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Research Article

**Drop-out mayors and graduate farmers:
Educational fertility differentials by occupa-
tional status and industry in six European
countries**

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Drop-out mayors and graduate farmers: Educational fertility differentials by occupational status and industry in six European countries

Bilal Barakat ¹

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Abstract

BACKGROUND

Understanding the relationship of education to fertility requires the disentangling of the potentially confounding effect of social status, which is highly correlated with education.

OBJECTIVE

We contribute to this aim by examining educational fertility differentials *within* occupational groups and industries across a broad swath of Central and Eastern Europe, specifically Austria, Greece, Hungary, Romania, Slovenia, and Switzerland.

METHODS

Cross-sectional individual-level census samples from the *Integrated Public Use Micro-data Series* (IPUMS) are sufficiently large to contain sizeable numbers of unusual combinations, e.g., university graduates in low-status jobs or primary school dropouts in professional categories. Completed cohort fertility, as well as the share childless and with high parity, are regressed on effects for educational attainment, occupation, industry, and *all* their interactions within a Bayesian framework, and the contributions to the outcome variation are analysed.

RESULTS

Education has a strong, consistent association with fertility outcomes when industry and occupation are held constant. Furthermore, fertility by industry and occupation yields fairly disparate patterns. We also find that differences in completed fertility across countries can be attributed to country-specific compositional differences in education, industry, and occupation, and to interaction effects. However, differences by country in the baseline rate of childlessness and high parity cannot be attributed to such compositional effects.

CONCLUSIONS

The educational fertility gradient in the settings studied cannot be attributed to an occupational composition effect.

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1. Introduction

Education is strongly related to fertility outcomes, but the theoretical model for this is still surprisingly lacking. This is true particularly with respect to disentangling the relationship between fertility and education, and other socio-economic correlates of education (Bollen, Glanville, and Stecklov 2001, 2007). Determining the respective impact of education (or its timing) and its resulting material and intangible consequences is extremely challenging because educational attainment and focal life choices, such as occupation and family formation, are likely both driven by underlying preferences about each (Hakim 2003; Lesthaeghe and Meekers 1987). Moreover, the relationships between education, career and fertility are complex. Higher fertility goals may discourage career and educational investment, but conversely, an investment in education and/or commitment to a career may lead to lower fertility (Becker 1981; Brewster and Rindfuss 2000). This may be unintentional, by postponing childbearing to the extent that realised fertility is lower than desired. Alternatively, many women place a high value on *both* family and career and search for balance between them (Kravdal 1994; Lappegård and Rønsen 2005; Liefbroer and Corijn 1999; Santow and Bracher 2001).

To date, there exists a great deal of research exploring the tempo effects of educational attainment on fertility, the relationship between fertility and women's labour, the proximate indicators of family or career orientations according to academic fields of study, and the direct and indirect quantum effects of education on fertility. However, all such studies are unable to completely overcome the difficulties associated with the fully recursive relationships involved. The ostensibly exogenous personal values that drive both educational attainment and career choices can be further shaped by the process of education and the accumulation of working experiences. We can neither assume that childbearing behaviour temporally follows educational matriculation, nor that the relationship between childbearing and career is one-way only. Efforts to establish causation are further complicated by differential contexts, shaped by institutional, cultural, and structural factors (Matysiak 2011). As Matysiak (2011, 59) points out, the "difficulty [in understanding causal mechanisms] still lies in the unavailability of appropriate data".

Therefore, rather than attempting to make causal claims about the direction of the association between education and fertility, the goal of the current study is to determine whether variation in women's fertility is primarily related to their level of education, or to characteristics of their careers. Here, the latter is operationalised via occupational status and industry of work. Education and occupation are both components of socio-economic status and are sometimes conflated in the fertility literature (cf. Hopcroft and Whitmeyer 2010). Our approach adds value to the literature by demonstrating whether these factors are associated with childbearing independently, or whether one is mediated by the other. Although our explicit focus is not the potential impact on fertility of a *mismatch* be-

tween these characteristics, examining their interactive effects is also essential. Research concerning migration, for instance, has already demonstrated that the correspondence between education and occupation especially matters for the decision to migrate (Quinn and Rubb 2005). Finally, we explore whether variation in fertility according to education and vocational characteristics is country-specific. The application of our findings to causal research is discussed in detail in Section 5.3.

We accomplish our aims by exploiting data that allows us to examine fertility outcomes within unique combinations of education, occupational status and industry. The Integrated Public Use Microdata Series (IPUMS) samples from six Central and Eastern European countries—Austria, Hungary, Greece, Romania, Slovenia, and Switzerland—contain sizeable numbers of women with relatively low educational attainment in high prestige occupations, and conversely, women with high educational attainment in low-prestige occupational groups. Fertility and education data are also available by industry of occupation. Moreover, we are able to examine relationships across different age cohorts to test whether or not sources of variation in fertility are a result of timing effects.

The paper is organised as follows: We first provide a brief review of the existing research detailing the ways in which fertility varies according to level of education. This is followed by a review of how vocational characteristics relate to fertility and how contextual circumstances may affect these relationships. Next, we provide details of the data source and model specifications, followed by univariate and multivariate results. We conclude with a discussion of the implications of this research in which we elaborate further the limitations and consequences of our findings for further research in general, but causal analysis in particular.

2. Theoretical framework

2.1 Education and fertility

Women's education has long been widely recognised as one of the most important factors affecting fertility outcomes, both at the macro and the individual level (Becker 1981; Caldwell 1980; Cochrane 1979, 1983; Kasarda, Bill, and West 1986), having both direct and indirect effects (Kasarda 1979). Especially in less developed regions, for reasons that are not entirely understood, even small increases in education seem to increase a woman's self-efficacy with respect to her ability to achieve her desired number of children and improve her own and her offspring's health (Jejeebjoy 1995; Martin 1995). Education is associated with more consistent contraceptive use (Jejeebjoy 1995; Kasarda 1979), as more highly educated women are more likely to be affected by images in the mass media presenting an idealised version of smaller and more prosperous families (Basu 2002). From a socialisation perspective, education broadens women's horizons and exposes them

to lifestyles and opportunities beyond motherhood (Lesthaeghe 1995). In sum, there is something unique and intrinsic about the process or content of education that seems to affect both reproductive behaviour and outcomes.

The decrease in fertility during the First Demographic Transition was undoubtedly driven in large part by increases in women's participation in education. One particular concern has been timing effects, as prolonged enrolment in school may inhibit fertility or its onset, but in turn, childbearing may preclude further educational attainment. The research examining event timing strongly suggests, however, that the effect of educational participation on fertility outcomes is far more powerful than the other way around. School enrolment and the completion of schooling is powerfully predictive of fertility tempo and hence, ultimate fertility, since enrolment tends to delay the onset of childbearing (Kravdal 1994; Lappegård and Rønsen 2005; Ní Bhrolcháin and Beaujouan 2012) and union formation (Billari and Philipov 2004; Blossfeld and Huinink 1991; Hoem 1986). These findings likely indicate a prevailing conflict between the roles of student and mother, to a greater or lesser extent depending on the institutional constraints on combining the responsibilities.

Research has also demonstrated that education influences family size preferences. More highly educated mothers are likely to place a high value on having well-educated offspring (Axinn 1993), and in most cases this would discourage bearing a large number of children (Lesthaeghe and Meekers 1987; Martin 1995). However, while research often finds a negative relationship between more years of education and fertility in more developed countries (Bagavos 2010; Liefbroer and Corijn 1999; Martín-García 2009; Muresan and Hoem 2010; Neyer and Hoem 2008), some studies have shown more nuanced effects of education on fertility. For instance, among Norwegian women, Kravdal (1994) found that once wages and partnership status were controlled, the suppressive effect of education on fertility virtually disappeared, and in another study that the educational gradient in fertility has weakened considerably among recent cohorts (Kravdal and Rindfuss 2008). Among Russian women, Billingsley (2011) demonstrated that women educated for professional careers postponed childbearing more often, but found virtually no difference in birth rates across educational attainment groups.

Given so much heterogeneity in findings concerning the relationship between educational attainment and fertility, more clarity has been sought by additionally examining how fertility relates to educational field of study. It has been hypothesised that field of study, which presumably foreshadows later vocational industry and occupational status, may affect fertility in at least two ways. First, field of study may reflect a woman's underlying attitudes towards children, her expected ability to combine family and career, and the speed at which she wishes to make the transition to first childbirth. Lappegård (2002) proposed that women preparing for fields of work that are female-dominated are thereby expressing a preference for a career where an affinity for children prevails. In addition,

female-dominated fields may indicate career paths in which job discontinuity, such as maternity leave or absence to care for young children, may be less problematic in terms of returning to the job market later. Her hypothesis was confirmed with results demonstrating that Norwegian women who had studied for nursing and teaching careers had the lowest probability of being childless and the highest probability of having a third birth. Similar results were found by Van Bavel (2010) among women in 21 European countries. Those who studied care-taking or pedagogical fields were less likely to postpone motherhood, regardless of years of education, suggesting that their field of study signified underlying values about motherhood and career. These conclusions regarding educational fields that attract family-minded women are also evident in studies of women in Sweden (Hoem, Neyer, and Andersson 2006), Austria (Neyer and Hoem 2008; Spielauer 2005) and Spain (Martín-García 2009), where field of study proved to be more strongly associated with fertility than educational attainment. Thus, to the extent that preparing for a career in care-taking or teaching is associated with higher fertility, it may be justifiable to conclude that realised fertility among these women reflected pre-existing attitudes and values about family. However, it must also be acknowledged that a woman's ideals concerning childbearing can be affected by family-minded friends and peers within such a course of study or her subsequent work environment. In any case, industry of work may serve to some extent as an indicator of fertility preferences.

A second reason for examining field of study is that as a likely correlate of a woman's later industry and occupation, it may then determine later flexibility that facilitates childbearing or the subsequent commitment to work that may hinder it. Careers in care-taking, such as nursing, offer the possibility of non-standard shifts and thus provide the flexibility (flexibility in scheduling as well as leaving and re-entering the labour market) required for combining working life and motherhood (Swanberg, Pitt-Catsoupes, and Drescher-Burke 2005). Additionally, teaching careers can be amenable to family life due to the correspondence of women's and children's daily and seasonal schedules. Beyond practical concerns, research has demonstrated that women who study for high-status occupations begin childbearing at much later ages, due to long educational investments that precluded a willingness to stall career advancement later due to motherhood. Martín-García (2009) demonstrated that women who had prepared for higher-status careers were apparently less willing to jeopardise a lucrative, high-status professional life with a rapid transition to childbearing. Similarly, Edwards (2002) noted that only a fraction of the rise in age at first birth over the last 30 years could be explained by the increase in educational attainment. Instead, the particularly lengthy educational requirements of certain high-ranking occupations were responsible for the shift in age at first birth, as longer waiting periods between the end of education and first births were observed among women who had prepared for such careers.

Explorations of the relationship between fertility and field of study have offered com-

elling insights into how career plans may reflect fertility aspirations, and field of study (or college major) correlates quite strongly with later job (i.e., approximately .80, see Robst 2007). Here, we are concerned with the extent to which occupational status or industry relate to realised fertility, whether via its utility in identifying prior preferences about motherhood, the flexibility each offers, or via its correspondence to lengthy educational investments. We therefore propose that actual reported occupation or industry of work are more proximate to fertility behaviour than field of study during schooling. Thus combining information about attainment, occupation and industry, as we do here, is preferable when analysing the relationship between fertility and vocational choice.

2.2 Compatibility between occupation, industry and childbearing

As discussed above, careers in certain industries, such as health or education, may feature characteristics that increase the compatibility between working life and motherhood. Non-standard working schedules or the prevalence of female colleagues, for example, provide a degree of convenience and camaraderie that are perhaps conducive to childbearing. Other industry traits may render having a child (or several children) more favourable, for instance, the job stability and primacy of employees' rights (i.e., maternity/paternity leave, and family health leave benefits) that often characterize positions in public administrative or service sectors (Adsera 2011; Hoem, Neyer, and Andersson 2006).

