in France (compare Table A4). Thus, the effect in France is clearly weaker than what the descriptive evidence suggests (see again Figure 1).

Other studies that focus on the estimation of the causal effect of education by means of educational reforms generally find no or a positive effect of education on fertility (e.g. Fort et al., 2016 for continental Europe, McCrary & Royer, 2011 for the United States, Monstad et al., 2008 for Norway). Cygan-Rehm and Maeder (2013) use a compulsory schooling reform in Germany and find a negative effect on the expected number of children. Their estimates are similar in size to ours: one additional year of schooling decreases the expected number of children by at least 0.1 and increases the probability of remaining childless by 5 percentage points. In line with them, we conclude that opportunity costs of having children are especially severe in Germany.

Our results confirm much lower fertility for females during educational periods of tertiary education. This postponement has been extensively stressed in the literature (e.g. Rindfuss et al., 1996, Ní Bhrolcháin & Beaujouan, 2012). Highly educated females have roughly 0.3 to 0.5 children less in their mid 20s than a female without vocational training. There is a catch up behaviour at higher ages: the difference in the expected number of children between high and low educated women narrows to around 0.1–0.2 when they are in their 40s. Again, these patterns are more pronounced for Germany than for France. The equivalent postponement effects for females with vocational training are much weaker.

5.1.3 | Wage

We also provide evidence of higher wages being associated with a lower expected number of children. Although this is found to be present in both countries, the estimated effect is again much stronger in magnitude for Germany than for France. We explain this by higher opportunity costs

due to a weaker work–family compatibility in Germany compared to France. In Germany, being in the highest earnings decile compared to the lowest quartile reduces the expected number of children by nearly 0.2. For Germany, higher wages are associated with a higher probability to stay childless (+5 percentage points when earning in the upper 5% of the earnings distribution compared to no wage or a wage in the lower quartile) and a reduced probability to have any positive number of children (compare Table A4). In contrast, for France, higher wages are associated with higher probabilities of having no or one child and with a reduced probability of having two or more children.

For France, there is weak evidence of a positive income effect at high wages. For French females in the top one percentile (around 6000 observations), the wage effect is not significantly negative. This is in line with our hypothesis about the consequences of aggregate transfers for children, see Section 4. This positive relation at high wage brackets is robust to different specifications of the econometric model and is of high interest as it differs from most previous studies. Several studies find a negative relationship between wages and fertility (e.g. Heckman & Walker, 1990, Jones & Tertilt, 2008). Causal analyses using exogenous and unexpected income shocks, however, find evidence of a positive effect of income on fertility (Lindo, 2010, Lovenheim & Mumford, 2013). Coupled with the available childcare opportunities, this could explain the positive wage effect at the top of the income distribution for France. Similarly, Hazan and Zoabi (2015) report a recent change in fertility patterns by education: they find higher fertility rates for young, highly educated American women than for medium educated females and trace this back to changes in the relative cost of childcare.

The pooled model gives much more sizeable effects of wages on fertility for both countries (see Tables A2 and A3). This supports the hypothesis of the presence of important sorting effects, for example, females with low preferences for children and strong preferences for career sort into high paid jobs. Models that do not take into account the endogeneity of the wage lead to estimates that are about 5–10 times larger (see again Table 1).

5.1.4 | Employment situation

The results also show the relevance of the current and past employment situation (other than wage) for fertility. Being employed (part-time and full-time) is estimated to reduce fertility in Germany as opposed to France, which confirms higher opportunity costs of fertility in Germany. Similarly, the French coefficient of non-employment during the past year is close to zero, while the estimate is significantly positive and important for Germany (+0.06). This suggests that the positive effect of reduced opportunity costs outweighs the negative effect of deteriorated economic security. The German data allows us to disentangle the effect of past unemployment from the effect of past inactivity, see Table S3. While having been unemployed is estimated to have virtually no effect on fertility, past inactivity increases the expected number of children by 0.2 children. This finding supports the results by Arntz et al. (2017) who find a high propensity for German women to have a second child during the job protection period of the first child.

The literature acknowledges the endogeneity of part-time work by noting that part-time work is associated with preferences for children (Francesconi, 2002, Adda et al., 2017). Our estimates confirm this sorting into part-time work: while the estimates of part-time work are large and positive for both countries in the pooled model (+0.22 in France and +0.18 in Germany), they are much smaller and partly negative when accounting for this endogeneity (+0.08 and -0.01 respectively). This sorting can best be seen by the example of teachers: naturally, being a teacher

does not increase fertility, but having a preference for children leads to an occupational choice that is more compatible with family life. For Germany, the pooled model estimates the number of children to be 0.22 higher for teachers than for females in other occupations, while the estimate is just 0.05 for the CRE model. This points to an endogenous sorting of females with a preference for children into the teaching profession in Germany. Interestingly, the opposite is found for France, where the estimated effect for the CRE model is smaller in size than for the pooled model.

Following Francesconi (2002), an increase in female wages serves as proxy for career advancement and is thus associated with additional opportunity costs. Therefore, we expect a negative association between career jumps and fertility. Not taking into account unobserved heterogeneity, we indeed find a negative estimate for Germany (-0.06). However, when allowing for sorting of career-oriented females in trajectories with wage promotions, the estimate turns positive ($+0.04$). Overall we find mixed results for the relationship between wage increases and fertility. For smaller increases there is evidence of a negative relationship, while for large increases it is found to be positive.

