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Structural Labour Market Change, Cognitive Work, and Fertility in Germany

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Abstract: Technological change and globalisation have been transforming the structure of labour demand in favour of workers performing cognitive tasks. Even though past research has found that labour force participation is an important determinant of fertility behaviour, few studies have addressed the fertility effects of the long-term structural changes of labour market. To fill this gap, we measure the cognitive task content of work at the occupation level using data from the Employment Survey of the German Federal Institute for Vocational Education and Training (BiBB). We link this contextual information with employment and fertility histories of women and men from the German Socio-Economic Panel 1984-2018 (GSOEP). With event history models, we find that fertility transitions of men working in occupations characterised by high cognitive task intensity are accelerated. We also observe elevated birth risks among women in occupations requiring cognitive labour. However, this pattern is more ambiguous, as we find that non-working women also experience elevated birth rates.

Keywords: structural labour market change, cognitive work, task content of work, fertility, Germany

JEL codes: J01, J11, J13

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1 Introduction

Over the last three decades, technological change and globalisation have led to substantial structural changes in the labour markets in advanced economies (World Bank 2019). These changes are reflected in the growing demand for workers with high cognitive-analytical skill levels that can be applied in the rapidly expanding high tech sector, or with the social and interpersonal skills that are required in highly specialised customer service, business, and management settings, but also in (health)care and education. The development of information and communication technologies has also changed the ways people work, granting – usually higher skilled – workers more flexible work schedules and greater work autonomy, albeit often at a price of having more responsibility for work outcomes (Van Echtelt et al. 2009; Kvande 2017). At the same time, the demand for workers who perform non-cognitive tasks, and in particular routine manual tasks, has been declining, as these sorts of job tasks can be easily automated or offshored to countries with lower labour costs (Acemoglu and Autor 2011; World Bank 2019). These developments, termed as structural labour market change, have led to increasing disparities in labour market opportunities between cognitive and non-cognitive workers, with the former having disproportionally better conditions for earning income and for flexibly organising their work schedule, albeit often at the cost of greater work demands.

Because of its rapid speed and important social consequences, structural labour market change has assumed a prominent position in economic and sociological research. For example, scholars have examined its impact on workers' employment and earning opportunities (Autor and Handel 2013; Autor and Dorn 2013; De la Rica et al. 2020), social and economic inequalities (Visintin et al. 2015; Fortin and Lemieux 2016; Brussevich et al. 2019; Oesch and Piccitto 2019), health (Adda and Fawaz 2020), and mortality (O'Brien et al. 2022). It can also affect demographic behaviours, such as fertility, as it greatly modifies the conditions for combining paid work and care, and determines not only current but also future opportunities for earning income and participating in the labour market. There has been a broad consensus among demographers that earning prospects (Oppenheimer 1997, Andersson 2000), job stability (Kreyenfeld et al 2012; Adsera 2011), and the compatibility of paid work with family life (Brewster ad Rindfuss 2000) are important determinants of family formation. To date, however, demographic research has been relatively silent on the question of how long-term structural change driven by globalisation and digitalisation affects childbearing behaviour. Most of the past research focused on the current labour market status of individuals; e.g., on their current (un)employment (Matysiak and Vignoli 2008; Adsera 2005), contract type

(Kreyenfeld 2010; Alderotti et al. 2021), earnings (Andersson et al. 2000) or work schedules (Begall et al. 2015; Sinyavskaya and Billingsley 2015). However, during a period of structural change, individuals' current labour market status may not reflect their future opportunities for earning labour market income or combining paid work with care. While the current labour market situation of an individual may improve as it is sensitive to cyclical developments in the economy, structural change in the labour market has enduring effects. By creating demand for highly skilled workers and facilitating the flexible organisation of working hours and work location, it can provide cognitive workers with more opportunities to find a job that offers better pay or that is more compatible with family life. At the same time, however, structural change can lead to the long-term deterioration of working conditions for lower skilled workers by making certain job tasks and occupations redundant (Arntz et al. 2017; Nedelkoska and Quintini 2018), and by depriving them of employee-oriented flexibility (Chung 2018).

In this study, we take a first step towards investigating how the increasing disparities in the labour market opportunities between cognitive and non-cognitive workers caused by long-term labour market structural change have affected first and higher order birth transitions in Germany. To this end, we make use of the task-based approach, which was proposed by Autor et al. (2003) and was widely implemented in labour market economics (e.g., Autor et al. 2006; 2015; Arntz et al. 2017; De la Rica et al. 2020). This approach presupposes that occupations consist of a variety of tasks that require certain skills. Since technology and globalisation change the structure of tasks – with some tasks being taken over by machines and others being offshored – they modify the demand for skills, and thus affect workers' labour market prospects. Occupations with more cognitive task content offer better labour market opportunities than occupations with low cognitive task content. However, while the spread of information and communication technologies provides cognitive workers with more flexibility in determining when and where they work, some studies have shown that flexible working may be associated with higher work demands (Van Echtelt et al. 2009; Kvande 2017).

We measure the task content of occupations using data from the Employment Survey of the German Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung [BiBB], Berlin, & Institut für Arbeitsmarkt- und Berufsforschung der Bundesanstalt für Arbeit [IAB], Nürnberg 1983, 1995, 2016; Jansen and Dostal 2015; Hall et al. 2020, 2020; Hall and Tiemann 2021). These data allow us to generate measures of cognitive task intensity (both analytic and interactive) at the three-digit occupation level. We then link these contextual occupation-specific data to micro-level data from the German Socio-Economic Panel (GSOEP, Goebel et al. 2018) for the years 1984-2018. We employ event history models to model the birth processes, with the task content being used as the main time-varying variable of interest. These data sources provide us with information from the early 1980s to 2018, which gives us the opportunity to examine a nearly four-decade period that encompasses the early as well as the advanced stages of digitalisation- and globalisation-driven labour market change.

2 Structural changes in the labour market

2.1 Changing demand for skills

The adoption of new technologies and globalisation have led to tremendous changes in the structure of labour demand (World Bank 2019; OECD 2020). These forces, among others, have led to an expansion of jobs in specific sectors of the economy (e.g., high tech, delivery, or export-oriented branches). New jobs, which did not exist before, were created as well (ICT professionals, social media managers, or digital influencers). Nonetheless, globalisation and digitalisation also destroyed jobs, destabilised work careers, and made work more demanding and irregular (World Bank 2019). This trend is likely to continue, as it has been estimated by Arntz et al. (2017) that in the OECD countries over the next two decades, around 10% of jobs that are currently done by humans will be fully performed by machines, and that in a further 25% of jobs around 50%-70% of tasks will be automated. The workers who are displaced by these developments are increasingly forced to accept unstable and fragmented employment in the form of fixed-term, part-time, or zero-hour/on-call contracts (Rubery 2015), which have expanded in Europe as a result of deregulation reforms undertaken by governments with the aim of increasing the competitiveness of European companies in the global market (Boeri et al. 2012; Bastianelli et al. 2022).

To describe the changes in the labour demand that have been caused, among other factors, by technology and globalisation, economists have proposed using a task-based approach (Acemoglu and Autor 2011; Autor et al. 2003). This approach presupposes that jobs and occupations are composed of a variety of job tasks. These tasks vary in their level of complexity and in the extent to which the need to perform them generates demand for workers with appropriate skills. Technology and globalisation have changed the structure of the tasks demanded in the labour market, with some tasks being taken over by machines and others being offshored to other countries. These developments have changed the demand for skills and affected workers' labour market opportunities.