Yet perhaps another salient feature of a woman's career is specific occupation. Occupation often dictates professional prestige and associated autonomy, earnings, wage profiles and employment security. All of these factors bear on the level of compatibility between working and family life. First, occupational status may decide the amount of autonomy a woman has to determine her daily schedule, in order to balance job tasks and child care. Citing Applebaum and Golden (2003) and Bond (2002), Swanberg, Pitt-Catsoupes, and Drescher-Burke (2005) report that someone serving in a professional, managerial or executive occupation is more than two and a half times as likely as those in semi-skilled jobs, such as craft workers, to be able to vary their working hours as they choose. Compared to those in manual labour occupations, such as unskilled operators, they are even more than three times as likely to be able to do so. This does not by itself answer the question of whether or not greater autonomy can off-set longer working hours with respect to their compatibility with family life. All else being equal, greater autonomy can, however, certainly be advantageous when attempting to balance roles and could facilitate higher fertility.

Second, occupational status is strongly linked to earning potential (Ganzeboom, De-Graaf, and Treiman 1992). On the one hand, a higher income may promote childbearing, since as every parent knows, children are expensive. Assuming that potential parents are rational actors, the expectation of feeding, clothing, nursing and providing education and

care for a child carries the anticipation of a substantial financial commitment. So in that sense, childbearing may be more compatible with an occupation that promises higher earnings. On the other hand, having children may interfere with a lucrative career path and thus present a particularly high opportunity cost for a woman in a high status occupation. Research exploring this tension has found that several factors may affect the relationship. Kravdal (1994) demonstrated that among women in stable partnerships, higher wages imparted no significant negative effect with the onset of childbearing, suggesting perhaps that women with higher wages could more easily afford child care. Other studies have shown that while women with higher status and higher paying careers may postpone having children for enough time to become established, they subsequently had rather high fertility owing to greater financial stability and job security (Cooney and Uhlenberg 1989; Hoem and Hoem 1989). However, the relationship likely also depends upon a woman's earnings trajectory, or wage profile. Indeed, several studies have shown that women with relatively high starting wages (as a result of higher educational attainment and occupational status) are more likely to postpone births than those with more slow growing wages (Kravdal 1994; Lappegård and Rønsen 2005; Van Bavel 2010). In sum, the weight of findings seems to suggest that higher prestige and income potential is not by any means a deterrent to fertility, and is perhaps even a stimulant, provided that women can achieve a sense of stability and balance in combining family and professional roles.

2.3 Context and compatibility

The research suggests, however, that employment stability and combining the roles of motherhood and career are dependent on structural and institutional contexts (Matysiak 2011). Period total fertility rates (TFR) in Europe have, on average, been declining over the past few decades (United Nations Population Division 2012). But between 1990 and 2000, with the collapse of the Soviet regime, TFR declined even more steeply in former Communist bloc countries such as Hungary, Romania and Slovenia. Some have associated this decline with the relative increase in opportunity costs in these countries. However, fertility also declined in countries such as Greece, Austria, and Switzerland, where no such change in returns to labour occurred. Researchers have therefore looked toward the effect on fertility of country-specific policies directed towards the combination of work and motherhood. Prevailing cultural attitudes concerning appropriate roles for women may influence such policies, creating incentives, whether intentional or not, that encourage women to make trade-offs between motherhood and labour force participation.

Matysiak (2011) presents a compelling analysis of fertility and policy contexts in European countries, suggesting that, in addition to cultural orientations about gender roles, fertility rates are associated with institutional country-level factors. These include the

obtainability of paid parental leave or the availability of affordable child care, and structural constraints such as women's unemployment levels or the prevalence of flexible work schedules. Her analysis concludes that countries with favourable policies and labour market characteristics, along with egalitarian attitudes towards women's roles, on average had higher TFRs. Support for similar conclusions has been offered by a number of other researchers examining individual country contexts (e.g., for Austria see Sobotka (2009); for Romania see Muresan et al. (2008); for Hungary see Kocourkova (2002); for Greece see Rendall et al. (2010)).

Yet the relationship between contextual factors and fertility outcomes is not entirely straightforward. Matysiak (2011) notes that some countries maintain relatively low fertility in spite of favourable policies and few institutional constraints while others demonstrate still below-replacement, but relatively high fertility. Hantrais (1997) also notes inconsistency in the impact of policies intended to stimulate fertility. While in some countries, such policies have caused fertility levels to decline more slowly than they might have otherwise, in others they have yielded little effect. Thus, in any analysis exploring the relationship between context and fertility, it is important to simultaneously consider the population on which the country-level policies are expected to have an impact. It may be that in any policy environment, fertility is more strongly affected by the compositional characteristics of its female population. It is possible that variation in fertility is less strongly related to education in a context where tertiary degree completion among women is commonplace, or conversely, more strongly related when it is not. If so, the effect on fertility of a policy designed to, say, facilitate the balance between a professional career and motherhood, would not be expected to be the same in these two contexts.

In the current study, though we do not explicitly analyse particular policies, we control for their impact to a certain extent by testing whether or not the relationships between women's educational and vocational characteristics and fertility outcomes vary according to country. In other words, in addition to analysing whether fertility is more strongly related to education, or whether variation is more strongly linked to vocational characteristics, we discover if being situated in a particular country explains further variation in fertility or if this interacts with the compositional characteristics of its female population.

3. Data and methods

3.1 Data source and transformations

The present analysis is based on individual-level census samples from Austria, Greece, Hungary, Romania, Slovenia, and Switzerland, from the two most recent rounds of censuses (around 2000 and 1990). This selection is based on the availability of the crucial variables of interest in the samples. These data have been harmonised and made available

for research use by the IPUMS project (Minnesota Population Center 2011). See Table 1 for details of the included samples. Person weights are constant within each sample and therefore ignored.

Table 1: Census samples utilized

Country	Year	Fraction (%)	Females 40–49
Austria	1991	10	50,370
	2001	10	57,230
Greece	1991	10	58,764
	2001	10	72,493
Hungary	1990	5	35,425
	2001	5	39,211
Romania	1992	10	135,293
	2002	10	153,413
Slovenia	2002	10	13,517
Switzerland	2000	5	24,716

Complete birth, educational or occupational histories are not available. Instead, three measures at census time are used as fertility indicators: the number of children ever born (CEB), the percent childless (CL), and parity 4 or higher (P4+). As a result, the analysis focuses mainly on women aged 40 to 49 years, whose birth histories can be assumed to be essentially complete.

For industry and occupation, both original, unharmonized, national census measures and variables were harmonized by IPUMS International. This means the national categories have been mapped to common categories as carefully as possible to achieve comparability.

The harmonized codes for occupational status conform to the International Standard Classification of Occupations (ISCO) scheme for 1988. There are ten main harmonized categories, in addition to four kinds of non-response or inapplicability. For increased clarity in our presentation, these are grouped into seven categories for purposes of the present analysis. Our aggregated occupation groups are shown in Table 2.

The harmonized codes for industry contain fifteen main harmonized categories, in addition to four kinds of non-response or inapplicability. For increased clarity in our presentation, these are grouped into nine categories for purposes of the present analysis. Our aggregated industry categories are displayed in Table 3.

Table 2: Aggregated occupation categories

Label	Categories
L,SO&M	Legislators, senior officials & managers
Prof	Professionals
T&AP	Technicians and associate professionals
CSWSMS	Clerks / Service workers and shop and market sales
C&RTW	Crafts and related trades workers
PMOAE	Plant & machine operators and assemblers / Elementary occ.
SA&FW	Skilled agricultural and fishery workers

Table 3: Aggregated industry categories

Label	Categories
A,F&F	Agriculture, fishing and forestry
H&R	Hotels and restaurants
CM	Construction/Mining
Manuf	Manufacturing
UTC	Utilities/Transportation & communications
EHSW	Education / Health and social work
W&RT	Wholesale and retail trade
PA&D	Public administration and defense
Service	Financial services & insurance/Real estate & business services

The harmonized education variable does not necessarily reflect any particular country's definition of the various levels of schooling in terms of terminology or the number of years of schooling. "[It] is an attempt to merge [...] samples that provide degrees, ones that provide actual years of schooling, and those that have some of both" (Minnesota Population Center 2011). The resulting measure is "largely comparable across countries". The four resulting education levels are: *less than primary completed*, *primary completed*, *secondary completed*, *university completed*, in addition to *unknown* and *not in universe* responses.

The harmonized variable was unavailable for Austria. Therefore, the Austrian unharmonized categories were mapped to the four levels above according to the scheme in Table 4, taking into account country knowledge and the IPUMS documentation on how the mapping was performed for the other five countries in this study. No persons were

Table 4: Education categories and Austrian mapping

Label	Category	Austrian categories
<P	less than primary	n.a.
P	primary completed	Compulsory (lower) secondary
S	secondary completed	Higher general secondary Higher technical & vocational secondary Intermediate technical & vocational Apprenticeship training
T	tertiary completed	Technical or vocational course (Academic) Intermediate degrees University, college

recorded as having failed to complete compulsory primary schooling in the Austrian sample.

An important caveat is that all three of these variables (industry, occupation, education) capture the situation *at the time of the census*. Because of the snapshot nature of the occupation variable, an analysis of the “not in universe” category, which encompasses those women who cannot be assigned an occupation because they are not economically active, has not been performed. Labour force participation at a particular point in time is likely to be somewhat less informative about past labour force participation than current occupation is of past occupation. With respect to tertiary education in particular, but also with respect to occupational and industry classification of the *current* job, it is likely that a share of the completed fertility was realised while the women were in different categories.

Fortunately, some empirical data are available for our investigation of this concern. The 2005 Eurobarometer Survey (European Commission 2005) queried both the respondents’ current occupational category, and the category of their first job at the time of labour market entry. Based on these data, Bukodi and Robert (2007) show that European labour markets show much more stability than change in terms of occupational category, and that this is true even of countries that underwent the transition to post-socialism. Indeed, a large majority of employed persons experienced no vertical worklife occupational category mobility, even in the most dynamic employment regimes. We have analysed these data further, specifically for females aged 45-49 at the time of survey in 2005 to match the 40-44 cohort in our year 2000 census round. Appropriate data were available for four of our six study countries, namely Austria, Greece, Hungary, and Slovenia. The results show that, with respect to our aggregated occupation categories, in Austria and Slovenia more than 80% of women had no occupational category change between their first and current job, and in both these countries, as well as Hungary, more than 90% shifted at

most one category up or down. Only in Greece is this share substantially lower, but still a large majority at over 60%. However, the fact that the results in our main analysis for Greece do not differ systematically compared to the other countries suggests that even such a relatively high level of occupational mobility is inconsequential for our analysis. Moreover, since these figures capture occupational mobility between the first job upon entry into the labour market and the current status in 2005, they overestimate the amount of mobility that affects our analysis. In part simply because some of it will have occurred over the period 2000-2005, i.e. after these cohorts were observed in the census sample we analyse, and partly because some births will have occurred after the first entry into the labour market. At the other end, some of the mobility will have occurred between occupation categories that do not differ in average fertility outcomes. Finally, Bukodi and Robert (2007) found higher education to be associated with greater upward and less downward mobility; in the context of our findings, the bias this creates would tend to decrease the apparent education differential, because the highly educated would be more likely to have been in a lower occupational category with higher fertility at the time of childbearing. In other words, occupational mobility could not explain an apparent educational fertility differential as an artefact. In sum, the empirical patterns of occupational mobility – or rather, of immobility – do not mark this as a cause for concern with respect to our main analysis.