With respect to tenure, we do not find evidence of substantial strategic adaptation of the timing of births to ensure eligibility for child benefits. For France, the effect increases in size with tenure. For Germany, the effect is zero for tenures of 1–3 years and negative for longer periods of tenure, presumably because it is more common for mothers in France to return to the same employer after childbirth than for mothers in Germany (Rodrigues & Vergnat, 2018 for France; Arntz et al., 2017 for Germany). For both countries, the estimated effect of tenure is much more positive in the pooled model. Again, this can be explained by sorting: females with relative preferences for career are more mobile, change their jobs more often and, therefore, have shorter tenure. Hence, the pooled model produces an estimate of the effect of tenure that is confounded with the effect of preferences for career and children.

5.2 | Robustness checks

The full set of results for the Poisson and linear regressions, in each case for the pooled, FE and CRE model, is given in the Appendix (Tables A2 and A3). Note that our coefficients of the CRE models are very close to the estimates of the FE models, both for the linear and the Poisson specification. This is reassuring as the FE model does not restrict correlations between a_i and the time varying covariates. We compute likelihood ratio tests by comparing the RE model with the CRE model to assess whether unobserved heterogeneity is correlated with the observed variables. The increase in the log likelihood when allowing for this correlation is substantial for both countries (from $-1,032,458$ to $-1,030,769$ for France and from $-1,198,888$ to $-1,192,702$ for Germany). Therefore, we reject the hypothesis of no improvement at p -values that are virtually zero.

To ensure the best possible comparability between both countries, we use comparable variables for France and Germany. In addition, we estimate a country-specific regression for each country separately by including additional covariates which are not available in the other dataset. For France, we add variables on being born overseas, marriage and living in Île-de-France. For Germany, we additionally control for nationality, federal states, former East Germany (interacted with cohorts) and split up past non-employment status in unemployed, inactive and unobserved. The results can be found in Tables S3 and S4. Importantly, our main estimates are unaffected by the inclusion of these extra variables. This implies that the individual effects do a good job in picking up unobserved heterogeneity in relation to the partner and ethnicity. While in France having been married increases the expected number of children by around

0.5, the effects of education, wages and employment remain virtually the same. For Germany, the inclusion of the additional variables, in particular living in former East Germany, leads to an increase in the negative effects of wage and education on fertility. The estimate of the effect of part-time work, however, becomes more positive and the difference between the pooled and CRE model becomes even larger. Additional robustness checks have been conducted using different cut-off dates when constructing the yearly panel. No relevant differences have been detected.

5.3 | Decomposition of country differences

The findings above reconcile the micro effects within a country and the macro effects between countries: within each country, higher opportunity costs in terms of foregone wages and employment opportunities generally harm fertility outcomes. However, the cross-country relation between female employment and fertility is positive: during our analysis period, the country with higher female labour force participation, France, has higher fertility rates. This can be explained by cross-country differences in the availability of childcare and, hence, higher opportunity costs of having children in Germany than in France. Using a decomposition of fertility differences between the two countries, we now show that the lower fertility in Germany is indeed due to differing responses to employment related characteristics.

There are pronounced differences in the sample averages of the number of children for France and Germany. While it is 1.04 for France, the equivalent value is just 0.65 for Germany (Table 2, column 1). As these figures are sample averages (over all females and periods), they should not be confused with average completed fertility. The CRE Poisson model predicts only slightly higher means than the actual average number for the two countries, indicating that the model explains average fertility well. The average predicted number of children is 0.33 higher in France than in Germany. To understand better what is driving the difference between the two countries, we use our regression results and decompose the expected difference into a part due to differences in β s, differences in unobserved heterogeneity (captured by ξ) and differences in the distribution of the observables x . The decomposition is outlined in Equation (11). The estimated decomposition terms are given Table 2.

The first decomposition term suggests that the $\hat{\beta}$ s for France are more favourable for fertility than those for Germany. As explained above, the main country differences in the ME are found for education and variables related to employment. Therefore, females in Germany would have a considerably higher number of children if they experienced the same less negative effects of

TABLE 2 Decomposition of country differences in the expected number of children

Raw differential	LHS	First RHS term	Second RHS term	Third RHS term
$\bar{y}_F - \bar{y}_D$	$\hat{E}(y_F) - \hat{E}(y_D)$	due to diff. $\hat{\beta}$	due to diff. $\hat{\xi}$	due to diff. x
(1.04–0.65)	(1.05–0.72)	(1.05–0.37)	(0.37–1.22)	(1.22–0.72)
0.39	0.33	0.68	–0.85	0.50

Notes: Estimated terms of the decomposition given in Equation (11).

Abbreviations: D, Germany; F, France.

wages and education on fertility as their counterparts in France. In contrast, the negative second term in relation to ξ suggests that unobservable heterogeneity is more favourable for fertility in Germany than in France. This sizeable non-zero second term highlights that controlling for unobserved individual heterogeneity is crucial since it avoids attributing too much explanatory power to the observed variables with which it is correlated. The last term shows that the composition of observables, such as age and wages, leads to higher fertility rates in France than in Germany. To summarise, the higher fertility in France is driven by more beneficial fertility responses to observables and a more favourable composition of the observable covariates. We explain the former by a better work family compatibility in the French system. The fertility gap between France and Germany would be much wider if females in Germany had not comparatively favourable unobservables such as stronger preferences for children. Therefore, our decomposition analysis finds no evidence of lower fertility in Germany being driven by lower preferences for children.