It has been widely demonstrated that workers who can perform abstract tasks (also called non-routine cognitive tasks) are in the greatest demand in the labour markets of the advanced economies (Autor et al. 2003; World Bank 2019; Cortes et al. 2021). Abstract tasks require creativity, problem-solving, and complex organisation and communication, and are not easy to automate or to offshore. These tasks can be more *analytical* (i.e., demanding the ability to process, analyse, and interpret data when making a decision) or *social/interpersonal* (i.e., requiring the ability to engage in interactions with people, teamwork, negotiations, conflict resolution, etc.). Apart from abstract tasks, workers may also do non-cognitive routine tasks (which are repetitive and involve following easily programmable rules) as well as non-cognitive manual tasks (which require motor skills or physical strength). In contrast to workers who do non-cognitive tasks, workers who are able to perform abstract tasks are more likely to be able to find and maintain employment (Autor et al. 2006; Deming 2017; Deming and Kahn 2018), and to experience upward occupational mobility (Fedorets 2019) and increases in pay (Borghans et al. 2014; Deming 2017). At the same time, the labour market opportunities of workers whose skill levels do not enable them to perform abstract tasks have been sharply deteriorating (World Bank 2019; Hardy et al. 2018). These processes have resulted in growing inequalities between cognitive and non-cognitive workers in terms of their earnings (Bacolod and Blum 2010; Borghans et al. 2014; Baumgarten et al. 2020), their occupational prestige and job satisfaction (Oesch and Piccitto 2019), and the precarity of their contract type (Peugny 2019) across many developed countries.

These changes in the labour market affect both women and men. However, women moved from non-cognitive to cognitive jobs more quickly than men (Bacolod and Blum 2010; Black and Spitz-Oener 2010). Whereas in the past jobs that involved routine/repetitive tasks were mainly performed by women, this pattern is currently observed only among older birth cohorts (Brussevich et al. 2019). Meanwhile, low-skilled jobs that involve manual tasks continue to be mainly performed by men (Yamaguchi 2016; Brussevich et al. 2019). At the same time, men are more likely than women to work in high-skilled occupations that involve performing intense analytical tasks as well as social/interpersonal tasks that require managerial skills (Liu and Grusky 2013; Matysiak et al. forthcoming). By contrast, in most European countries, women are overrepresented in occupations that involve social/interpersonal tasks oriented towards providing interactive services to others (e.g., care, healthcare, teaching), and that are often associated with lower wage returns (England 2005; Liu and Grusky 2013; Matysiak et al. forthcoming).

2.2 Work autonomy and flexible working hours

As well as increasing the demand for workers who can perform abstract tasks, technological change and globalisation have also granted these workers greater job autonomy. Closely related to the rise of information and communication technologies, opportunities to work flexible hours or to engage in home-based teleworking have increased rapidly in recent years (Arntz et al. 2022; Rubery 2015); a process that was further accelerated during the COVID-19 pandemic (Lott and Abendroth 2022). The flexibility to choose when and where work is performed has increased mostly for workers with cognitive skills, such as managers and professionals, but much less so for workers who perform non-cognitive job tasks (Chung 2018). As this flexibility can make it easier for workers to adjust their work hours to the needs of their family, it has the potential to facilitate work-life balance (Demerouti et al. 2014). Empirical research has, however, also pointed out some potential negative consequences of work schedule and workplace location flexibility, such as longer working hours (Kvande 2009; Felstead and Hanseke 2017), around-the-clock-availability (Presser 2003), more fragmented working time, and blurred boundaries between paid work and family life (Lott and Abendroth 2022) – all of which can ultimately lead to an intensification of work-family conflicts.

In parallel, increasing pressure on companies to innovate, adjust to the continuously changing environment, and operate across different time zones has led to changes in organisations aimed at increasing workers' productivity, which have, in turn, resulted in increased work demands (Greenan et al. 2013; Green 2004). These organisational changes have been accompanied by the introduction of incentive structures (e.g., performance-related pay) and project work, as well as by the decentralisation of decision-making, which have given workers more work autonomy, but have also made them more responsible for work outcomes (Piva et al. 2005; Van Echtelt 2007). This organisation of work has led to the emergence of "boundary-less work cultures" in which workers decide for themselves how much time they spend on a given task, and are rewarded for the tasks they have successfully completed (Kvande 2017). This arrangement is most common among cognitive workers in knowledge-intensive organisations that offer excellent prospects for professional growth and high levels of job autonomy – but at the price of high levels of commitment to work (Blair-Loy 2009).

These discussed structural labour market transformations will likely have serious implications for fertility behaviour, as they greatly alter the conditions for earning income and combining paid work with childcare, which have been shown to be important determinants of family formation (Oppenheimer 1997; Brewster and Rindfuss 2000; McDonald 2000). We investigate their consequences for birth transitions in the German context.

3 Labour market changes and fertility behavior

3.1 Country context

This study is conducted in Germany. Germany's labour market is known for its heavy demand for high-skilled labour (Spitz-Oener 2006; Rohrbach-Schmidt and Tiemann 2013). Germany has the single largest software market in Europe (European IT Observatory 2020) and one of the largest ICT markets in the world (European IT Observatory 2020), and it is among the global leaders in robotisation. The transformation of Germany's economy into a knowledge economy began in the late 1960s. Germany maintained its manufacturing traditions, but invested strongly in modernisation and digitalisation of manufacturing (Thelen 2020). Like other developed countries, it also experienced a substantial increase in occupational complexity, with abstract job tasks, both analytical and social/interpersonal in nature, becoming increasingly important (Spitz-Oener 2006). These changes took place within all occupational and occupation-educational groups (Spitz-Oener 2006), and occurred more quickly among women, who frequently moved out of jobs that became automated, than they did among men (Black and Spitz-Oener 2010). It has also been demonstrated that the increase in the demand for workers who perform more abstract tasks has been responsible for a sizable proportion of wage inequalities, which have increased substantially since the 1970s (Koomen and Backes-Geller 2022).

The structure of the labour market makes Germany an ideal testcase to examine the consequences digital transformation on family behavior. It is also ideal to showcase the gender differences of this transformation due to its strongly gendered care patterns. Germany used to adhere to a conservative welfare state model (Esping-Andersen 1990; Amable 2003) that was based on strong employment protections and coordinated bargaining systems (Amable 2003: 15). The sole breadwinner model was supported by the tax and transfer system, and the limited availability of full-time day care inhibited the labour market integration of mothers. In 2007, a parental leave reform was enacted that introduced an income-related parental leave that also included a "paternity quota" (Henninger et al. 2008). Furthermore, full-time day care has been systematically expanded since 2005, and, in 2013, a legal right to a daycare slot was introduced for all children aged one year and older. Nevertheless, employment patterns remained gendered.

Many women in Germany still switch to part-time employment or leave the labour market altogether after they have children (Boll and Lagemann 2019; Müller and Wrohlich 2020).