The rationale for the present study is that the sizes of different education-occupation or education-industry cells differ by several orders of magnitude, because of high correlation between these characteristics. The Spearman rank order correlation between the education and occupation classes is approximately 0.65.

3.2 Model specifications

Across all model alternatives below, the mean completed fertility λ is assumed to be a log-linear function of the predictors:

$$\log \lambda_i = \mu + \sum_{m=1}^M \beta_{j_i^m}^{(m)}$$

Here, j_i^m is the appropriate index for individual i , and $\beta^{(m)}$ is the vector of coefficients of “batch” m , and M is the total number of batches. Each batch collects the dummy coefficients for one effect, which could either be a main effect or an interaction. For example, if the dummies for the different education categories represent the first batch of coefficients, then the β_j^1 would be the coefficients corresponding to the education categories, j_i^1 would be the index of the education category of individual i , and $\beta_{j_i^1}^1$ the corresponding coefficient. The probability model connecting the predicted value λ_i with the observed

counts is a Poisson³ count model:

$$y_i \sim \text{Poisson}(\lambda_i)$$

The models for the share childless and the share with parity 4 or greater are structured analogously, but with binomial outcomes and logits as the linear predictor, as is standard for binary outcomes.

4. Analysis and results

Following a descriptive overview of the main apparent patterns in the data (subsection 4.1), a sequence of inferential models is fitted to investigate different aspects and refine the final specification. Because we wish to fit a model containing all two-, three-, and four-way interactions between education, occupation, industry, and country, it is crucial to maximise the sample size. Two ways of doing this are tested. The first is to expand the age range of women considered. The second is to pool two different census rounds. The first approach is followed in subsection 4.2, which fits a fully saturated interaction model to observations from the year 2000 census round only, but includes the age range 35–54.⁴ The model in subsection 4.3 retains only the predictors identified as most important. This simplification along one dimension allows increased complexity in another, however. In particular, this model interacts the main predictors with time and is fitted to data from both census rounds, in order to examine the presence of changes over time (respectively between cohorts, which cannot be distinguished here). Here, the age range is restricted to 40–49, so there is no overlap between observed cohorts at the two points in time, which are ten years apart. Because the changes over time are found to be minor, the final analysis (subsection 4.4) is based on the sample that pools the two census rounds, with ages 40–49, and returns to the full interaction model.

4.1 Univariate relationships

Figures 1, 3, and 2 display the level of our fertility outcomes by level of education, industry, and occupation group respectively, in each case for women aged 40–49 during the 2000–02 census round. With regard to education, the expected pattern of a negative univariate association of education with fertility is on the whole confirmed, with some important caveats. Firstly, there are large differences in the size of the education differential between countries, ranging from less than 1 child in Greece to almost 2 children

³An alternative specification in terms of a Gamma count model (Winkelmann 2008) to account for underdispersion was also implemented. The results do not change the substantive conclusions and are not shown here.

⁴An auxiliary analysis confirmed that for the study population, fertility was essentially complete by age 35.

in Romania. For the latter, this greater differential is actually achieved at both ends: the highest education group has a lower average CEB than the other countries, and the lowest group has a higher average CEB. In Austria the education differential between the top and bottom education level is smallest among the countries.

Similar observations can be made with respect to childlessness. For education levels of primary and up, more education is consistently associated with a higher proportion of childless women in all countries. There is strikingly less variation in the gradient between countries than for CEB. Together with the fact that the differences in childlessness (of less than 10 percentage points) fall short of explaining the differences in CEB, this suggests that the effect of education is stronger at higher birth parities.

The seemingly anomalous pattern of the “less than primary” group being associated with particularly high childlessness, counter to the education effect at higher levels, may be a result of negative selection bias. In all six countries the completion of primary school is expected universally. Among those who did not complete the primary level we would expect to find a disproportionate number of those with health or other challenging issues that at the same time would impact the likelihood of experiencing a childbearing event. Another possible explanation is that women with especially low levels of education may be unreliable reporters of their fertility, perhaps for the same underlying reasons. Further information regarding health status or cognitive ability would be necessary to further investigate this pattern, but in its absence we can only speculate.

With respect to CEB and industry group (Figure 3), there is relatively little variation as compared to education levels and occupation groups. This is true even between what might *a priori* be considered extremes, such as Education, Health and Social Work (EHSW) on the one hand and Construction and Mining (CM) on the other. The sole exception is Agriculture, Fishing and Forestry (A,F&F), which can easily be explained by a natural rural bias of these industries. When it comes to differences in CEB by occupation (Figure 2), again the outlier Skilled Agriculture and Fishery Workers (SA&FW) is likely to be biased upwards because of its rural predominance.

Figure 1: Fertility outcomes by education (women aged 40–49, 2000–02 census round)

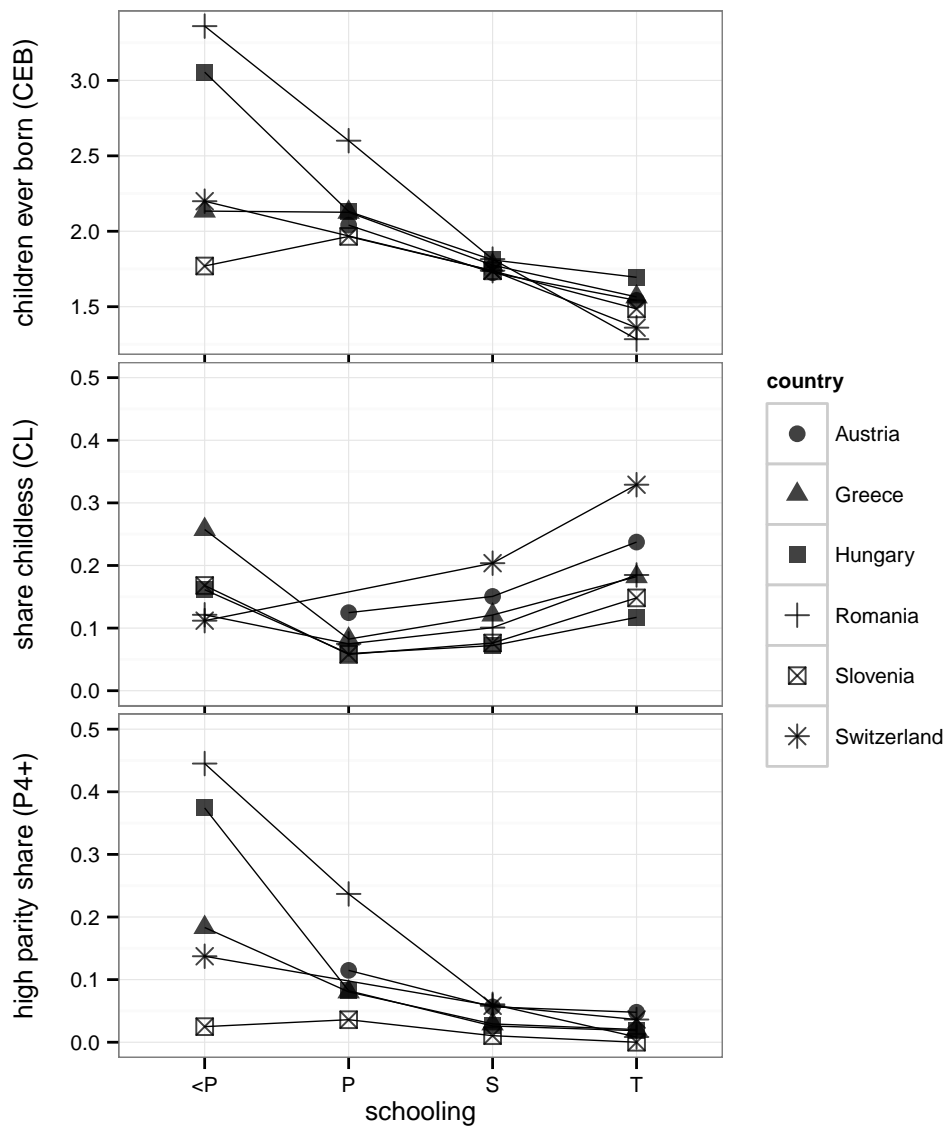


Figure 2: Fertility outcomes by occupation (women aged 40–49, 2000–02 census round)

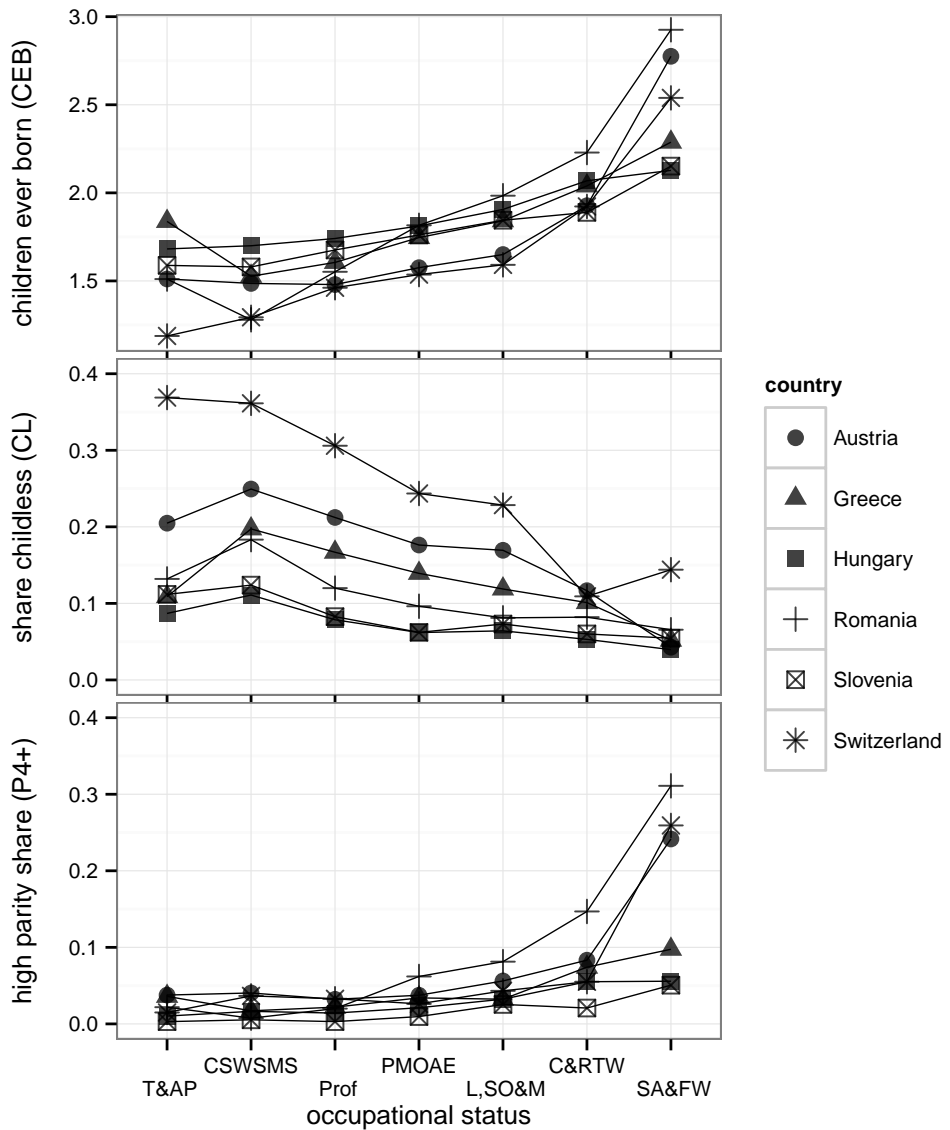
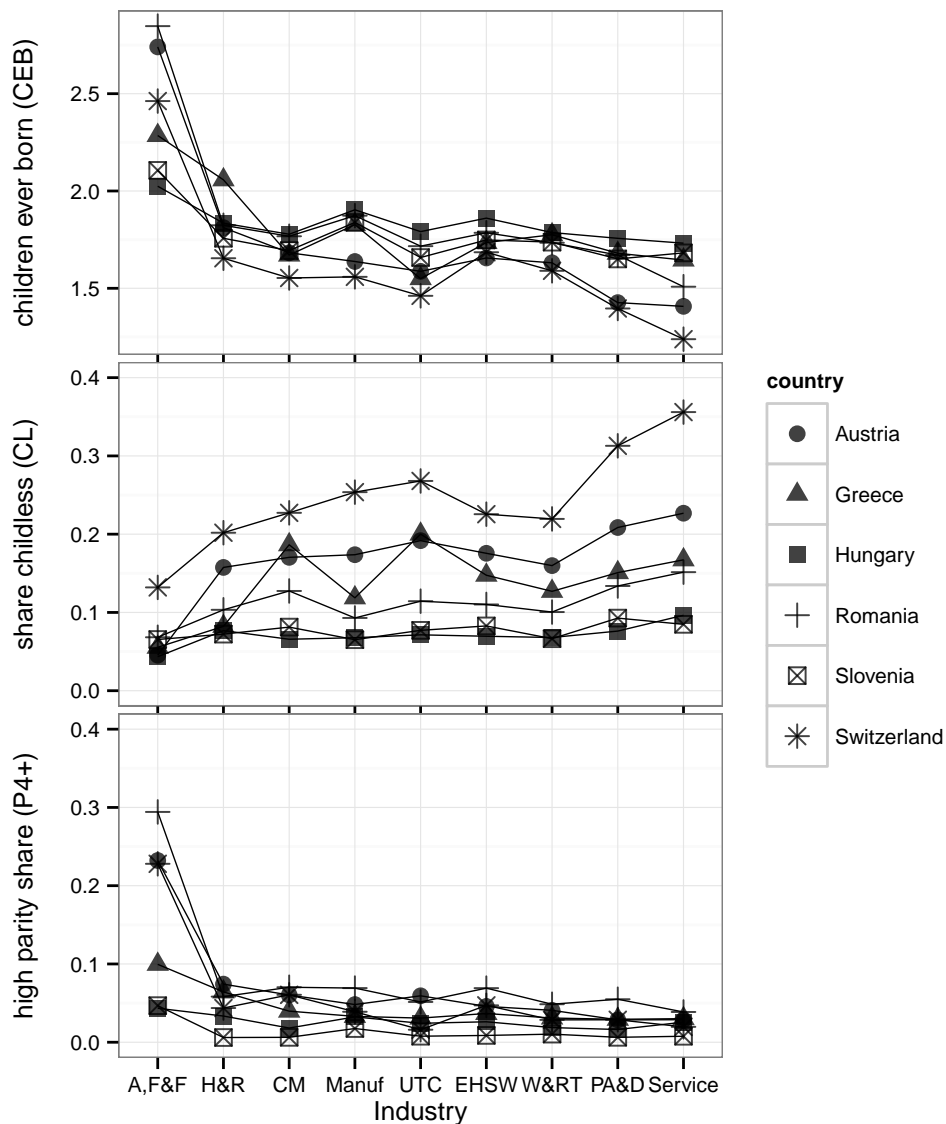