6 | CONCLUSIONS

We reason in detail that a panel analysis of fertility gives better results than an analysis based on cross-sectional or pooled data. We demonstrate the relevance of accounting for individual heterogeneity by providing empirical results that differ substantially from results obtained by usual analytical approaches without panel dimension. Most cross-country comparisons of fertility are based on census information or cross-sectional surveys. These data sources, such as the Fertility and Family Survey (FFS), are sometimes internationally harmonised and exist for a range of countries. They contain detailed information about fertility but they lack a longitudinal dimension which makes the application of panel techniques impossible. Other harmonised panel data sets with focus on fertility such as the Generations and Gender Survey (GGS) lack precision about the professional career compared to the daily administrative data of our study. A more targeted approach would be to conduct panel surveys that are directly linked to administrative data sources to enhance these data structures.

We provide detailed results of a cross-country comparison of factors determining fertility behaviour in France and Germany. While most result patterns are similar for both countries, they often differ substantially in strength. We provide evidence of the female's professional career being highly important for fertility decisions, just as education, and confirm negative wage effects for large parts of the income distribution. These effects are more pronounced for Germany than for France. We provide evidence of adjustments taking place not only with respect to the number of children, but also with respect to the timing of births. Highly educated women have a strong tendency to postpone births to a later age when career advancements have already taken place.

We explain the differences in the results for France and Germany by different societal approaches to childcare and other parenthood-related aspects. Lower fertility in Germany compared to France results from stronger negative responses to education and employment due to greater opportunity costs of having children, rather than from lower preferences for children. This is an important finding since it implies that there is scope for policymakers to influence fertility decisions by determining the opportunity costs—a proposition controversially discussed in the literature (see Gauthier, 2007 for a review and discussion on the effectiveness of policies in raising fertility). While this policy conclusion is rather broad, it provides a foundation for analyses investigating the effectiveness of particular country-specific policy measures to reduce opportunity costs

of having children. For example, it provides important support for national studies finding significant positive effects of increases in public childcare on fertility (e.g. Bauernschuster et al., 2016 for an assessment of the effectiveness of the introduction of universal child care in Germany in raising fertility). Along these lines, we reason that the apparent paradox of ‘higher female labour force participation rates - higher fertility rates’ that has been observed on the macro level is actually compatible with family policies and public provision of day-care that mitigate the negative economic consequences of having children.

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SUPPORTING INFORMATION

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APPENDIX

A.1 Additional results

TABLE A1 Description of the independent variables

	Time variant	Description	Share in %	
			France	Germany
Age	Yes	<u>18–22 years</u>	16.1	17.9
		23–27 years	19.7	21.1
		28–32 years	20.3	21.2
		33–37 years	19.7	18.2
		38–45 years	24.2	21.6
Education	No	<u>No VT</u>	13.4	20.7
		VT	55.2	66.9
		TE	31.4	12.4
Employment	Yes	<u>Not employed</u>	53.5	42.9
		Part-time	15.9	19.0
		Full-time	30.6	38.1
Past employment	Yes	Not employed	50.4	50.8
Gross wage	Yes	<u>0 or <25%</u>	64.1	56.9
		<50%	11.4	14.4
		<75%	12.0	14.3
		<90%	7.5	8.6
		<95%	2.5	2.9
		<99%	2.0	2.3
Change in wage relative to past year	Yes	<u>Negative</u>	18.3	21.2
		positive	30.4	45.5
		>median	51.3	33.3
Tenure at firm	Yes	<u><6 months</u>	12.1	45.0
		6–11 months	4.0	7.0
		12–23 months	10.6	9.9
		24–36 months	8.4	7.1
		>36 months	65.0	31.0
Child-friendly profession	Yes	Yes	2.2	1.7
Twins	Yes	Yes	0.6	0.7
Multiples	Yes	Yes	0.5	0.0
Birth cohort	No	<u>1949–1958</u>	9.1	8.2
		1959–1968	36.9	32.4
		1969–1978	39.5	44.2
		1979–1989	14.5	15.2

TABLE A1 (Continued)

Factor	Time variant	Description	Share in %	
			France	Germany
Year	Yes	<u>1994–1996</u>	20.0	19.8
		1997–1999	21.7	21.2
		2000–2002	22.6	22.1
		2003–2005	22.1	22.3
		2006–2007	13.6	14.6
<i>Variables only observed for France</i>				
Île-de-France	Yes	Yes	21.1	
Married	Yes	Yes	31.8	
Born overseas	No	Yes	2.0	
<i>Variables only observed for Germany</i>				
Former GDR	No	Yes		14.6
Federal state	Yes	<u>No info.</u>		21.5
		SH & MV		3.3
		LS & B		6.7
		NRW		17.3
		Hesse		6.7
		RP & S		4.4
		BW		11.4
		Bavaria		12.6
		B & H		5.3
		S & B		6.4
		T & SA		4.4
Foreign nationality	No	Yes		30.6
Unempl. last year	Yes	Yes		15.0
Inactive last year	Yes	Yes		13.1
Unobs. last year	Yes	Yes		30.9

Notes: Reference categories of the following regressions are underscored.