3.2 Structural labour market change and fertility

Major theoretical approaches in fertility research have posited that men earning a steady income and having stable employment are crucial prerequisites for family formation in male breadwinner societies. In line with these arguments, empirical research has shown that couples in which the male partner is employed and has high earnings are more likely to transition to a first or a second birth, while couples in which the male partner is unemployed or has a term-limited working contract are more likely to postpone fertility until the uncertainty around the man's labour market position is resolved (Kreyenfeld et al. 2012). At the same time, it has been argued that the impact of women's economic activity on fertility is more ambiguous. On the one hand, it has been observed that women's earnings facilitate family formation and increase family stability through the mechanism of resource pooling (Oppenheimer 1997; Sigle-Rushton 2010; Matysiak and Vignoli 2013), especially during periods when men's employment is less stable (Macunovich 1996). On the other hand, it has been argued that due to the combination of gendered care patterns and the incompatibility of employment and family, having children is linked to high opportunity costs for women. It has been assumed that women who are on a promising career track and have very high chances of increasing their earnings are likely to postpone the transition to motherhood or to remain childless altogether (Gustafsson 2001). However, more recent theoretical approaches have predicted a shift in the association between women's work opportunities and fertility in response to the expansion of policies that facilitate work-family reconciliation by increasing access to childcare and income-related parental leave (Brewster and Rindfuss 2000), the spread of more egalitarian gender role attitudes (Esping-Andersen and Billari 2015), and greater involvement by men in childcare and housework (McDonald 2000; Goldscheider et al. 2015). Furthermore, growing economic uncertainties may erode the basis of the traditional family model while also increasing levels of flexibility to choose when and where work is performed, which may, in turn, increase the compatibility of paid work and childcare, thereby promoting the emergence of dual earner-dual carer families. While the results of empirical research on such developments are still mixed (Marynissen et al. 2020; Alderotti et al. 2021), there are some signs of ongoing social change (Greulich et al. 2017; Lambert and Kreyenfeld 2023).

Given that the labour market opportunities of women and men clearly affect their childbearing behaviours, it is highly likely that the ongoing process of structural labour market change will affect fertility by creating increasing and permanent differences in the conditions for family formation between highly skilled cognitive workers and lower skilled non-cognitive workers. We expect, however, these effects to differ between women and men due to the differential social roles that are culturally assigned to each gender. These effects may also change over time with changes in gender and care patterns, improvements in levels of welfare support for work and family reconciliation, and changes in conditions for earning income and combining paid work and care caused by technology- and globalisation-driven labour market transformations.

Among men, we expect performing cognitive work to be positively associated with entry into parenthood and subsequent childbearing, irrespective of whether they are in an occupation that requires them to perform analytical or social/interpersonal tasks, since both kinds of occupations offer good earning opportunities for men. We also anticipate that the disparities in fertility transitions between male cognitive and non-cognitive workers will increase over time as structural change in the labour market progresses, thereby improving the employment, earnings, and flexible work opportunities of male cognitive workers relative to those of male non-cognitive workers. However, these improvements in the conditions for family formation among male cognitive workers may be offset by increasing work demands in knowledge-intensive occupations.

Among women, by contrast, we expect that performing cognitive work results in opportunity costs and thus negative effect on birth transitions, at least in the time periods when they are considered the main childcare providers. The opportunity costs, and thus the negative effects, are likely to be particularly high in occupations that have high analytical task intensity as in case of women they offer a steeper career trajectory and place considerable demands on workers' time than they are in occupations with high social/interpersonal task intensity. This is because women who work in occupations that involve interactive service tasks (e.g., care, healthcare, teaching, nursing) tend to be less well paid and to have fixed working hours in comparison to men (Liu and Grusky 2013; Matysiak et al. forthcoming). With time, as women are increasingly present in the labour market and men increase their participation in childcare, we may, however, observe a weakening of the negative role of women's cognitive work for birth transitions.

Finally, we need to consider that educational participation and first entry into the labour market may differ strongly depending on the type of occupation. This aspect is particularly relevant for first birth analysis, as it entails that the fertility schedule may differ strongly by occupation. An increase in the first birth rate among workers who perform abstract tasks could be attributed to an acceleration of the transition to the first birth after first labour market entry or at later ages. We also expect this acceleration to be stronger among women who perform analytical tasks rather than social/interactive tasks, while we expect to observe no important differences among men depending on which of these two types of tasks they perform.

4 Data and measures

4.1 Data sources

In order to answer our research questions, we first construct measures of the cognitive task content of occupations. To this end, we use data from the Employment Surveys of the German Federal Institute for Vocational Education and Training (BiBB) for the years 1979, 1986, 1992, 1999, 2006, 2012, and 2018. Next, we link these indicators with micro-data from the German Socio-Economic Panel (GSOEP) (1984-2018) in order to model the relationships between the cognitive task content of work and birth transitions. The Employment Survey of the German Federal Institute for Vocational Education and Training (BiBB) is a repetitive cross-sectional survey that has been conducted every six years since 1979. It contains detailed information on job characteristics, such as on tasks performed at work (e.g., programming, cleaning, teaching), work locations, work schedules, working hours, contract types, and wages. So far, seven waves have been conducted. These data allow us to identify which occupations mainly involve abstract tasks, and to differentiate between analytic and interactive task content. The GSOEP is an ongoing longitudinal panel survey with about 20,000 survey participants in 11,000 households per year that has been conducted annually since 1984. It provides complete fertility histories and rich employment and occupational information.

4.2 Measures of the cognitive content of occupations

We assess the cognitive content of occupations using two measures that distinguish between *analytic and social/interpersonal task content*. By doing so, we build on the framework for quantitatively assessing the task content of work that was first proposed by Autor et al. (2003), and that was adapted to the German context by Spitz-Oener (2006) and Rohrbach-Schmidt and

Tiemann (2013).[1] We classify tasks as "analytic" or "interactive" following the criterion validation method suggested in Rohrbach-Schmidt and Tiemann (2013). The analytic domain quantifies activities like programming or researching, which are performed in a dynamic manner without using one's hands, while the interactive domain quantifies non-repetitive tasks that require human interaction, such as consulting or managing. The exact task items that we measure and their availability in consecutive waves are displayed in Table 1.

[1] Measures for routine and manual tasks are also used in the literature (e.g., Autor et al. 2003, Autor et al. 2006). However, Rohrbach-Schmidt and Tiemann (2013) showed that routine and manual tasks are not measured consistently in the BIBB surveys, and thus that they should not be used in a longitudinal setting. They recommended using only the analytic and interactive task measures, and measuring the decreasing demand for the routine and manual tasks indirectly by assuming that a person who has low analytic/interactive task content also has high routine/manual task content. Research on the task content of work in other developed economies has shown that it is indeed the case that an increase in analytic/interactive task intensity is accompanied by a decrease in routine/manual task intensity (see Autor et al. 2006 for the US; Hardy et al. 2018 for Europe; Spitz-Oener 2006 and Antonczyk et al. 2009 for Germany). Following Spitz-Oener (2006) and Rohrbach-Schmidt and Tiemann (2013), we refer to the measures we use as "analytic task measure" and "interactive task measure".

Table 1. Availability and classification of the task items

Number	Task Item	Waves Available	Task Category
1	Investigating	1999, 2006, 2012, 2018	Analytic
2	Organising	All	Analytic
3	Researching	All except 1999	Analytic
4	Programming	All except 1999	Analytic
5	Applying law	1979, 1986, 1992	Analytic
6	Teaching	All	Interactive
7	Consulting	All	Interactive
8	Buying	All	Interactive
9	Promoting	All except 1986	Interactive
10	Managing	1979, 1986, 1992	Interactive
11	Negotiating	1979, 1999	Interactive

We derive the measures of the cognitive content of occupations using data from the Employment Surveys of the German Federal Institute for Vocational Education and Training (BiBB) . Unfortunately, the samples are not comparable across the consecutive waves unless they are restricted. Thus, following the recommendation of Rohrbach-Schmidt and Tiemann (2013), we restrict the data in order to balance the samples. This includes keeping records only for employed individuals who were from western Germany, had German citizenship, were aged 15 to 64 (active workforce), and were working between 10 and 168 hours a month. Using these data, we apply the following formulas:

$$j\ task\ measure_{ot} = \frac{\sum_{i=1}^{N} j\ task\ measure_{oit}}{N} \qquad \text{Eq. 1}$$

where

$$j\ task\ measure_{oit} = \frac{no.of\ items\ in\ category\ j\ performed\ by\ i\ in\ t}{total\ no.of\ items\ in\ category\ j\ at\ time\ t} \times 100. \qquad \text{Eq. 2}$$

and o – occupation, i – individual, $j \in \{analytic, interactive\}$, and $t \in \{1979, 1986, 1992, 1999, 2006, 2012, 2018\}$. *Eq. 2* corresponds to the measure first developed in Spitz-Oener (2006) and applied in (among others) Spitz-Oener (2010) and Rohrbach-Schmidt and Tiemann (2013). It ranges from zero to 100 and quantifies the degree to which an individual's work requires them to apply analytic or interactive skills. For example, suppose that a worker performs four tasks classified as "analytic" out of five considered analytic task items (see Table 2). Then, her analytic task measure is (4/5)×100=80. We average *Eq. 2* over individuals in order to obtain *Eq. 1* – a measure at an occupation level that can then be merged with individual data from the GSOEP by three-digit occupational codes. We interpret this as reflecting the extent to which an occupation is intensive in analytic or interactive tasks. Since we have measures for seven points in time, a simple linear interpolation is performed in order to obtain observations between the available time points.