Figure 3: Fertility outcomes by industry (women aged 40–49, 2000–02 census round)



4.2 Interactions

A key objective of the present study is to analyse education differentials *within* occupation groups and industries.

There is a fairly consistent pattern, evident in Figure 4, that in all countries, within the majority of occupation groups, there is an educational fertility differential in the expected direction. This suggests that education has a depressing effect on number of children independent of social status, income, and other factors normally associated with occupational status. In these and the following graphs, education-occupation dyads with fewer than 20 individuals have not been plotted. For many country-occupation combinations, every step up the education scale is associated with fewer children. In quite a few cases however, the difference between completed secondary and completed tertiary is marginal, non-existent or negative, especially in Austria. Nevertheless, even in these cases fertility is higher for the lowest than the highest education category in virtually all country-occupation combinations. The same patterns were confirmed when we examined the extremes of the parity distribution — childlessness and those with four or more children (results not shown). There was, on the whole, a consistent education differential in the expected direction in all countries.

The above analysis was repeated with education level by industry (see Figure 5). Compared to occupation, the industry of work appears to have relatively little effect on education differentials. In particular, education differentials universally persist even in industries intuitively associated with a selection bias towards “child-friendly” women, namely education and health and social work (EHSW). Considering CL did not change these conclusions (results not shown). The results for the industry variable suggest that, perhaps unsurprisingly, industry of work at time of survey is a poor proxy for field of study, since the latter has been shown to matter to fertility more than attainment (Lappegård and Rønsen 2005).

In order to maximize the number of observations even for rare combinations, a preliminary model is fitted to the CEB of all women aged 35–54 in the data from the year 2000 census round. Here and in the following subsections, interactions are included that contain dozens or hundreds of dummy variables for specific combinations of predictors. The discussion of results therefore focuses on the amount of variation accounted for by different batches of coefficients (all occupation dummies, for example, or all occupation \times education dummies). This tactic can be considered to be a form of Bayesian ANOVA (Gelman 2005). It is similar to classical ANOVA, but can deal with heavily unbalanced data, and can straightforwardly be applied to arbitrary models. The size of the standard deviation for each batch of coefficients indicates its relative importance as a source of variation in the outcome. For example, consider the coefficients corresponding to the different education dummy indicators. A large standard deviation of

these coefficients means that they differ considerably, and accordingly, the values of the underlying characteristic differ considerably in their effect on the outcome. In the example, it means that the effect of one education category on predicted fertility will be very different than the effect of another education category. Conversely, if a coefficient batch had a very small standard deviation, this would imply that the coefficients belonging to different levels of the corresponding variable are almost equal. In other words, changing the level of said variable would have little effect on the outcome. Since we consider only (ordered) categorical predictors, questions of scaling do not arise. For our data, the estimated standard deviations are displayed in Figure 6.

While the uncertainty surrounding the estimates is substantial, as evidenced by the width of the estimation intervals, there is a clear indication that education and occupation are the most important sources of variation in CEB independent of country. This is not to say, however, that their effects are not mediated by the country setting. In fact, the interactions of country with education and occupation respectively are the next most influential sets of predictors. Next is the main industry effect, followed by its country interaction. The other interactions are minor compared to the main effects above. Overall, the pattern is broadly similar with respect to childlessness and high parities. The notable exception is the variation in the country coefficients. For CEB country-specific education, occupation, industry effects and interactions were key. By contrast, for CL the overall country means differ substantially, as evidenced by the fact that the estimated country effects exhibit a large variation. For high parities, the same pattern can be observed with respect to the country effect. This is unsurprising: if the overall conditional country means are almost equal, but the amount of childlessness differs, then the above-average range of the parity distribution should also differ. Regarding childlessness, again, the association with occupational status is even more dependent on context than that of mean completed fertility: the variation in the main occupation coefficients is likely less than that among the country \times occupation coefficients, and of a similar magnitude to the occupation \times industry interaction.

The next models will focus on the six most influential variance components seen here: education, occupation, industry, and their country interactions.

4.3 Changes over time

The reduced set of predictors established above allows us to include time as an additional dimension, without the results becoming too unwieldy.

Figure 4: Children ever born (CEB) by education and occupation (women aged 40–49, 2000–02 census round)

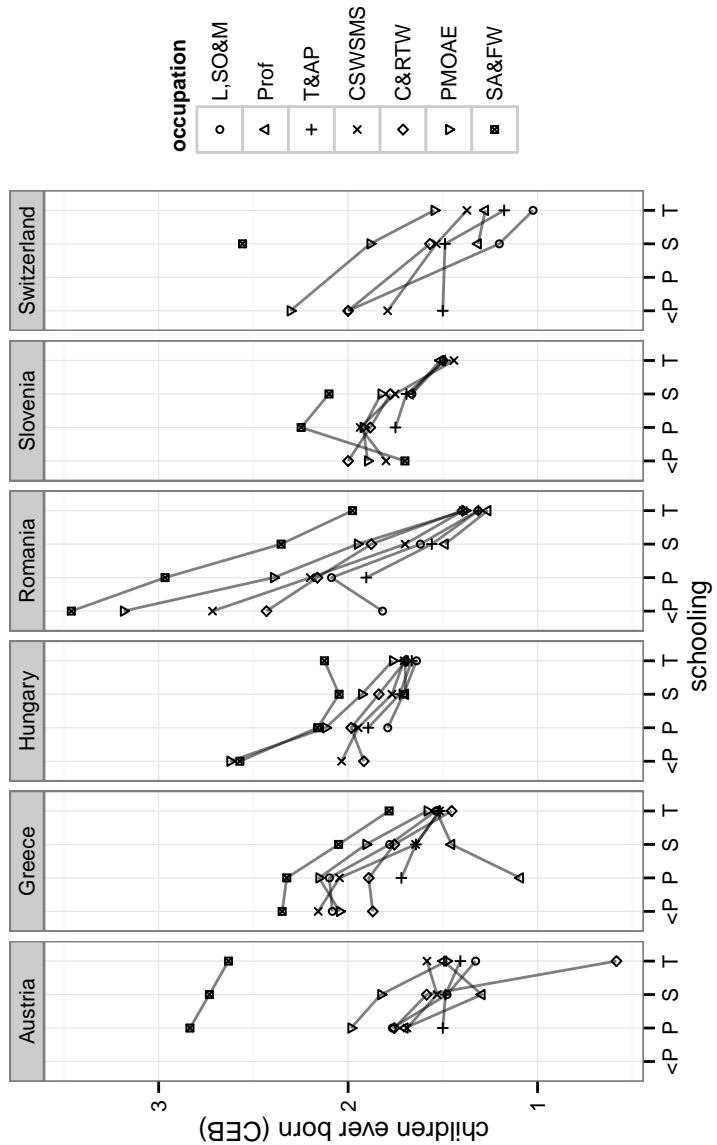


Figure 5: Children ever born (CEB) by education and industry (women aged 40–49, 2000–02 census round)