Abbreviations: B & H, Berlin & Hamburg; BW, Baden-Wuerttemberg; LS & B, Lower Saxony & Bremen; NRW, North Rhine-Westphalia; RP & S, Rhineland-Palatinate & Saarland; S & B, Saxony & Brandenburg; SH & MV, Schleswig-Holstein & Mecklenburg-Western Pomerania; T & SA, Thuringia & Saxony-Anhalt.

TABLE A2 Baseline results France

	Linear			Poisson				
	OLS	FE	CRE	Pooled		FE	CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Education × Age</i>								
<i>No Vocational Training—Ref. Category: without vocational training, aged 18–22</i>								
23–27	0.38*** (0.01)	0.22*** (0.01)	0.22*** (0.01)	1.69*** (0.02)	0.36*** (0.00)	1.52*** (0.03)	1.48*** (0.02)	0.44*** (0.00)
28–32	0.95*** (0.01)	0.64*** (0.01)	0.63*** (0.01)	2.41*** (0.02)	0.95*** (0.00)	2.16*** (0.03)	2.09*** (0.02)	1.00*** (0.00)
33–37	1.36*** (0.02)	0.85*** (0.02)	0.85*** (0.01)	2.70*** (0.02)	1.38*** (0.01)	2.29*** (0.03)	2.21*** (0.03)	1.20*** (0.00)
38–45	1.58*** (0.02)	0.78*** (0.02)	0.78*** (0.01)	2.80*** (0.02)	1.52*** (0.01)	2.19*** (0.03)	2.10*** (0.03)	1.09*** (0.00)
<i>Vocational Training—Ref. Category: without vocational training, same age group</i>								
18–22	–0.00 (0.00)		0.09*** (0.01)	–0.07** (0.03)	–0.07 (0.05)		0.07* (0.03)	0.01 (0.01)
23–27	–0.02* (0.01)	–0.09*** (0.01)	0.01 (0.01)	–0.05*** (0.03)	–0.03** (0.01)	–0.14*** (0.03)	0.00 (0.03)	–0.00 (0.01)
28–32	–0.03*** (0.01)	–0.16*** (0.01)	–0.06*** (0.01)	–0.02*** (0.03)	–0.02 (0.01)	–0.23*** (0.03)	–0.06*** (0.03)	–0.08*** (0.01)
33–37	–0.03 (0.01)	–0.20*** (0.02)	–0.10*** (0.02)	–0.01* (0.03)	–0.02 (0.01)	–0.27*** (0.03)	–0.08*** (0.03)	–0.11*** (0.01)
38–45	–0.08*** (0.02)	–0.21*** (0.02)	–0.10*** (0.02)	–0.03*** (0.00)	–0.06*** (0.02)	–0.2*** (0.03)	–0.07*** (0.03)	–0.09*** (0.01)
<i>Tertiary Education—Ref. Category: without vocational training, same age group</i>								
18–22	–0.08*** (0.00)		–0.07*** (0.01)	–2.10*** (0.05)	–0.09*** (0.01)		–2.03*** (0.05)	–0.14*** (0.01)
23–27	–0.27*** (0.01)	–0.22*** (0.01)	–0.28*** (0.01)	1.01*** (0.05)	–0.35*** (0.01)	1.05*** (0.05)	–0.96*** (0.05)	–0.43*** (0.01)
28–32	–0.29*** (0.01)	–0.24*** (0.02)	–0.30*** (0.01)	–0.32*** (0.05)	–0.31*** (0.01)	1.67*** (0.05)	–0.32*** (0.05)	–0.35*** (0.01)
33–37	–0.20*** (0.01)	–0.11*** (0.02)	–0.18*** (0.02)	–0.12*** (0.05)	–0.18*** (0.01)	1.88*** (0.05)	–0.12*** (0.05)	–0.16*** (0.01)
38–45	–0.21*** (0.02)	–0.01 (0.02)	–0.09*** (0.02)	–0.10*** (0.00)	–0.16*** (0.01)	1.94*** (0.05)	–0.05*** (0.01)	–0.06*** (0.01)

TABLE A2 (Continued)