4.3 Analytical sample

Next, we use the GSOEP data to perform the analysis of birth transitions. This analysis is conducted separately for women and men. We investigate the transition to the first birth separately from the transition to the second or the third order birth. While second and third birth transitions are quite rare, we have to pool second and third births in one model to obtain a reasonable number of birth transitions. However, we control for birth parity. Transitions to fourth and higher order births are not covered, as they are very rare in Germany.

We focus on respondents with German citizenship aged 20 to 48. We do not include respondents below age 20, because these individuals are predominantly in education; thus, the current labour market situation of these respondents is unlikely to be a determinant of their fertility. We also exclude persons with non-German citizenship because their fertility behaviour would require special consideration. We include data for the years 1984-2018. As we lag the main covariates by two years, we observe fertility in the period from 1986 to 2018 (see below). Thus, we cover a large part of the period when Germany was undergoing the transition to becoming a knowledge economy, including the structural labour market change caused by globalisation and digitalisation (Thelen 2020; Dauth et al. 2021). It should also be noted that East Germany is only included after reunification. Finally, we limit the sample to respondents who provided valid information in the birth biographies (the fraction of missing information is around 2%). We have organised our data in long format, with each survey year contributing one entry to our sample. Thus, individuals are censored when they drop out of the survey or when they reach age 48 (Table A1 summarises the information on the sizes of our samples).

4.4 Analytical Strategy

Having annual data at our disposal, we model it using hazard models with a complementary log-log function of form:

$$\log\left[-\log\left(1-\lambda_{i,t}\right)\right] = \alpha_t + \beta x_{i,t-2} \qquad \text{Eq. 3}$$

where the fitted probability $\widehat{\lambda_{i,i}}$ can be expressed

$$\hat{\lambda_{i,t}} = 1 - \exp[\text{-}\exp(\beta' x_{i,t-2})] \qquad \text{Eq. 4}$$

The function from *(Eq. 3)* is sometimes referred to as a "gompit" model, due to its relationship to the Gompertz distribution (Box-Steffensmeier and Jones 2004). As the function from *(Eq. 3)* is asymmetric, it is suitable for survival analysis based on data with relatively few failures. For this reason, the gompit model has been relatively popular in fertility research (Gerster et al. 2007). We include duration in a piecewise constant hazard fashion. The process time α_t for the first birth is the respondent's biological age divided into five intervals: 20-24, 25-29, 30-34, 35-39, 40-48.

The models, as specified above, allow for the assessment of the general relationship between the cognitive content of women's and men's work and their fertility transitions. We are, however, also interested in investigating how these relationships changed over time. To this end, we interact individuals' task measures with time period.

Finally, we suspect that before individuals can enter occupations that require cognitive skills, they often have to complete lengthy periods of education. Thus, labour market entry may occur later in life for persons working in occupations that require cognitive labour. If individuals enter the labour market when they are older, they may have reached a point in their life course that leads them to accelerate childbearing. This conundrum is relevant for us, as our event history model relies on the proportionality assumption that requires the covariates to have the same effect at all durations. An acceleration of childbirth after labour market entry is not "built in" to this model. Thus, the results may be biased if the proportional hazard assumption is not relaxed. In order to test for this possibility, we interact individuals' task measures with age in the first birth model.

Unfortunately, our sample size prohibits us from conducting reliable interpretable models with interactions for higher order births. Thus, we perform the above described interactions only in the first birth hazard models, while for higher order births, we present only the basic models without interactions. Workers with low task measures are our reference group in all models. To facilitate the interpretability of our findings, we first present the odds ratios of task measures from the basic models without interactions. Then, we present the average predicted probabilities of task measures interacted with period and age (separately). Full model results are presented in Tables A2-A5 in the appendix.

5 Results

5.1 Cognitive work: descriptive results

Before discussing our findings on cognitive task intensity and birth transitions, we present some descriptive information on our measures of the task content of work. First, we examine whether the cognitive task measures we constructed are indeed associated with higher wage returns, more flexibility (in terms of time schedule and work location), longer work demands and higher work pressure as past research on cognitive work suggested. In this way we check whether our measures indeed reflect the phenomena we discussed earlier in the paper. Second, we also study the developments in cognitive task measures over time in order to see whether our measures indicate an increase in cognitive task content of work as it could be expected based on the past literature.

In order to examine our task measures of cognitive task content are indeed related to higher wage returns, greater flexibility but also higher work intensity we pooled three waves of the BiBB Employment Survey (2006, 2012, 2018). We next regressed our measures (measured on the continuous scale) against the following set of work characteristics: working overtime (binary), working under pressure (ordinal with four levels, with higher values reflecting more work pressure), working from home (binary), monthly gross wages, as well as time dummies and the following socio-demographic characteristics: gender, age, education[2]. The findings

[2] The models that include a dummy for working from home are estimates based on the 2006 and 2018 waves, since the 2012 wave did not contain this variable.

from these models are presented in Table 3. They are largely in line with our expectations and suggest that workers who are employed in occupations that require them to perform cognitive tasks enjoy greater work flexibility, but also experience more job strain and work longer hours. We also find a significant positive relationship of the analytic task measure with wages, although there is no effect for the interactive measure after we control for working from home (see the differences between column 2 and 4 of Table 2).

Table 2. Beta coefficients from pooled OLS regression. Outcome variable: Task measure (analytical or interactive).