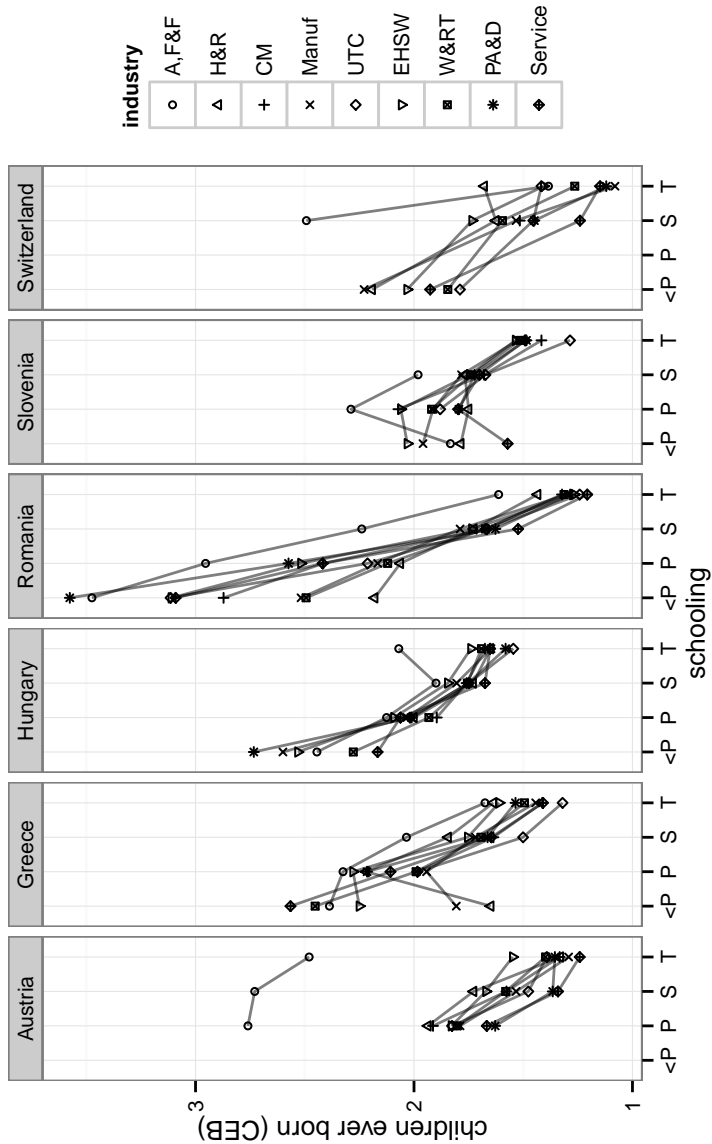
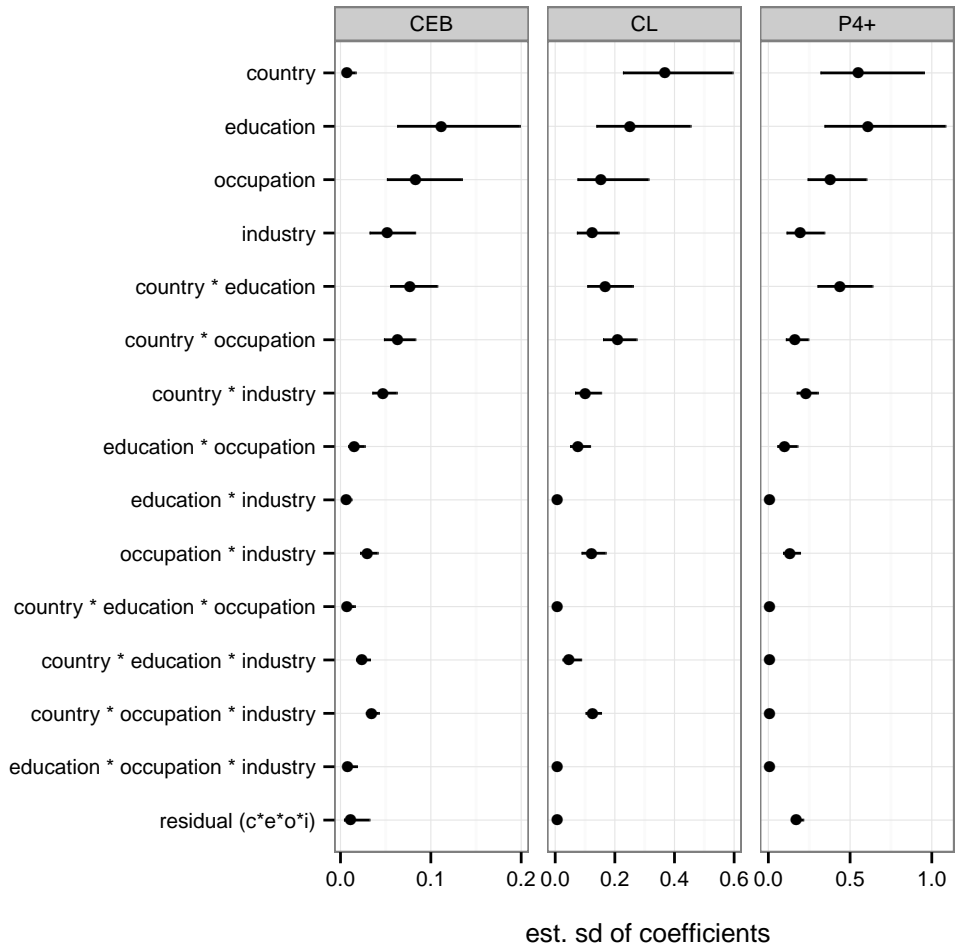


Figure 6: ANOVA display for model regressing CEB, CL, and P4+ on all interactions of education, occupation, industry, and country



Note: Point: posterior median, Bar: posterior 90 percent interval (.05–.95 interpercentile range).

Mirroring the absence of an independent country effect (which is confirmed here, see Figure 7), there is no secular time trend. In other words, the change in average CEB

between the earlier and later census rounds is entirely due to changes in the composition of the education, occupation, and industry of employment of women.

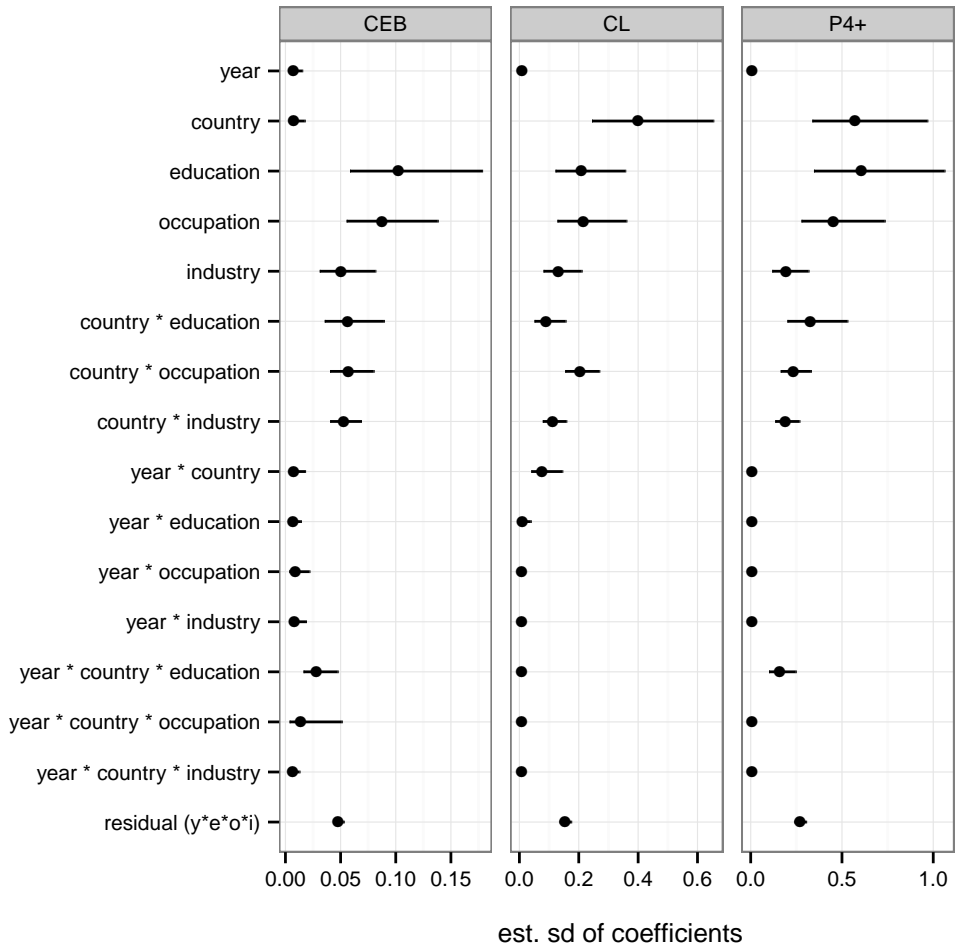
There is virtually no change over time in the direct association of the fertility outcomes with country, education, occupation, or industry. The higher-order interactions involving time are also negligible, with the exception of the time change in the country \times education interaction. Even this, however, remains smaller than the six dominant components selected earlier. In particular, all time interactions exhibit less variation than the residuals.

4.4 Main parameter estimates

Based on the absence of significant changes over time, observations from both census rounds are pooled in the final analysis. Figure 8 displays the estimated parameters for the education and occupation categories. There remains a clear and consistent education differential after controlling for occupation and industry, as well as country context. The magnitude of the largest negative and positive effects of education and occupation respectively are broadly similar. The smaller magnitude of occupation as a variance component is mainly due to the fact that the fertility differences between the three highest occupation categories are minimal. For studies in which occupation serves purely as a control variable rather than a factor of intrinsic interest, it might therefore be appropriate to collapse these groups. We also see that the difference in average fertility between the two lowest education groups is mostly due to a reduction in high parity. Conversely, the difference between the two highest education groups results mostly from an increase in childlessness.

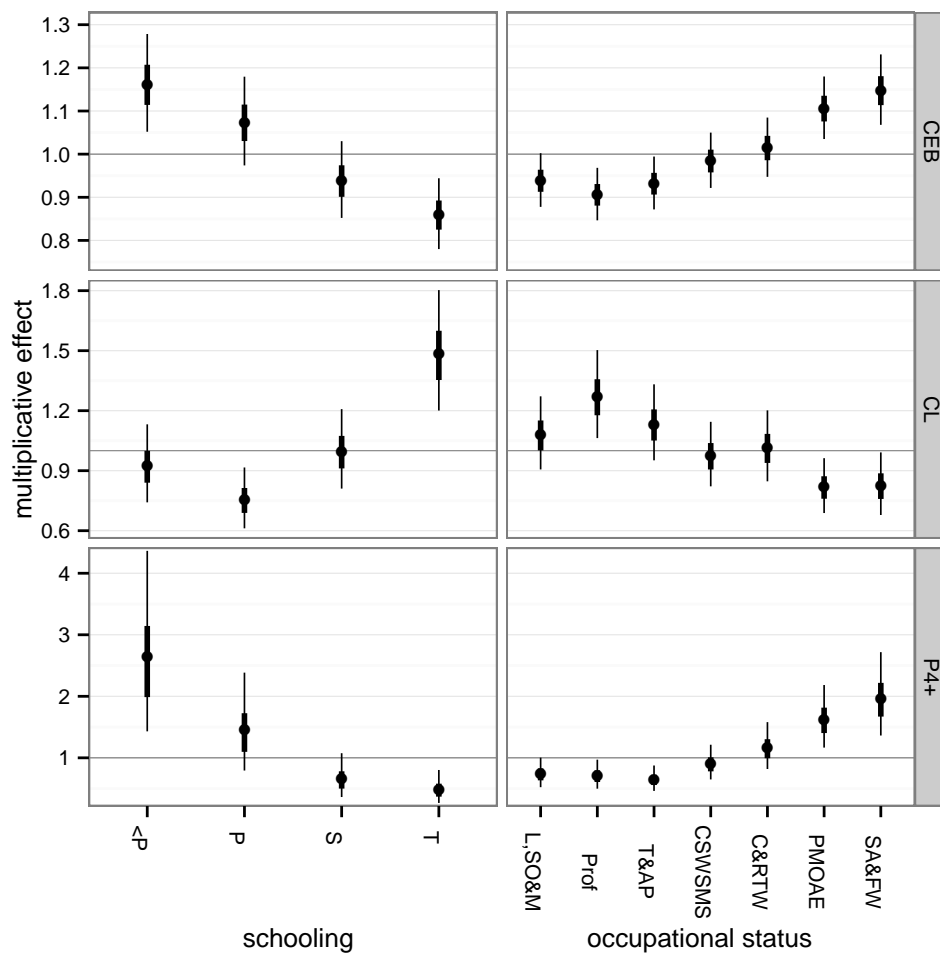
Because the interaction between education and occupation is marginal, their combined effect can be approximated by adding their parameters at the linear predictor scale. Equivalently, the effects in Figure 8 may be multiplied (tables corresponding to the figures are in the Appendix). In the following, this will be referred to as the “main effects only” model. In Figure 9, we compare these estimates based on the main effects only, with the predicted values from the fully saturated model that includes all interactions. We also compare both with the observed outcomes. The number of possible education-occupation-industry combinations is large, but we focus on “graduate farmers” (education: tertiary, occupation: SA&FW, industry: A,F&F) on the one hand and “drop-out leaders” (education: less than complete primary, occupation: L,SO&M, industry: PA&D) on the other. These rare combinations of characteristics are not picked out for maximal effect, but because they are estimated on the least amount of data. Of particular interest is therefore: a) their variability, b) the specific interaction effect, and c) the information gained compared to simple estimates based on the observed cases, in light of the overall fit of the model.