	Linear			Poisson				
	OLS	FE	CRE	Pooled		FE	CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Employment—Ref. Category: not employed</i>								
Part-time	0.20*** (0.01)	0.06*** (0.00)	0.06*** (0.00)	0.19*** (0.00)	0.22*** (0.01)	0.07*** (0.01)	0.08*** (0.01)	0.08*** (0.00)
Full-time	-0.10*** (0.01)	-0.04*** (0.00)	-0.04*** (0.00)	-0.06*** (0.01)	-0.06*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.00)
<i>Past employment—Ref. Category: employed</i>								
Not empl.	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)	0.01** (0.00)	0.01** (0.00)	-0.01** (0.00)	-0.01** (0.00)	-0.01*** (0.00)
<i>Wage—Ref. Category: 0 or in the first to 24th wage percentile</i>								
25%–49%	-0.01 (0.01)	-0.03*** (0.00)	-0.03*** (0.00)	-0.03*** (0.00)	-0.03*** (0.01)	-0.04*** (0.00)	-0.04*** (0.00)	-0.04*** (0.00)
50%–74%	-0.07*** (0.01)	-0.05*** (0.00)	-0.05*** (0.00)	-0.08*** (0.00)	-0.08*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.00)
75%–89%	-0.14*** (0.01)	-0.07*** (0.00)	-0.07*** (0.00)	-0.12*** (0.01)	-0.12*** (0.01)	-0.04*** (0.01)	-0.05*** (0.01)	-0.05*** (0.00)
90%–94%	-0.21*** (0.01)	-0.09*** (0.00)	-0.09*** (0.00)	-0.17*** (0.01)	-0.17*** (0.01)	-0.04*** (0.01)	-0.05*** (0.01)	-0.05*** (0.00)
95%–98%	-0.23*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.18*** (0.01)	-0.18*** (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.02*** (0.01)
99%–100%	-0.21*** (0.03)	-0.04*** (0.01)	-0.04** (0.01)	-0.15*** (0.01)	-0.15*** (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.01)
<i>Wage Increase—Ref. Category: 0 or negative</i>								
>0	-0.02*** (0.00)	-0.04*** (0.00)	-0.04*** (0.00)	-0.03*** (0.00)	-0.03*** (0.00)	-0.05*** (0.00)	-0.05*** (0.00)	-0.05*** (0.00)
>median	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.03*** (0.00)	0.04*** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01*** (0.00)
<i>Tenure in months—Ref. Category: 0–5 months</i>								
6–11	0.00 (0.01)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02* (0.01)	-0.01*** (0.01)	-0.02*** (0.01)	-0.02*** (0.01)	-0.02*** (0.00)
12–23	0.08*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.06*** (0.00)	0.06*** (0.00)	0.01* (0.01)	0.01** (0.01)	0.01*** (0.00)
24–35	0.09*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.09*** (0.01)	0.09*** (0.01)	0.03*** (0.01)	0.04*** (0.01)	0.04*** (0.00)
≥36	0.11*** (0.01)	0.05*** (0.00)	0.05*** (0.00)	0.13*** (0.00)	0.13*** (0.01)	0.07*** (0.00)	0.08*** (0.00)	0.08*** (0.00)

TABLE A2 (Continued)

	Linear			Poisson				
	OLS	FE	CRE	Pooled		FE	CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Occupational Choice—Ref. Category: not teacher</i>								
Teacher	−0.12*** (0.02)	−0.00 (0.01)	−0.01 (0.01)	−0.11*** (0.01)	−0.11*** (0.02)	0.02 (0.01)	−0.04** (0.01)	−0.04*** (0.01)
<i>Cohort- Ref. Category: 1949–1958</i>								
1959–1968	−0.19*** (0.01)		−0.06* (0.03)	−0.12*** (0.00)	−0.14*** (0.01)		0.02 (0.03)	0.02 (0.03)
1969–1978	−0.40*** (0.02)		−0.11*** (0.04)	−0.30*** (0.01)	−0.31*** (0.01)		−0.08 (0.05)	−0.08* (0.03)
1979–1989	−0.48*** (0.02)		−0.10 (0.05)	−0.58*** (0.01)	−0.54*** (0.02)		−0.08 (0.07)	−0.08 (0.05)
<i>Year—Ref. Category: 1994–1996</i>								
1997–1999	−0.01*** (0.00)	0.10*** (0.00)	0.10*** (0.00)	−0.03*** (0.00)	−0.03*** (0.00)	0.06*** (0.00)	0.06*** (0.00)	0.06*** (0.00)
2000–2002	0.02*** (0.00)	0.23*** (0.00)	0.23*** (0.00)	−0.00 (0.00)	−0.00 (0.00)	0.16*** (0.00)	0.16*** (0.00)	0.16*** (0.00)
2003–2005	0.07*** (0.01)	0.37*** (0.00)	0.37*** (0.00)	0.05*** (0.00)	0.05*** (0.01)	0.28*** (0.01)	0.28*** (0.01)	0.29*** (0.00)
2006–2007	0.08*** (0.01)	0.48*** (0.00)	0.48*** (0.00)	0.07*** (0.00)	0.07*** (0.01)	0.39*** (0.01)	0.39*** (0.01)	0.43*** (0.00)
Constant	0.39*** (0.02)	0.37*** (0.00)	0.04 (0.11)	−2.19*** (0.02)			−1.94*** (0.05)	
Obs.	1,155,439	1,155,439	1,155,439	1,155,439	1,155,439	813,637	1,155,439	1,155,439
LL				−1,288,786		−716,521	−1,030,769	

Notes: SEs based on 100 bootstrap replications (this value was chosen due to very long computing times). AME denotes average marginal effect. Controlling for twins and multiples.