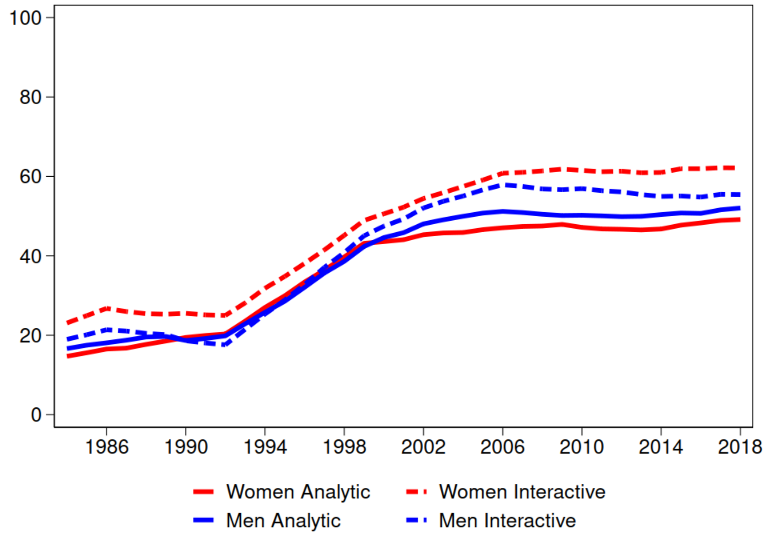
Covariate	(1)	(2)	(3)	(4)
	Analytical	Interactive	Analytical	Interactive
Overtime: Yes	4.219***	3.294***	4.272***	5.435***
Reference: No	(0.248)	(0.297)	(0.326)	(0.388)
Working under pressure (1	4.857***	5.253***	4.052***	4.264***
(low) - 4 (high)*)*	(0.141)	(0.169)	(0.174)	(0.207)
Monthly gross wage in euros	0.0205***	0.0169***	0.0136***	0.00212
	(0.00312)	(0.00373)	(0.00404)	(0.00480)
Gender=Women	-5.321***	2.830***	-5.329***	3.745***
Reference: Men	(0.225)	(0.270)	(0.278)	(0.330)
Age	-0.181***	-0.0432***	-0.189***	-0.0549***
	(0.0107)	(0.0128)	(0.0131)	(0.0155)
Middle educated	11.19***	13.93***	8.646***	10.19***
Reference: Low	(0.449)	(0.537)	(0.500)	(0.594)
Highly educated	25.55***	25.72***	18.57***	16.26***
Reference: Low	(0.462)	(0.553)	(0.539)	(0.641)

Year=2012	4.130***	3.667***	-	-
Reference: 2006	(0.295)	(0.353)		
Year=2018	9.373***	6.432***	7.953***	4.412***
Reference: 2006	(0.299)	(0.357)	(0.306)	(0.364)
Work from home	-	-	12.67***	14.69***
Reference: no			(0.322)	(0.382)
Constant	21.70***	18.99***	24.94***	21.84***
	(0.803)	(0.960)	(0.939)	(1.117)
N	42753	42776	26809	26814
Adjusted R2	0.1856	0.1054	0.2357	0.1577

*Note: *** 1% ** 5% * 10%. Standard errors in parentheses.*

Second, we also tested whether our measures point to an increase in the cognitive task content of work in Germany, as it would be expected on the basis of past research. Figure 1 displays the mean of the task measures for our first birth SOEP sample (childless women and men). The steep increase in both measures between 1984 and 2018 suggests that the German labour market indeed underwent a huge transformation over this 30-year period towards more cognitive work intensity. Around the year 2000, interactive tasks became even more common than analytic tasks, which is consistent with findings from the US (Deming 2017). Finally, the plot indicates that the analytic task measure is slightly higher for men than for women, while the interactive task measure is higher for women than for men. This observation was expected, as women are overrepresented in professions that require human interactions (Anelli et al. 2021), but are underrepresented in STEM (Eurostat 2022).

Figure 1. Mean of task measures for childless women and men

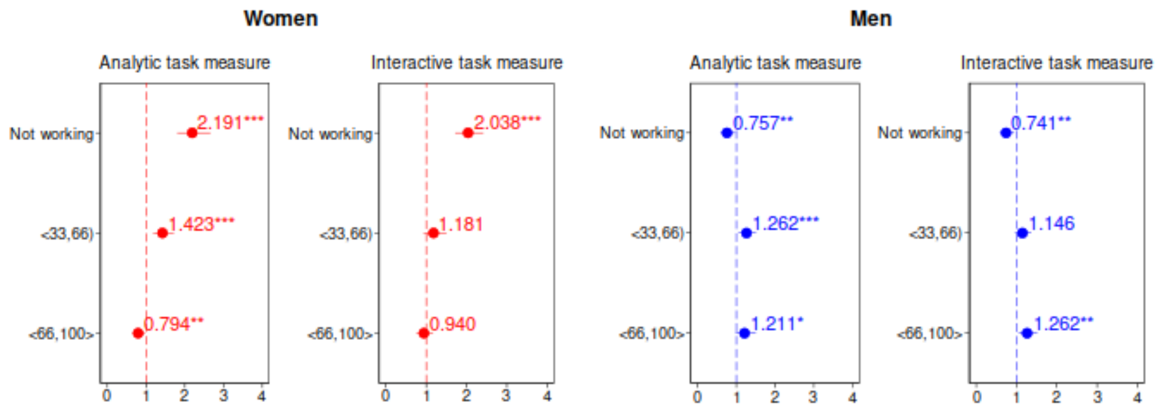


Source: Unweighted estimates from employed respondents in analytical sample. Person-years=58,404 for women, 73,931 for men.

5.2 *Cognitive work and birth transitions: main effects*

We now move to a discussion of the relationships between cognitive work and birth transitions. Figure 2 presents the odds ratios of the respondents' task measures from our initial first birth models. Compared to working women with low cognitive task intensity, women who are not working have odds of entering parenthood that are 100% higher. We do not find a statistically significant association between increased interactive task intensity and first birth risk for women. However, women with a medium analytic task intensity have odds of entering parenthood that are 47% higher than those of their peers with a low analytic task intensity. Finally, women who work in highly analytic occupations have lower odds (by 25%) of transitioning to a first birth compared to the reference level. The observed relationship is strikingly different for men. Men who are not working have significantly lower odds of entering parenthood than working men with low cognitive task intensity. At the same time, men with medium or high cognitive work intensity have increased odds (20%) of having a first birth. While working in an occupation with high analytical and interactive task content seems to be associated with an acceleration of the transition to the first birth among men, the high first birth risks among women who are not in the labour market dominate the pattern.

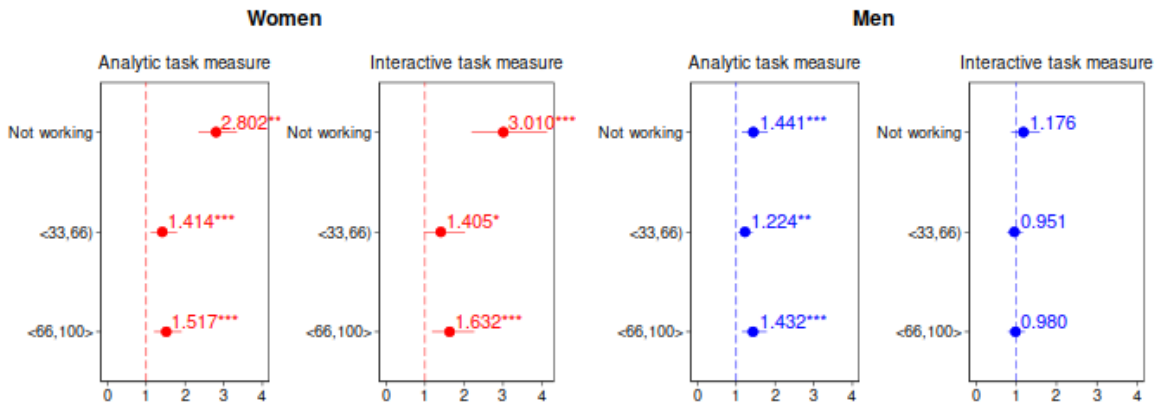
Figure 2. Odds ratios and 95% confidence level. Effect of respondents' task measures on first birth risks.



Note: Further controls in the model are: age (time-varying), period, residence (western vs. eastern Germany), number of siblings, education, and union status. Reference category: low task measure <0,33). N=59,756 for women, 66,084 for men.

Figure 3 reports the odds ratios of cognitive task measures from the basic models for higher order births. As was the case for first births risks, women who did not work two years before their first birth have strongly elevated second and higher order birth risks. However, the association between the cognitive task intensity and higher order fertility is more similar for women and men than it is for first birth risks. Higher order birth risks tend to rise with an increase in the analytic/interactive content of work for both women and men, but the effect is a slightly weaker for men's interactive tasks.