Figure 7: ANOVA display for model regressing CEB, CL, and P4+ on main effects and interactions, including time



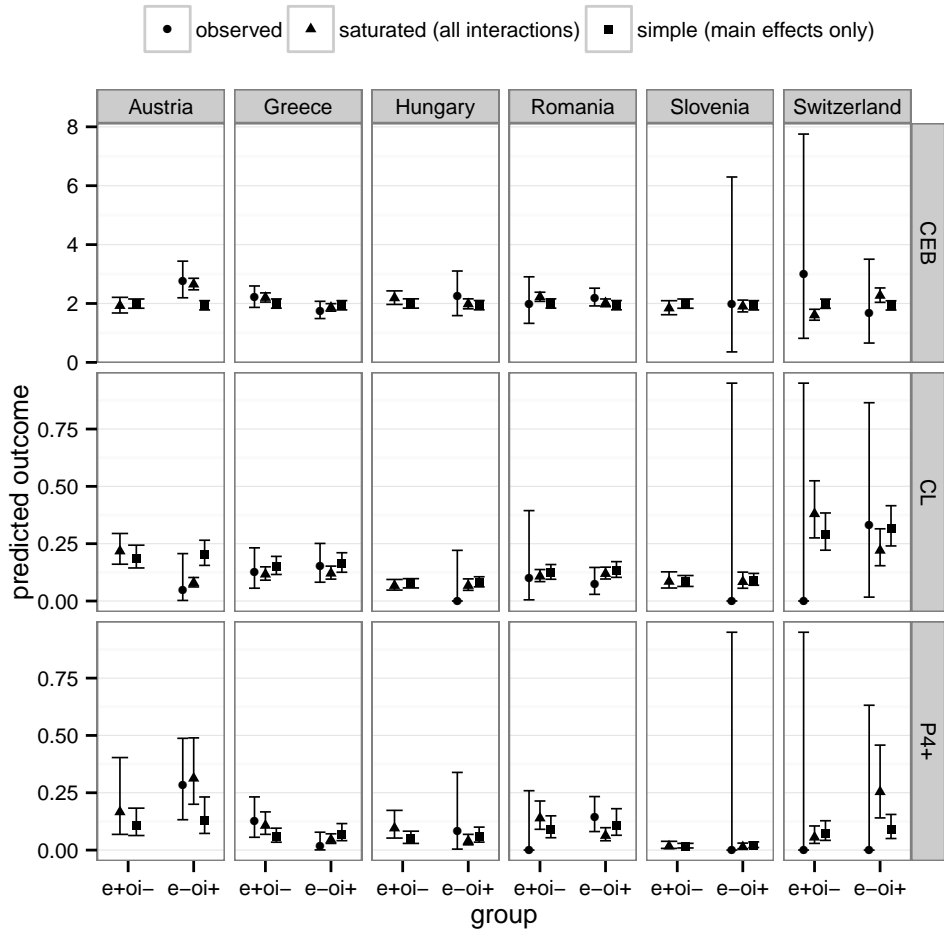
Note: Point: posterior median, Bar: posterior 90 percent interval (.05–.95 interpercentile range).

Figure 8: Education and occupation effects on predicted fertility outcomes in full interaction model, pooled census rounds



Note: Point: posterior mean, Thick bar: posterior 50 percent interval (interquartile range), Thin bar: posterior 90 percent interval (.05–.95 interpercentile range).

Figure 9: Predicted outcomes (CEB, CL, P4+) for edge combinations: “e+oi-” for high education, low occupational and industry status (i.e., education: tertiary, occupation: SA&FW, industry: A,F&F); and “e-oi+” for low education and high occupational and industry status (i.e., education: less than complete primary, occupation: L,SO&M, industry: PA&D)



Note: Point: posterior mean, Bar: posterior 90 percent interval (.05–.95 interpercentile range). Observed values and (exact) 90 percent confidence intervals; simple prediction using only main effects (country, education, occupation, industry), saturated prediction from full saturated interaction model.

In discussing these results, it is helpful to think of the data in a way in which each combination of education \times occupation \times industry \times country is a cell in a multi-dimensional table. The first thing to note is that even in these large samples, the above combinations are absent or extremely rare in some countries. This means that attempting to estimate or predict the outcomes in these cells based only on the observations they themselves contain is, in most cases, not very informative. This is reflected in the large confidence intervals for the true means underlying the observed values.

Even the simple model with only main effects generates prediction intervals that overlap with the standard confidence intervals for the observed means. The prediction intervals for the simple model are based almost entirely on information from outside the cells in question, while the confidence intervals for the observed means are based exclusively on observations inside them. Since the simple model captures the conclusion of a consistently negative association between education and completed fertility among the women in the study population, this means that the rare combinations provide no strong evidence that would contradict this general pattern. Regardless of whether we consider the effect of all interactions (the difference between the simple and saturated model predictions) or only of the individual residuals in the rare cells (the difference between the observed outcomes and the simple model predictions), there is a balance between overestimates and underestimates, i.e. between cases where the main effect is reinforced or mediated.

It may seem a counterintuitive observation that the saturated model does not necessarily shift closer to the observed values than does the simple model. This is explained by the fact that the 2 to 3-way interactions are codetermined by observations for combinations of predictor values that are outside the table in Figure 9. The 4-way interaction, which the fully saturated model includes as one among many, of course always contributes a shift towards the observed value. Examining all education-occupation interaction coefficients jointly, not just the “corner cases” shown here, does not indicate any systematic pattern. In particular, there are no consistent signs along the off-diagonals that could be interpreted as tentative evidence of systematic associations of education-occupation “mismatch” on fertility outcomes.

In terms of the width of the prediction intervals, the model-based estimates represent a large information gain compared to the naive estimation based on the observations in individual cells. This reflects the result noted earlier, in Figures 6 and 7, that the standard deviation of the 4-way interactions is relatively small. This means that, in order to change the outcomes significantly, the coefficients corresponding to the rare country, education, occupation, and industry combinations shown in Figure 9 would not only need to run counter to the overall education differential, but would have to be extremely and atypically large compared to other 4-way interactions.

The fit to the rare combinations needs to be examined separately, as above, because they naturally have little impact on overall fit statistics. The fully saturated CEB model

has a correlation coefficient $> .99$ with the cell means weighted by population. Treating all cell means as equally important targets to fit, in other words calculating the unweighted correlation coefficient between predicted and mean CEB, gives a correlation coefficient of .65. Of course, taking the latter as the measure would ignore the fact that we are not fitting exactly-known cell means, but that the cells with large and small counts differ in terms of the precision with which their mean to be fitted is actually known. The correlation based on weighting cells by \sqrt{N} to reflect the approximate variance of their corresponding means gives a correlation coefficient of .92.

It is important to note the difference here between weighting that occurs because the estimates from sparse cells have greater uncertainty, and weighting that occurs because the resulting estimate is intended to reflect the population composition. The full model estimated here fits the cells with large populations better than the rare combinations only for the former reason. If the means for each combination of country, education, occupation, and industry were known exactly, then the estimate of the education level coefficients, for example, would not depend on the distribution of the population among these cells. This is a direct consequence of the sum-to-zero constraints on the different coefficient batches in the variance decomposition performed here. To see this, note that in the fully saturated model with all interactions, improving the fit in a sparse cell does not involve a trade-off with the fit or predicted mean of a more populated cell. However, without changing the actual predicted values in other cells, changing one of the four-way interaction coefficients changes lower-degree interactions and potentially main effect coefficients within which it is nested, purely in accounting terms, because at each level of interaction, the coefficients should sum to zero. The main effect education coefficients, for example, are therefore a function of how the values of the estimated cell means can be attributed to different levels of interaction.

Weighting is also the main technical difference between the present analysis and matching techniques. In principle, the fully saturated model could be interpreted from a matching perspective instead of a regression perspective. A matching approach in this setting would essentially amount to matching individuals on occupation, industry, and country, and for each combination comparing the fertility outcomes at different levels of education. However, matching estimators are typically designed to approximate some population-averaged effect (be it across the total population, or some sub-population with respect to “treatment” status), and weighted accordingly. In this case, the main education effects, for example, would therefore be a function of the estimated cell means as well as their population weights.

5. Discussion

5.1 Key implications

The contribution of the present study consists in systematically disentangling the independent and joint associations between education, occupation, and industry with fertility outcomes, in a cross-country comparison. The conditional associations uncovered point to a number of key conclusions.

The educational gradient in completed fertility, within homogeneous occupational categories, is steeper than the corresponding occupational fertility gradient within homogeneous education groups. One interpretation of this result is that it would be inconsistent with attempts to explain educational fertility differentials as being largely driven by income effects. After all, we would expect income to be determined by occupation rather than by educational attainment *per se*. Since both education and occupation affect social status directly as well as indirectly, the results imply that using one or the other as a proxy for social status in the analysis of fertility will be incomplete at best, or worse misleading.

Another warning that can be extracted from the analysis is the need to carefully distinguish between industry and occupation. As is evident from many of the results above, the conclusions along these two dimensions differ substantially. This issue needs to be carefully considered when disaggregating education by “subject of study”, since some disciplines (such as law) tend to predetermine an occupational category, while others, especially vocational training, may instead guide towards particular industries (tourism).

While national panel or register data sets are indispensable for sophisticated causal estimation, sources as rich as those used by Kravdal (2007), for example, are not available for a large number of countries, much less in a harmonised form. Studies extracting the maximum of information from such national sources are therefore unable to estimate country effects in a cross-country model. Also, comparative international data sets resulting from coordinated surveys never reach a sufficient sample size to reliably estimate the three- and four-way interactions in the above model, because most of the rare cells would remain unobserved. The country \times education \times occupation \times industry interaction component, for example, consists of over 1000 indicator variables. Our result concerning negligible interactions is reassuring, therefore, because it confirms that little information is lost when using simpler data, and indicates which effects and interactions are important to include in simpler models.

Strikingly, the *net* country association with average completed fertility is estimated to be slight. The influence of the country setting on the level of completed cohort fertility is estimated to occur almost entirely through the interaction with education, occupation, and industry, and, to a lesser extent, their two-way interactions involving industry. In other words, observed differences between the study countries in completed fertility level

can, for these cohorts, be attributed almost entirely to differences in composition. While the countries in question do form an almost contiguous block in central and south-eastern Europe, their diversity along dimensions not covered in the present analysis is enormous, if we compare Switzerland with Greece, for instance. This suggests the result may well hold more generally.

On the one hand, this insight complicates future cross-country analysis. Specifically, it means that, even once data have been harmonised, adding only independent country effects represents a misspecification. On the other hand, it suggests that searching for additional country characteristics omitted here may not be necessary in order to capture between-country heterogeneity in completed fertility. Even at the individual level, the implication is that additional strong predictors of completed fertility need only be sought among those personal characteristics whose average level does not differ between the countries investigated here.

5.2 Limitations and directions for further research

The fact that the analysis provides useful information by itself and for future research does not mean it lacks in limitations. The data exploited in the present study are deep in some dimensions, but limited in others.