* $p < 0.05$,

** $p < 0.01$,

*** $p < 0.001$.

TABLE A3 Baseline results Germany

	Linear			Poisson				
	OLS	FE	CRE	Pooled		FE	CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Education × Age</i>								
<i>No vocational training—Ref. Category: without vocational training, aged 18–22</i>								
23–27	0.24*** (0.00)	0.09*** (0.00)	0.09*** (0.00)	1.26*** (0.01)	0.23*** (0.00)	0.91*** (0.01)	0.90*** (0.01)	0.32*** (0.00)
28–32	0.57*** (0.01)	0.24*** (0.01)	0.25*** (0.01)	1.78*** (0.01)	0.54*** (0.00)	1.22*** (0.02)	1.20*** (0.02)	0.59*** (0.00)
33–37	0.84*** (0.01)	0.33*** (0.01)	0.33*** (0.01)	2.09*** (0.01)	0.80*** (0.00)	1.29*** (0.02)	1.26*** (0.02)	0.68*** (0.00)
38–45	1.04*** (0.01)	0.30*** (0.01)	0.30*** (0.01)	2.25*** (0.01)	0.99*** (0.00)	1.23*** (0.02)	1.19*** (0.02)	0.63*** (0.00)
<i>Vocational training—Ref. Category: without vocational training, same age group</i>								
18–22	-0.01*** (0.00)		-0.02*** (0.00)	-0.73*** (0.02)	-0.06*** (0.00)		-0.70*** (0.02)	-0.13*** (0.01)
23–27	-0.02*** (0.01)	-0.02*** (0.00)	-0.05*** (0.00)	-0.28*** (0.02)	-0.10*** (0.00)	0.34*** (0.02)	-0.32*** (0.02)	-0.17*** (0.01)
28–32	-0.02*** (0.01)	-0.01* (0.01)	-0.03*** (0.01)	-0.06*** (0.02)	-0.03*** (0.01)	0.51*** (0.02)	-0.15*** (0.02)	-0.12*** (0.01)
33–37	0.01 (0.01)	0.00 (0.01)	-0.02*** (0.01)	0.01* (0.02)	0.01 (0.01)	0.54*** (0.02)	-0.10*** (0.02)	-0.09*** (0.01)
38–45	-0.01* (0.01)	-0.00 (0.01)	-0.03** (0.01)	0.01*** (0.01)	0.01 (0.01)	0.54*** (0.02)	-0.10*** (0.02)	-0.08*** (0.01)
<i>Tertiary education—Ref. Category: without vocational training, same age group</i>								
18–22	-0.11*** (0.00)		-0.10*** (0.00)	-2.79*** (0.07)	-0.11*** (0.00)		-2.47*** (0.07)	-0.24*** (0.01)
23–27	-0.25*** (0.00)	-0.12*** (0.00)	-0.23*** (0.00)	-2.02*** (0.07)	-0.33*** (0.01)	0.82*** (0.08)	-1.56*** (0.07)	-0.50*** (0.01)
28–32	-0.32*** (0.01)	-0.18*** (0.01)	-0.28*** (0.01)	-0.82*** (0.07)	-0.37*** (0.01)	1.54*** (0.08)	-0.76*** (0.07)	-0.46*** (0.01)
33–37	-0.27*** (0.01)	-0.12*** (0.01)	-0.23*** (0.01)	-0.31*** (0.07)	-0.24*** (0.01)	1.83*** (0.08)	-0.43*** (0.07)	-0.32*** (0.01)
38–45	-0.20*** (0.02)	-0.09*** (0.01)	-0.19*** (0.01)	-0.11*** (0.07)	-0.12*** (0.02)	1.88*** (0.08)	-0.35*** (0.07)	-0.25*** (0.01)

TABLE A3 (Continued)

	Linear			Poisson				
	OLS	FE	CRE	Pooled		FE	CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Employment—Ref. Category: not employed</i>								
Part-time	0.18*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.26*** (0.00)	0.18*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Full-time	-0.01* (0.00)	-0.05*** (0.00)	-0.05*** (0.00)	-0.02*** (0.00)	-0.01 (0.00)	-0.11*** (0.00)	-0.11*** (0.00)	-0.08*** (0.00)
<i>Past employment- Ref. Category: employed</i>								
Not empl.	0.25*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.36*** (0.00)	0.24*** (0.00)	0.09*** (0.00)	0.09*** (0.00)	0.06*** (0.00)
<i>Wage—Ref. Category: 0 or in the first to 24th wage percentile</i>								
25–49%	-0.05*** (0.00)	-0.04*** (0.00)	-0.04*** (0.00)	-0.07*** (0.00)	-0.05*** (0.00)	-0.04*** (0.00)	-0.04*** (0.00)	-0.03*** (0.00)
50%–74%	-0.18*** (0.00)	-0.10*** (0.00)	-0.10*** (0.00)	-0.24*** (0.00)	-0.16*** (0.00)	-0.10*** (0.00)	-0.11*** (0.00)	-0.08*** (0.00)
75%–89%	-0.28*** (0.01)	-0.15*** (0.00)	-0.15*** (0.00)	-0.41*** (0.00)	-0.25*** (0.01)	-0.17*** (0.01)	-0.18*** (0.01)	-0.13*** (0.00)
90%–94%	-0.38*** (0.01)	-0.18*** (0.00)	-0.18*** (0.00)	-0.54*** (0.01)	-0.30*** (0.01)	-0.20*** (0.01)	-0.21*** (0.01)	-0.14*** (0.00)
95%–98%	-0.47*** (0.01)	-0.19*** (0.00)	-0.19*** (0.00)	-0.72*** (0.01)	-0.38*** (0.01)	-0.22*** (0.01)	-0.25*** (0.01)	-0.16*** (0.01)
99%–100%	-0.56*** (0.02)	-0.17*** (0.01)	-0.17*** (0.01)	-0.94*** (0.02)	-0.44*** (0.01)	-0.22** (0.02)	-0.24*** (0.02)	-0.16*** (0.01)
<i>Wage Increase—Ref. Category: 0 or negative</i>								
>0	0.03*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.03*** (0.00)	0.02*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
>median	-0.09*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	-0.10*** (0.00)	-0.06*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.04*** (0.00)
<i>Tenure in months—Ref. Category: 0–5 months</i>								
6–11	-0.03*** (0.00)	-0.01*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)	-0.07*** (0.00)	-0.06*** (0.01)	-0.05*** (0.01)	-0.04*** (0.00)
12–23	0.08*** (0.00)	0.00** (0.00)	0.00** (0.00)	0.08*** (0.00)	0.06*** (0.00)	0.00*** (0.00)	0.00 (0.00)	0.00* (0.00)
24–35	0.10*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	0.11*** (0.00)	0.08*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
≥36	0.02*** (0.00)	-0.03*** (0.00)	-0.03** (0.00)	0.04*** (0.00)	0.03*** (0.00)	-0.05*** (0.00)	-0.05*** (0.00)	-0.03*** (0.00)