Figure 3. Odds ratios and 95% confidence level. Effect of respondents' task measures on higher order birth risks. 95% confidence intervals.



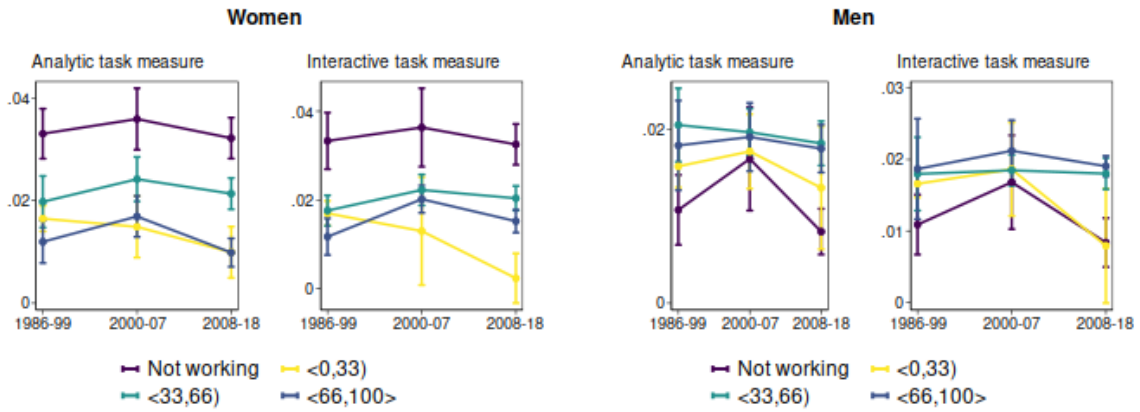
Note: Further controls in the model are: age (time-varying), period, residence (western vs. eastern Germany), number of siblings, education, union status, age of first child, and birth parity. Reference category: low task measure <0,33). N=18,434 for women, 16,908 for men.

Overall, these results imply that employed individuals who perform cognitive tasks progress to the first and to subsequent births more rapidly than others, except for childless women in occupations with high analytic task content.

5.3 Cognitive work and first birth: developments over time

In the second step of our analysis, we interacted the task measures with the calendar period in order to study how birth risks evolved over time for people with different levels of cognitive task intensity. Due to sample size restrictions, this analysis was only conducted for first births. Figure 4 presents the average predicted annual probabilities from those estimations. The findings are similar for both of the task measures. We note a decline over time in first birth probabilities for women with low cognitive task intensity (both analytical and social/interactive) and for non-working men. A less steep decline in first birth probabilities is also found for men with low social/interactive task intensity, but no similar trend is observed for men in occupations with low analytical task content. At the same time, we see that first birth probabilities hardly changed over time for women and men with medium or higher levels of cognitive task intensity. The only exception is that of women with high social/interactive task intensity, among whom first birth probabilities increased somewhat from the 1990s until the mid-2000s; however no further change is observed thereafter. Overall, we find that there was little change in the relationship between performing cognitive work and first birth transition risks for women and men in occupations with high cognitive task intensity. However, it seems that change did occur at the lower tail of the distribution. In particular, we observe that the birth probabilities of women and men in jobs with low interactive task intensity declined over time (for related findings, see Lambert and Kreyenfeld 2023).

Figure 4. Average predicted probabilities from first birth models: interaction of respondents' task measures with period. 95% confidence intervals.

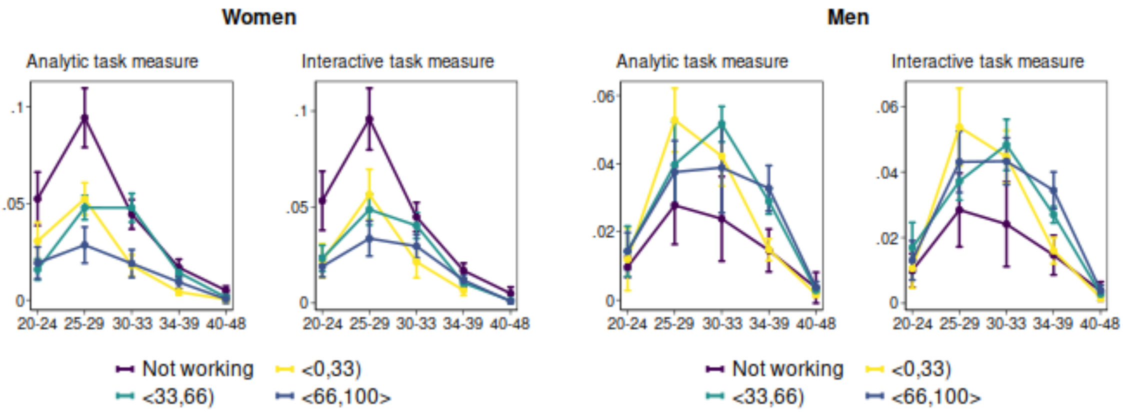


Note: Further controls in the model are: age (time-varying), residence (western vs. eastern Germany), number of siblings, education, and union status. N=59,225 for women, 64,945 for men.

5.4 Cognitive work and first birth: tempo effects

In a final step, we interacted task measures with the baseline (age) in the first birth model. We assumed that among respondents with high task intensities, the transition to the first birth would be accelerated at higher ages, as they entered the labour market later, and may have postponed childbearing due to career considerations. Thus, they would be expected to face greater pressure to have children in a shorter time window. The results presented in Figure 5 partially support this view. The fertility schedule for women and men with higher task intensities (33-66% and 66-100%) are clearly different from those for other men and women. Particularly among men, we see that the birth risks for these groups peak at later ages.

Figure 5. Average predicted probabilities from first birth models: interaction of respondents' task measures with age (time-varying). 95% confidence intervals.



Note: Further controls in the model are: period, residence (western vs. eastern Germany), woman's number of siblings, education, and union status. N=59,225 for women, 64,945 for men.

6 Discussion

Globalisation and technological change have led to tremendous changes in the labour market. These changes, which are reflected in increased demand for cognitive skills and the expansion of flexible work schedules, but also in a greater emphasis on workers' performance, particularly in knowledge-intensive sectors, have led to a divergence of labour market opportunities for cognitive and non-cognitive workers. Moreover, while a large body of demographic research has demonstrated that labour market opportunities are important determinants of fertility behaviours, hardly any research has been conducted on how these diverging opportunities between cognitive and non-cognitive workers have affected their childbearing behaviours. In this study, we sought to fill this research gap. Drawing on the literature on the task content of occupations, we classified occupations into three groups ranging from those that involve low cognitive work to those that involve highly cognitive work. We conducted our study in Germany, which transitioned to a knowledge economy starting in the late 1960s, and currently has a strong demand for highly skilled labour.

The results of our analysis support the findings from prior labour market research, which indicated that the German labour market has undergone a massive transformation in recent years (Baumgarten et al. 2020; Koomen and Backes-Geller 2022). Based on a sample of nulliparous women, we have shown that the share of women and men working in occupations that are characterised by high cognitive task intensity has skyrocketed. At the same time, we found that the impact that occupational features have on birth behaviour has changed. These changes were shown to be most pronounced at the lower end of the distribution. Indeed, we observed that the first birth risks decreased between 1986 and 2018 for all workers with low cognitive task intensity and for non-employed men, while they remained unchanged or even increased slightly for women with high cognitive social/interactive task intensity. These findings suggest that the structural changes in labour demand brought about by technology and globalisation have led to important shifts in the conditions for family formation. These conditions have improved for women and men who have adjusted to current labour market demands by performing cognitive tasks. These improvements may, in turn, have been driven by better employment and/or earning opportunities, as well as by an increase in the flexibility to determine when and where work is performed, which gradually expanded with the spread of information and communication technologies. At the same time, the conditions for earning income and combining paid work with family life worsened for all other workers, who were being increasingly left behind, not only in terms of their options for engaging in economic activity and earning income, but also for having a family. Importantly, the large and even the slight increases in first birth probabilities we observed among women who were working in occupations that required them to perform analytical tasks may signify an important change in gender roles, with the woman's economic position becoming an increasingly important factor in family formation. Nonetheless, it is also noteworthy that we found that non-working women were the most likely to enter motherhood and to have subsequent births over the whole period of our analysis, which suggests that the economic inactivity of women is still highly related to family formation in Germany.