In particular, they are cross-sectional, and both the predictors and outcomes of a decades-long process are observed only after the fact. One particularly restrictive constraint resulting from this is the necessity to exclude women who are not in the labour force at the time of the census. As mentioned in Section 3.1, while the education and occupation at age 40–49 can be expected to be a reasonable approximation of the overall career characteristics for a majority of women, this is not the case for economic inactivity, much less unemployment. We therefore cannot distinguish between women who never worked and those who stopped working. The former group in particular is likely to have its own fertility profile, which is missed entirely. Only the two most recent census rounds made the requisite variables available for a significant number of European countries. Real longitudinal analysis is impossible, even in terms of pseudo-cohorts. As already mentioned, the nature of the fertility indicators means completed fertility can only be estimated for relatively high ages, and so the conclusions are not very current. While we do not expect a strong distortion to result from this, the results may, in principle, be influenced by mortality differentials by education, occupation, or indeed interactions of these factors with the mortality gradient by parity. More serious is the fact that no data is available on proximate determinants of fertility to control for indirect effects of education or occupational status through contraceptive use, for example. In the absence of such data, it remains unclear whether education works through behavioural changes or attitudinal/agency changes. In the generation of women examined, the occupation of the

husband no doubt also plays a major role in determining social status. In principle, the IPUMS data allows this information to be linked in, paving the way for further analysis in this direction. The absence of data on urban/rural residence means that the coefficients of occupations with a strong rural (or urban) bias is not well identified, especially for the category of “Skilled agricultural and fishery workers”. Not least, despite standardisation, nominally equivalent levels of education may represent quite different experiences in different countries, in terms of content, selectivity, prestige, and simply duration. An open question that cannot be conclusively answered based on the data at hand is to what extent the association between higher education and lower fertility is caused by selection, reflecting the fact that early and high fertility may represent an obstacle to attaining further education.

5.3 Causal aspects

Conditional associational analysis is complementary to “all-cause” analysis and benefits from careful consideration of counterfactuals in its own right (Morgan and Winship 2007). Though the cross-sectional nature of our data prohibits conclusive causal conclusions, a consideration of causal structures is necessary, because under certain conditions, conditioning on occupation could *introduce* bias.

Consider the generic causal graph in Figure 10. In general, it would be possible to identify the direct causal effect between education and fertility $E \rightarrow F$, say, if all other paths connecting E and F either contain a variable that is being conditioned on, or contain a segment with the pattern $\dots \rightarrow Y \leftarrow Z \dots$. The key insight is that conditioning on Y in the above case “unblocks” the path and creates a spurious association between X and Z (Pearl 2000; Morgan and Winship 2007). In the present situation, if occupation acts causally on the number of children ($O \rightarrow F$), then conditioning on occupation removes a source of bias in estimating the causal association (in whichever direction) between education and fertility; if, conversely, fertility has a negative causal impact on occupation ($O \leftarrow F$), then conditioning on occupation will *introduce* a new bias in estimating the education effect. In particular, given the prevailing directions of association, it would lead to an *underestimate* of the negative association between education and fertility.

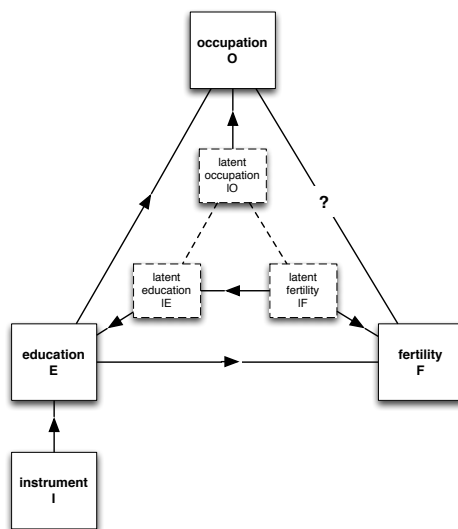
In terms of strict identifiability, the present results cannot distinguish between the cases of $E \rightarrow O \rightarrow F$ and $E \rightarrow O \leftarrow F$ in the expanded structure that includes the latent preferences. Nevertheless, in combination with Occam’s principle, our results suggests that $O \rightarrow F$ should be assumed until proven otherwise. This is the simpler explanation, because of the approximate independence we do in fact observe between the conditional pairwise associations between O and F on the one hand and E and F on the other. Assuming the pattern $E \rightarrow O \rightarrow F$ would imply this approximate independence without additional assumptions. By contrast, the $E \rightarrow O \leftarrow F$ pattern does not, in general, induce an association

between education and fertility that is consistent at different levels of occupation. Since we do, however, observe such consistency, we would have to assume that the effect of fertility on occupation takes some rather specific functional form to be consistent with the data. The assumption $O \rightarrow F$ can therefore not be deduced from our results, but it is consistent with them with fewer assumptions than $O \leftarrow F$ is.

The implications of this for causally ambitious research on the education-fertility link are problematic. Note that in the case of $O \leftarrow F$, there would be no need to condition on realised occupation in causal studies attempting to capture some of the latent variables, or exploiting an instrument for education. If however, as we argue above, we have to assume the possibility of $O \rightarrow F$, then conditioning on occupation is necessary, but insufficient, to estimate the relative importance of the paths $E \rightarrow F$ and $F \rightarrow IF \rightarrow IE \rightarrow E$.

The necessity of conditioning on occupation is easy to meet in a superficial way. However, it is difficult to envisage the collection of a data set that is sufficiently rich in event history and captures proxy variables for latent dispositions, but at the same time large enough to create sufficient overlap between high education and low occupation categories. This is a serious limitation: being able to assess the extent to which educational fertility differentials are consistent across substrata of the population is important in this context, and also because the existence of “treatment heterogeneity” makes a methodological and substantive difference in causal analysis (Brand and Davis 2011). An analysis in the present style therefore provides an important piece of the puzzle, by answering this isolated question with data where the high education and low occupation categories do overlap to some extent.

Figure 10: Stylised causal structures connecting education, occupation, and fertility



Moreover, on succeeding in conditioning on realised occupation, the formerly blocked path $E \rightarrow O \leftarrow IO$ becomes unblocked, and with it, the entire path $(I \rightarrow)E \rightarrow O \leftarrow IO \dots IF \rightarrow F$. This means that even with access to a valid instrument for education *and* to latent education propensities, estimates of $E \rightarrow F$ would remain biased through occupation. Conditioning on the latent fertility dispositions, by contrast, blocks the link between education and fertility through occupation and the latents.

In other words, the consistency of the conditional association we have shown between education and completed fertility, across different occupational categories, does not carry a direct causal interpretation of its own, but does have ramifications for causal research efforts. Firstly, that conditioning on occupation is prudent. Secondly, that identifying the causal effect of education on fertility may be helped more by accounting for the latent drivers of fertility than by accounting for the latent drivers of education, because the latter but not the former avoid the potential net bias introduced by conditioning on occupation. Thirdly, it shows that the possible lack of overlap between limiting education and occupation categories (i.e., “edge” categories) in causally richer datasets need not unduly limit interpretation, because treatment heterogeneity with respect to educational fertility differentials does not vary strongly across occupations.

6. Conclusions

An understanding of the interplay of education and occupation in influencing fertility is vital to assessing the likely impact of long-term labour market trends on demographic change. One of the obstacles to research in this area is the fact that education and occupational status tend to be highly correlated. The present study is based on samples large enough to contain sizeable counts of rare combinations, such as university graduates in elementary jobs or primary school drop-outs in high-status occupations. As a result, we are able to examine fertility gradients across virtually the entire range of education levels *within* occupation groups, and to perform statistical inference on these effects. Moreover, this is done in a way that is comparable across several different countries.

Based on the analysis presented here, it can be asserted that among the populations investigated, fertility varies by education level, even conditional on occupation level and industry. Moreover, the association between completed fertility and education is stronger in general than the association with completed fertility of the other two factors. This association is broadly consistent across a number of countries. Moreover, differences between the study-countries in terms of completed fertility can be explained almost entirely through composition effects and contextual interactions with education, occupation, and industry.

The existence of a consistent conditional association between education and completed fertility appears to be incompatible with explanations that attribute educational fertility differentials to differences in average income or social status, which we expect to be related more to occupation than educational attainment *per se*. The observed pattern of associations suggests that observed conditional differences in completed fertility are connected with the personal properties of highly educated women. This leaves open the important, but separate, question of whether these properties result from or resulted in their higher education.

7. Acknowledgements

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Appendix: Tabulations

Table 5: Mean fertility outcomes by country and schooling (cf. Fig. 1)

outcome	schooling	Austria	Greece	Hungary	Romania	Slovenia	Switzerland
CEB	<P	.	2.13	3.05	3.36	1.77	2.20
CEB	P	2.04	2.13	2.13	2.60	1.97	.
CEB	S	1.72	1.77	1.81	1.82	1.74	1.74
CEB	T	1.54	1.56	1.69	1.28	1.49	1.36
CL	<P	.	0.26	0.16	0.12	0.17	0.11
CL	P	0.12	0.08	0.06	0.07	0.06	.
CL	S	0.15	0.12	0.07	0.10	0.08	0.20
CL	T	0.24	0.18	0.12	0.18	0.15	0.33
P4+	<P	.	0.18	0.37	0.45	0.02	0.14
P4+	P	0.11	0.08	0.08	0.24	0.04	.
P4+	S	0.06	0.03	0.03	0.06	0.01	0.06
P4+	T	0.05	0.02	0.02	0.01	0.00	0.04

Table 6: Mean fertility outcomes by country and occupational status (cf. Fig. 2)

outcome	occupation	Austria	Greece	Hungary	Romania	Slovenia	Switzerland
CEB	L,SO&M	1.51	1.84	1.68	1.51	1.59	1.19
CEB	Prof	1.49	1.53	1.70	1.28	1.58	1.29
CEB	T&AP	1.48	1.61	1.74	1.55	1.68	1.46
CEB	CSWSMS	1.58	1.75	1.81	1.82	1.76	1.54
CEB	C&RTW	1.65	1.84	1.91	1.98	1.84	1.59
CEB	PMOAE	1.93	2.04	2.07	2.23	1.89	1.92
CEB	SA&FW	2.78	2.29	2.13	2.93	2.15	2.54
CL	L,SO&M	0.20	0.11	0.09	0.13	0.11	0.37
CL	Prof	0.25	0.20	0.11	0.18	0.12	0.36
CL	T&AP	0.21	0.17	0.08	0.12	0.08	0.31
CL	CSWSMS	0.18	0.14	0.06	0.10	0.06	0.24
CL	C&RTW	0.17	0.12	0.06	0.08	0.07	0.23
CL	PMOAE	0.12	0.10	0.05	0.08	0.06	0.11
CL	SA&FW	0.04	0.05	0.04	0.07	0.05	0.14
P4+	L,SO&M	0.04	0.04	0.01	0.02	0.00	0.01
P4+	Prof	0.04	0.02	0.02	0.01	0.01	0.04
P4+	T&AP	0.03	0.02	0.01	0.02	0.00	0.03
P4+	CSWSMS	0.04	0.03	0.02	0.06	0.01	0.03
P4+	C&RTW	0.06	0.03	0.03	0.08	0.03	0.04
P4+	PMOAE	0.08	0.07	0.06	0.15	0.02	0.06
P4+	SA&FW	0.24	0.10	0.06	0.31	0.05	0.26