TABLE A3 (Continued)

	Linear			Poisson				
	OLS	FE	CRE	Pooled	FE		CRE	
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}	$\hat{\beta}$	$\hat{\beta}$	\widehat{AME}
<i>Occupational Choice—Ref. Category: not teacher</i>								
Teacher	0.18*** (0.01)	0.02*** (0.00)	0.03*** (0.00)	0.29*** (0.01)	0.22*** (0.01)	0.04** (0.01)	0.07*** (0.01)	0.05*** (0.01)
<i>Cohort- Ref. Category: 1949-58</i>								
1959–1968	–0.18*** (0.01)		–0.04* (0.00)	–0.10*** (0.00)	–0.07*** (0.01)		–0.01 (0.04)	–0.01 (0.02)
1969–1978	–0.37*** (0.01)		0.00 (0.03)	–0.34*** (0.01)	–0.23*** (0.01)		0.08 (0.06)	0.06* (0.03)
1979–1989	–0.41*** (0.01)		0.00 (0.04)	–1.25*** (0.01)	–0.56*** (0.01)		–0.07 (0.08)	–0.05* (0.05)
<i>Year—Ref. Category: 1994-1996</i>								
1997–1999	–0.03*** (0.00)	0.07*** (0.00)	0.07*** (0.00)	–0.08*** (0.00)	–0.06*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.03*** (0.00)
2000–2002	–0.05*** (0.00)	0.15*** (0.00)	0.15*** (0.00)	–0.12*** (0.00)	–0.08*** (0.00)	0.16*** (0.00)	0.17*** (0.00)	0.11*** (0.00)
2003–2005	–0.10*** (0.00)	0.21*** (0.00)	0.21*** (0.00)	–0.18*** (0.00)	–0.12*** (0.01)	0.26*** (0.01)	0.26*** (0.01)	0.19*** (0.00)
2006–2007	–0.15*** (0.01)	0.25*** (0.00)	0.25*** (0.00)	–0.22*** (0.00)	–0.15*** (0.01)	0.37*** (0.01)	0.37*** (0.01)	0.28*** (0.00)
Constant	0.39*** (0.01)	0.38*** (0.00)	–1.67*** (0.08)	–1.95*** (0.01)			–6.98*** (0.17)	
Obs.	1,908,071	1,908,071	1,908,071	1,908,071	1,908,071	912,028	1,908,071	1,908,071
LL				–1,722,231		–789,594	–1,192,702	

Notes: SEs based on 100 bootstrap replications (this value was chosen due to very long computing times). AME denotes average marginal effect. Controlling for twins and multiples.

* $p < 0.05$,

** $p < 0.01$,

*** $p < 0.001$.

TABLE A4 Average marginal effect on the conditional probability of having 0 to many children

	France					Germany				
	0	1	2	3	4+	0	1	2	3	4+
<i>No VT</i>	32.7	32.2	19.4	9.3	6.4	54.4	25.9	10.9	4.6	4.0
VT	+1.5	+0.8	-0.4	-0.7	-1.1	+3.8	-1.4	-1.0	-0.6	-0.8
TE	+8.3	-3.0	-2.4	-1.5	-1.4	+13.7	-5.5	-3.7	-2.1	-2.3
<i>Non-employed</i>	46.3	25.9	15.2	7.5	5.1	60.8	22.0	9.4	4.1	3.5
PT	-1.9	-0.4	+0.6	+0.7	+1.0	+0.3	-0.0	-0.1	-0.1	-0.1
FT	-0.8	-0.1	+0.2	+0.3	+0.4	+2.4	-0.4	-0.7	-0.5	-0.7
<i>0–24 pct</i>	45.3	25.6	15.5	7.9	5.7	60.5	22.1	9.5	4.1	3.6
<i>25–49 pct</i>	+1.0	+0.2	-0.3	-0.5	-0.6	+0.8	-0.1	-0.2	-0.2	-0.3
<i>50–74 pct</i>	+1.2	+0.2	-0.4	-0.5	-0.6	+2.4	-0.4	-0.8	-0.6	-0.7
<i>75–89 pct</i>	+1.2	+0.2	-0.3	-0.4	-0.6	+4.0	-0.7	-1.2	-0.9	-1.1
<i>90–94 pct</i>	+1.2	+0.2	-0.4	-0.5	-0.6	+4.6	-0.9	-1.5	-1.0	-1.3
<i>95–98 pct</i>	+0.4	+0.1	-0.1	-0.2	-0.2	+5.3	-1.0	-1.7	-1.2	-1.4
<i>99–100 pct</i>	-0.3	-0.1	+0.1	+0.1	+0.2	+5.1	-1.0	-1.6	-1.1	-1.4
<i>1949–1958</i>	44.9	26.0	15.7	7.9	5.5	62.2	21.4	9.0	3.9	3.4
<i>1959–1968</i>	-0.3	-0.1	+0.1	+0.1	+0.2	+0.3	-0.1	-0.1	-0.1	-0.1
<i>1969–1978</i>	+2.2	+0.4	-0.7	-0.8	-1.0	-1.7	+0.2	+0.5	+0.4	+0.6
<i>1979–1988</i>	+2.1	+0.4	-0.7	-0.8	-1.0	+1.5	-0.3	-0.4	-0.3	-0.4

Notes: In percentage points. Based on the Poisson CRE estimates, see Tables A2 and A3.