Despite being novel, our study has important limitations. Due to data constraints, we could not perform a more detailed assessment of the task content of occupations that do not require cognitive skills. Although research has established at least two types of such tasks – namely, repetitive/routine tasks, which are most likely to be automated or offshored; and nonroutine manual tasks – we were not able to quantify them in a consistently longitudinal setting (Rohrbach-Schmidt and Tiemann 2013). Thus, while we could draw conclusions about the fertility behaviours of individuals who performed occupations with low cognitive task content, we could not examine whether the workers who were at greatest risk of being affected by the ongoing changes (i.e., those who were performing routine tasks) were most likely to suppress their fertility behaviours. Furthermore, we were not able to measure the task content of work at the individual level because information about job tasks is usually not available in longitudinal surveys. For this reason, we had to rely on occupational task measures. While such measures have been widely applied in top-level research in labour economics (Autor et al. 2003, Autor and Dorn 2013), they conflate the variation in work tasks across individual jobs (Autor and Handel 2013).

Finally, our models suffered from some methodological shortcomings. Selection was an omnipresent problem. We could not rule out the possibility that women (and men) selected themselves into occupations based on their fertility intentions, which may have even affected the first occupation they chose post-education. This issue was alleviated to some extent in the models for higher order births, which is also when women are most likely to change their occupations to accommodate family obligations into paid work. In these models we fixed task measures on the level from the birth year of the first child, though we cannot exclude the possibility that some individuals might have chosen certain occupations already at the early stages in their careers when they already may have had some family plans. Furthermore, the sample of first-time parents may be selected as well. For example, women (and increasingly men) who were working in occupations that made it difficult to combine work and family life may have consciously chosen to remain childless, and thus never entered the risk pool for having a higher order birth. Moreover, the results may have been affected by the use of a standard proportional hazard model for the investigation. This model conflated the timing and the quantum effects of fertility, which may be a shortcoming, because prior studies have shown that particularly career-oriented women and men tend to accelerate the transition to the first birth at advanced ages, and to space their further births more closely together. We speculated that this issue might also apply to women and men working in occupations with high analytical task content. We employed interaction models (of the task measures and the baseline hazard) to address this concern. Future research should establish to what extent this alleviated first birth risk is caused by tempo effects, and to what extent it can be attributed to quantum effects. Mixture cure models might be a promising tool for addressing this problem (see, e.g., Lambert and Kreyenfeld 2023).

Despite these limitations, our study is one of the first to investigate the impact of structural labour market change on fertility. There are only a few previous studies that have addressed this problem, namely Seltzer (2019) and Matysiak et al. (2023), but they adopted a macro-level approach. In our study, we made a first step towards providing a theoretical conceptualisation and empirical assessment of labour market prospects and their role in fertility at the individual level. More research on this topic that applies more refined measures and a cross-country comparative framework is needed. In particular, it remains unclear whether the improving conditions for family formation experienced by cognitive workers relative to non-cognitive workers are caused by better employment and earning opportunities or by the expansion of flexible work schedules that allow workers to better organise their professional activities around their family obligations. For example, men in cognitive jobs may be progressing more rapidly to having another child because they have the economic means to do so, or because their employment conditions allow them to be an involved father who can combine care and family work. It is obviously vital to tease these two components apart because they lead us to completely different conclusions about the gendered effects of the digital transformation of the labour market. The role of growing work demands in the knowledge-intensive sectors is another factor that may affect workers' fertility behaviours, and that has not been sufficiently addressed up to now.

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Appendix

Table A1. Sample sizes. Numbers in the table indicate the sample sizes used for the regression analysis, given missing information (due to lagging or incomplete information in the SOEP).

	Women First Birth	**Men First Birth**	**Women Higher Order Birth**	**Men Higher Order Birth**
Persons	10,077	9,307	2,447	1,996
Person-years	59,756	66,084	18,434	16,908
Events	1,296	1,139	1,304	1,014

Table A2. Full results from first birth models without interactions. Odds ratios.

Covariate	(1) Women	(2) Women	(3) Men	(4) Men
	1st birth	1st birth	1st birth	1st birth
Age=25-29	0.653***	0.672***	1.150***	1.154***
Reference: 20-24	(0.0920)	(0.0868)	(0.149)	(0.145)
Age=30-33	0.192*	0.204**	1.158***	1.165***
Reference: 20-24	(0.114)	(0.0901)	(0.159)	(0.155)
Age=34-39	-0.938***	-0.926***	0.556***	0.566***
Reference: 20-24	(0.107)	(0.107)	(0.167)	(0.160)
Age=40-48	-2.841***	-2.818***	-1.642***	-1.634***
Reference: 20-24	(0.242)	(0.254)	(0.223)	(0.208)
Analytic=NA	-0.00453	-	0.145	-
Reference: Low	(0.345)		(0.218)	
Analytic=Not Working	0.785***	-	-0.278**	-
Reference: Low	(0.0993)		(0.127)	
Analytic=Medium	0.352***	-	0.233***	-
Reference: Low	(0.0963)		(0.0903)	
Analytic=High	-0.231**	-	0.191*	-
Reference: Low	(0.105)		(0.110)	
Period=2000-2007	0.117	0.186**	0.0315	0.0477
Reference: 1986-1999	(0.0821)	(0.0819)	(0.0861)	(0.0865)
Period=2008-2018	-0.0620	0.0272	-0.108	-0.0917
Reference: 1986-1999	(0.0785)	(0.0743)	(0.0892)	(0.105)
Number of siblings=1	0.183**	0.197**	0.0445	0.0478
Reference: 0	(0.0881)	(0.0816)	(0.102)	(0.0981)
Number of siblings=2 or more	0.0497	0.0516	0.0102	0.0101
Reference: 0	(0.0713)	(0.0841)	(0.0815)	(0.0944)

Residence=East Germany *Reference: West*	-0.210***	-0.225***	-0.328***	-0.340***
	(0.0649)	(0.0748)	(0.0801)	(0.0804)
In union=1 *Reference: 0*	0.535***	0.528***	0.842***	0.845***
	(0.0648)	(0.0670)	(0.0789)	(0.0843)
Education=Low *Reference: In education*	0.118	0.161	0.147	0.180
	(0.169)	(0.150)	(0.176)	(0.161)
Education=Middle *Reference: In education*	0.631***	0.704***	0.153	0.199
	(0.129)	(0.130)	(0.164)	(0.160)
Education=High *Reference: In education*	1.332***	1.433***	0.663***	0.712***
	(0.147)	(0.149)	(0.166)	(0.173)
Interactive=NA *Reference: Low*	-	-0.0915	-	0.112
		(0.367)		(0.258)
Interactive=Not working *Reference: Low*	-	0.712***	-	-0.300**
		(0.0870)		(0.122)
Interactive=Medium *Reference: Low*	-	0.167	-	0.136
		(0.122)		(0.0890)
Interactive=High *Reference: Low*	-	-0.0621	-	0.233**
		(0.111)		(0.0940)
Constant	-4.949***	-5.002***	-5.137***	-5.165***
	(0.138)	(0.155)	(0.187)	(0.208)
N	190428	190428	190428	190428
AIC	11355.6	11387.4	10417.3	10419.7
BIC	11538.4	11570.2	10600.2	10602.5

*Note: *** 1% ** 5% * 10%. Standard errors in parentheses. All variables except for baseline (person's age) and period are time-varying and are measured two years before the birth event.*

Table A3. Full results from higher order models without interactions. Odds ratios.