Table 7: Mean fertility outcomes by country and industry (cf. Fig. 3)

outcome	industry	Austria	Greece	Hungary	Romania	Slovenia	Switzerland
CEB	A,F&F	2.74	2.29	2.02	2.85	2.11	2.46
CEB	H&R	1.81	2.06	1.83	1.82	1.76	1.65
CEB	CM	1.68	1.67	1.78	1.77	1.69	1.55
CEB	Manuf	1.64	1.83	1.90	1.87	1.84	1.56
CEB	UTC	1.59	1.55	1.79	1.72	1.66	1.46
CEB	EHSW	1.66	1.74	1.86	1.79	1.75	1.69
CEB	W&RT	1.63	1.78	1.79	1.73	1.74	1.59
CEB	PA&D	1.43	1.68	1.76	1.67	1.65	1.40
CEB	Service	1.41	1.65	1.73	1.51	1.68	1.24
CL	A,F&F	0.05	0.06	0.04	0.07	0.07	0.13
CL	H&R	0.16	0.08	0.08	0.10	0.07	0.20
CL	CM	0.17	0.19	0.07	0.13	0.08	0.23
CL	Manuf	0.17	0.12	0.07	0.09	0.07	0.25
CL	UTC	0.19	0.20	0.07	0.11	0.08	0.27
CL	EHSW	0.18	0.15	0.07	0.11	0.08	0.23
CL	W&RT	0.16	0.13	0.07	0.10	0.07	0.22
CL	PA&D	0.21	0.15	0.08	0.13	0.09	0.31
CL	Service	0.23	0.17	0.10	0.15	0.08	0.36
P4+	A,F&F	0.23	0.10	0.04	0.29	0.05	0.23
P4+	H&R	0.07	0.06	0.03	0.06	0.01	0.04
P4+	CM	0.06	0.04	0.02	0.07	0.01	0.06
P4+	Manuf	0.05	0.03	0.03	0.07	0.02	0.04
P4+	UTC	0.06	0.03	0.02	0.05	0.01	0.02
P4+	EHSW	0.05	0.04	0.03	0.07	0.01	0.05
P4+	W&RT	0.04	0.03	0.02	0.05	0.01	0.03
P4+	PA&D	0.03	0.03	0.02	0.05	0.01	0.03
P4+	Service	0.03	0.03	0.03	0.04	0.01	0.02

Table 8: Posterior distribution of the estimated standard deviation of coefficient batches of main and interaction effects of country, education, occupation, and industry on children ever born (CEB) (cf. Fig. 6)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
country	0.006	0.017	0.010	0.007	0.005	0.003
education	0.099	0.199	0.141	0.112	0.088	0.063
occupation	0.076	0.134	0.101	0.083	0.068	0.051
industry	0.048	0.083	0.063	0.052	0.043	0.032
country * education	0.074	0.107	0.088	0.077	0.067	0.055
country * occupation	0.061	0.083	0.071	0.063	0.056	0.048
country * industry	0.045	0.062	0.053	0.047	0.042	0.035
education * occupation	0.014	0.027	0.019	0.015	0.012	0.009
education * industry	0.005	0.012	0.008	0.006	0.005	0.003
occupation * industry	0.029	0.041	0.034	0.030	0.026	0.022
country * education * occupation	0.006	0.016	0.010	0.007	0.005	0.003
country * education * industry	0.023	0.033	0.027	0.024	0.021	0.017
country * occupation * industry	0.034	0.043	0.038	0.035	0.032	0.028
education * occupation * industry	0.006	0.018	0.011	0.008	0.006	0.004
residual (c*e*o*i)	0.007	0.032	0.017	0.011	0.007	0.004

Table 9: Posterior distribution of the estimated standard deviation of coefficient batches of main and interaction effects of country, education, occupation, and industry on childlessness (CL) (cf. Fig. 6)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
country	0.337	0.595	0.448	0.368	0.302	0.227
education	0.220	0.454	0.320	0.250	0.196	0.138
occupation	0.127	0.313	0.205	0.153	0.114	0.075
industry	0.112	0.213	0.155	0.124	0.100	0.073
country * education	0.156	0.260	0.201	0.168	0.140	0.108
country * occupation	0.204	0.273	0.233	0.209	0.187	0.160
country * industry	0.095	0.154	0.120	0.101	0.085	0.066
education * occupation	0.072	0.117	0.091	0.077	0.064	0.050
education * industry	0.005	0.015	0.009	0.007	0.005	0.003
occupation * industry	0.118	0.169	0.140	0.122	0.107	0.089
country * education * occupation	0.006	0.017	0.010	0.007	0.005	0.003
country * education * industry	0.040	0.087	0.060	0.046	0.036	0.025
country * occupation * industry	0.123	0.154	0.136	0.125	0.115	0.102
education * occupation * industry	0.006	0.016	0.010	0.007	0.005	0.003
residual (c*e*o*i)	0.005	0.018	0.010	0.007	0.005	0.003

Table 10: Posterior distribution of the estimated standard deviation of coefficient batches of main and interaction effects of country, education, occupation, and industry on the share with parity four or higher (P4+) (cf. Fig. 6)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
country	0.494	0.952	0.690	0.551	0.440	0.319
education	0.540	1.083	0.772	0.610	0.482	0.344
occupation	0.352	0.600	0.458	0.380	0.315	0.240
industry	0.174	0.343	0.246	0.196	0.155	0.112
country * education	0.416	0.637	0.511	0.438	0.375	0.301
country * occupation	0.152	0.245	0.192	0.162	0.137	0.107
country * industry	0.223	0.303	0.257	0.229	0.205	0.174
education * occupation	0.088	0.178	0.126	0.099	0.078	0.056
education * industry	0.006	0.018	0.011	0.008	0.005	0.003
occupation * industry	0.125	0.194	0.154	0.132	0.112	0.090
country * education * occupation	0.006	0.016	0.010	0.007	0.005	0.003
country * education * industry	0.006	0.018	0.011	0.007	0.005	0.003
country * occupation * industry	0.006	0.018	0.011	0.008	0.005	0.003
education * occupation * industry	0.006	0.022	0.012	0.008	0.006	0.003
residual (c*e*o*i)	0.169	0.214	0.188	0.172	0.157	0.138

Table 11: Posterior distribution of the estimated standard deviation of coefficient batches of strong (interaction) effects on CEB and their interaction with time (cf. Fig. 7)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
year	0.006	0.015	0.010	0.007	0.005	0.003
country	0.006	0.018	0.010	0.007	0.005	0.003
education	0.091	0.178	0.128	0.102	0.081	0.059
occupation	0.081	0.138	0.106	0.088	0.073	0.055
industry	0.046	0.082	0.061	0.050	0.041	0.031
country * education	0.052	0.089	0.068	0.056	0.047	0.036
country * occupation	0.055	0.080	0.065	0.057	0.049	0.040
country * industry	0.051	0.068	0.059	0.053	0.047	0.041
year * country	0.006	0.018	0.011	0.007	0.005	0.003
year * education	0.005	0.014	0.009	0.007	0.005	0.003
year * occupation	0.007	0.022	0.013	0.009	0.006	0.004
year * industry	0.006	0.019	0.011	0.008	0.006	0.003
year * country * education	0.025	0.047	0.035	0.028	0.022	0.016
year * country * occupation	0.007	0.051	0.024	0.014	0.008	0.004
year * country * industry	0.006	0.013	0.009	0.007	0.005	0.003
residual (y*e*o*i)	0.048	0.053	0.050	0.048	0.046	0.043

Table 12: Posterior distribution of the estimated standard deviation of coefficient batches of strong (interaction) effects on CL and their interaction with time (cf. Fig. 7)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
year	0.006	0.021	0.012	0.008	0.006	0.003
country	0.366	0.653	0.489	0.400	0.327	0.245
education	0.187	0.357	0.260	0.208	0.167	0.122
occupation	0.195	0.361	0.266	0.215	0.174	0.128
industry	0.120	0.210	0.159	0.131	0.108	0.081
country * education	0.079	0.156	0.112	0.089	0.071	0.051
country * occupation	0.198	0.269	0.229	0.204	0.182	0.154
country * industry	0.107	0.158	0.129	0.112	0.097	0.079
year * country	0.066	0.145	0.099	0.076	0.059	0.040
year * education	0.004	0.038	0.016	0.009	0.005	0.002
year * occupation	0.006	0.016	0.010	0.007	0.005	0.003
year * industry	0.006	0.016	0.010	0.007	0.005	0.003
year * country * education	0.005	0.018	0.011	0.007	0.005	0.003
year * country * occupation	0.006	0.017	0.010	0.007	0.005	0.003
year * country * industry	0.006	0.015	0.010	0.007	0.005	0.003
residual (y*e*o*i)	0.153	0.175	0.162	0.154	0.146	0.136

Table 13: Posterior distribution of the estimated standard deviation of coefficient batches of strong (interaction) effects on P4+ and their interaction with time (cf. Fig. 7)

effects	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
year	0.006	0.014	0.009	0.007	0.005	0.003
country	0.516	0.968	0.709	0.572	0.461	0.338
education	0.540	1.062	0.763	0.607	0.482	0.347
occupation	0.414	0.734	0.552	0.452	0.370	0.278
industry	0.177	0.317	0.237	0.193	0.158	0.118
country * education	0.299	0.530	0.398	0.326	0.268	0.201
country * occupation	0.223	0.330	0.269	0.233	0.202	0.165
country * industry	0.182	0.267	0.218	0.190	0.165	0.135
year * country	0.006	0.015	0.010	0.007	0.005	0.003
year * education	0.006	0.016	0.010	0.007	0.005	0.003
year * occupation	0.006	0.016	0.010	0.007	0.005	0.003
year * industry	0.006	0.017	0.010	0.007	0.005	0.003
year * country * education	0.146	0.247	0.190	0.158	0.131	0.101
year * country * occupation	0.006	0.016	0.010	0.007	0.005	0.003
year * country * industry	0.006	0.016	0.010	0.007	0.005	0.003
residual (y*e*o*i)	0.269	0.304	0.283	0.270	0.258	0.240

Table 14: Posterior distribution of multiplicative educ & occ effects on CEB (cf. Fig. 8)

effect	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
<P	1.162	1.052	1.114	1.160	1.207	1.279
P	1.074	0.974	1.030	1.072	1.115	1.180
S	0.939	0.852	0.901	0.937	0.974	1.030
T	0.860	0.780	0.825	0.858	0.892	0.944
L,SO&M	0.939	0.878	0.913	0.938	0.964	1.002
Prof	0.906	0.847	0.881	0.905	0.931	0.968
T&AP	0.932	0.872	0.906	0.931	0.957	0.994
CSWSMS	0.985	0.922	0.958	0.984	1.010	1.050
C&RTW	1.015	0.947	0.986	1.014	1.042	1.085
PMOAE	1.106	1.035	1.076	1.105	1.135	1.180
SA&FW	1.148	1.068	1.114	1.147	1.181	1.231

Table 15: Posterior distribution of multiplicative educ & occ effects on CL (cf. Fig. 8)

effect	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
<P	0.924	0.742	0.840	0.916	0.999	1.132
P	0.754	0.612	0.689	0.749	0.813	0.916
S	0.997	0.810	0.911	0.989	1.074	1.208
T	1.483	1.201	1.353	1.471	1.600	1.803
L,SO&M	1.080	0.906	1.001	1.074	1.151	1.272
Prof	1.271	1.063	1.177	1.264	1.357	1.503
T&AP	1.132	0.952	1.051	1.126	1.206	1.332
CSWSMS	0.975	0.822	0.906	0.970	1.038	1.144
C&RTW	1.015	0.847	0.939	1.009	1.084	1.202
PMOAE	0.818	0.688	0.760	0.814	0.872	0.963
SA&FW	0.826	0.678	0.759	0.820	0.887	0.991

Table 16: Posterior distribution of multiplicative educ & occ effects on P4+ (cf. Fig. 8)

effect	mean	.05 quant	.25 quant	.5 quant	.75 quant	.95 quant
<P	2.648	1.430	1.987	2.499	3.143	4.364
P	1.456	0.794	1.098	1.376	1.725	2.385
S	0.660	0.363	0.500	0.625	0.781	1.075
T	0.490	0.267	0.369	0.463	0.580	0.803
L,SO&M	0.740	0.523	0.634	0.725	0.829	1.004
Prof	0.711	0.499	0.607	0.696	0.798	0.971
T&AP	0.649	0.463	0.558	0.637	0.726	0.875
CSWSMS	0.904	0.649	0.780	0.887	1.009	1.213
C&RTW	1.161	0.819	0.994	1.138	1.302	1.580
PMOAE	1.626	1.166	1.403	1.596	1.816	2.184
SA&FW	1.968	1.363	1.670	1.925	2.218	2.717