Abbreviations: FT, Full-time; PT, Part-time; TE, Tertiary education; VT, Vocational training.

A.2 Decomposition of cohort changes and the distribution of unobserved heterogeneity

The results in Table 1 and Figure 2 suggest that the ME of the cohort variables on fertility are surprisingly small. Previous literature has claimed that changes across cohorts are important determinants for the overall decline in fertility. This appendix provides two further analyses. First, we show that the distribution of unobserved heterogeneity is strongly related with the cohort variables, making the latter endogenous in cross-sectional analysis and, therefore, invalidating classic regression analysis. Second, we apply a decomposition to understand better what is driving the decline in average unconditional fertility across cohorts.

To make the point that the distribution of unobserved heterogeneity differs across cohorts, we consider the implied Gamma densities of the unobserved heterogeneity a_i as outlined in Section 2.1. As shown in Figure A1, these densities differ importantly. In particular, they shift to lower values of the a 's for later cohorts. This shows that the cohort variables are endogenous in a cross sectional analysis. The strong left shift for the 1979–1989 born cohort is mainly due to the incomplete fertility for this group at the end of our analysis period.

To understand better what is driving the decline in average unconditional fertility across cohorts, we apply the decomposition in Equation (10). For this purpose, we compare two females that differ in various aspects, in particular, a representative female of one cohort and one from another cohort. We set \mathbf{x}_A and \mathbf{x}_B to the average values of the observables for cohort 1949–1958 and any other cohort, respectively. Consequently, $\bar{\mathbf{x}}_A$ contains the cohort averages of the individual averages of the time varying variables for cohort 1949–1958 and analogously for $\bar{\mathbf{x}}_B$. The results for this *mutatis mutandis* empirical exercise are given in Table A5.

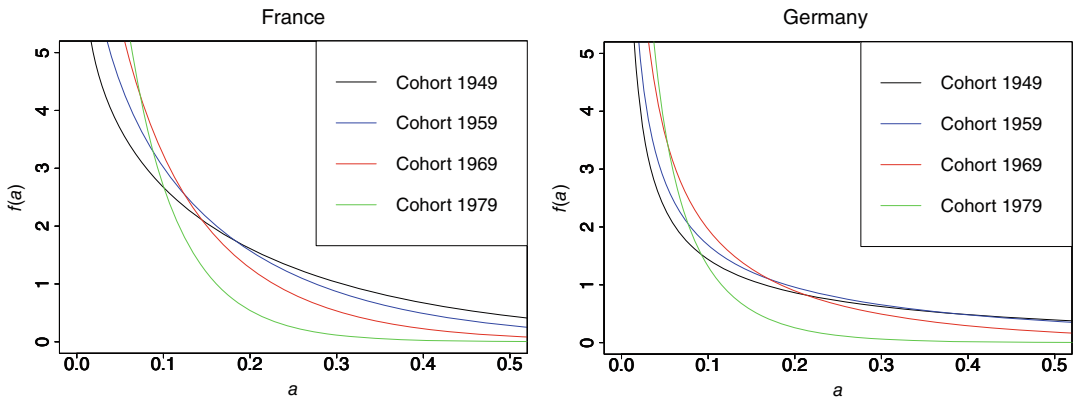


FIGURE A1 Conditional densities of unobserved heterogeneity by birth cohort. Gamma density of the unobserved heterogeneity a_i across cohorts. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A5 Decomposition of the expected number of children by cohort

	Total (LHS)	First term due to changes in x_A	Second term due to changes in \bar{x}_A
France: reference category (B): women born in 1949–1958			
1959–1968	−0.24	+0.32	−0.56
1969–1978	−1.28	−0.84	−0.44
1979–1988	−1.59	−1.36	−0.22
Germany: reference category (B): women born in 1949–1958			
1959–1968	−0.25	+0.44	−0.69
1969–1978	−0.88	−0.02	−0.86
1979–1988	−1.07	−0.58	−0.49

Notes. Decomposition according to Equation (10).

The decomposition isolates the contribution to the change in average fertility over cohorts (LHS) that is due to changes in observed covariates (first term) from what is due to changes in unobserved characteristics (second term). It can be seen that the decrease in fertility is due to both: females have different fertility patterns across cohorts due to changes in observables such as age, education and wages. Surprisingly, for both countries the cohort 1959–1968 has more favourable observables than the first birth cohort. Thus, education and increased labour force participation is not found to explain the reduction in fertility for this cohort. For this group the decline is strongly driven by changes in unobservables. For later cohorts, the composition of observables becomes less favourable for fertility, but changes in unobservables still play an important role. The much greater role of the covariates that is found for the youngest cohort can be explained by the fact that this cohort was not at the end of its reproductive cycle at the end of our analysis period. The results provide evidence of unobservables playing an important role for explaining the fertility decline over cohorts. Increased labour force participation and higher educational attainment do not suffice to explain this.