Covariate	(1) Women	(2) Women	(3) Men	(4) Men
	2nd or 3rd birth	2nd or 3rd birth	2nd or 3rd birth	2nd or 3rd birth
Age of first child=6-10	-0.338***	-0.341***	-0.513***	-0.537***
Reference: 0-5	(0.101)	(0.0868)	(0.0978)	(0.0680)
Age of first child=11-26	-1.175***	-1.181***	-1.601***	-1.671***
Reference: 0-5	(0.174)	(0.184)	(0.213)	(0.165)
Analytic=NA	1.220***	-	0.488***	-
Reference: Low	(0.100)		(0.130)	
Analytic=Not Working	1.031***	-	0.365***	-
Reference: Low	(0.0905)		(0.118)	
Analytic=Medium	0.346***	-	0.202**	-
Reference: Low	(0.123)		(0.0794)	
Analytic=High	0.417***	-	0.359***	-
Reference: Low	(0.119)		(0.113)	
Period=2000-2007	-0.0779	-0.0775	-0.201*	-0.0966
Reference: 1986-1999	(0.0832)	(0.0587)	(0.105)	(0.101)
Period=2008-2018	0.101	0.0952	-0.0612	0.0715
Reference: 1986-1999	(0.0818)	(0.0694)	(0.106)	(0.106)
Age=25-29	0.103	0.106	0.255	0.246
Reference: 20-24	(0.144)	(0.149)	(0.325)	(0.349)
Age=30-33	0.170	0.175	0.589*	0.586
Reference: 20-24	(0.141)	(0.153)	(0.333)	(0.356)
Age=34-39	-0.159	-0.150	0.459	0.458
Reference: 20-24	(0.173)	(0.155)	(0.330)	(0.358)
Age=40-48	-1.117***	-1.104***	-0.218	-0.229

Reference: 20-24	(0.218)	(0.232)	(0.365)	(0.391)
Number of siblings=1	0.0773	0.0785	0.193**	0.188**
Reference: 0	(0.0658)	(0.0723)	(0.0788)	(0.0904)
Number of siblings=2 or more	0.143*	0.142**	0.366***	0.350***
Reference: 0	(0.0795)	(0.0613)	(0.0757)	(0.0875)
Residence=East Germany	-0.279***	-0.276***	-0.269***	-0.267***
Reference: West	(0.0775)	(0.0760)	(0.0590)	(0.0854)
In union=1	0.930***	0.926***	0.701***	0.683***
Reference: 0	(0.129)	(0.116)	(0.114)	(0.132)
Education=Low	-0.0429	-0.0521	-0.478**	-0.564**
Reference: In education	(0.218)	(0.197)	(0.229)	(0.242)
Education=Middle	0.00672	0.00182	-0.305	-0.377**
Reference: In education	(0.218)	(0.162)	(0.231)	(0.191)
Education=High	0.291	0.288	0.0406	0.0472
Reference: In education	(0.212)	(0.178)	(0.228)	(0.197)
Parity=Third Birth	-1.054***	-1.054***	-0.897***	-0.890***
Reference: Second	(0.0843)	(0.0723)	(0.0936)	(0.102)
Interactive=NA	-	1.291***	-	0.292**
Reference: Low		(0.152)		(0.137)
Interactive=Not working	-	1.102***	-	0.162
Reference: Low		(0.162)		(0.153)
Interactive=Medium	-	0.340*	-	-0.0504
Reference: Low		(0.187)		(0.105)
Interactive=High	-	0.490***	-	-0.0197
Reference: Low		(0.167)		(0.109)
Constant	-3.759***	-3.825***	-3.281***	-3.079***

	(0.236)	(0.301)	(0.355)	(0.380)
N	41026	41026	41026	41026
AIC	8455.6	8455.3	6982.2	6991.0
BIC	8636.6	8636.3	7163.2	7172.0

*Note: *** 1% ** 5% * 10%. Standard errors in parentheses. Task measures are fixed on the level from the birth year of the first child. All other variables except for baseline (age of the first child) and period are time-varying and are measured two years before the birth event.*

Table A4. Full results from first birth models with interaction of task measures with period. Odds ratios.

Covariate	(1) Women	(2) Women	(3) Men	(4) Men
	1st birth	1st birth	1st birth	1st birth
Age=25-29 *Reference: 20-24*	0.651*** (0.0873)	0.668*** (0.0950)	1.143*** (0.138)	1.148*** (0.158)
Age=30-33 *Reference: 20-24*	0.188* (0.108)	0.197* (0.102)	1.169*** (0.136)	1.177*** (0.144)
Age=34-39 *Reference: 20-24*	-0.933*** (0.111)	-0.924*** (0.113)	0.557*** (0.147)	0.568*** (0.142)
Age=40-48 *Reference: 20-24*	-2.830*** (0.236)	-2.810*** (0.224)	-1.637*** (0.196)	-1.628*** (0.162)
Analytic=Not Working # Period=2000-2007 *Reference: Not Working # 1986-1999*	0.0861 (0.138)	-	0.443* (0.237)	-
Analytic=Not Working # Period=2008-2018 *Reference: Not Working # 1986-1999*	-0.0272 (0.0987)	-	-0.268 (0.270)	-
Analytic=Low # Period=1986-1999 *Reference: Not Working # 1986-1999*	-0.712*** (0.110)	-	0.389* (0.221)	-
Analytic=Low # Period=2000-2007 *Reference: Not Working # 1986-1999*	-0.816*** (0.235)	-	0.495** (0.231)	-
Analytic=Low # Period=2008-2018 *Reference: Not Working # 1986-1999*	-1.227*** (0.270)	-	0.216 (0.305)	-
Analytic=Medium # Period=1986-1999 *Reference: Not Working # 1986-1999*	-0.527*** (0.178)	-	0.659*** (0.228)	-
Analytic=Medium # Period=2000-2007 *Reference: Not Working # 1986-1999*	-0.321** (0.133)	-	0.616*** (0.227)	-

Analytic=Medium # Period=2008-2018 *Reference: Not Working # 1986-1999*	-0.449*** (0.118)	-	0.547*** (0.196)	-
Analytic=High # Period=1986-1999 *Reference: Not Working # 1986-1999*	-1.038*** (0.191)	-	0.534*** (0.189)	-
Analytic=High # Period=2000-2007 *Reference: Not Working # 1986-1999*	-0.687*** (0.154)	-	0.587*** (0.212)	-
Analytic=High # Period=2008-2018 *Reference: Not Working # 1986-1999*	-1.233*** (0.148)	-	0.513** (0.206)	-
Residence=East Germany *Reference: West*	-0.217*** (0.0672)	-0.226*** (0.0722)	-0.316*** (0.0824)	-0.327*** (0.0862)
Number of siblings=1 *Reference: 0*	0.189** (0.0790)	0.199*** (0.0724)	0.0496 (0.0895)	0.0521 (0.0689)
Number of siblings=2 or more *Reference: 0*	0.0606 (0.0881)	0.0593 (0.0723)	0.0178 (0.0965)	0.0176 (0.0837)
Education=Low *Reference: In education*	0.119 (0.172)	0.161 (0.129)	0.145 (0.194)	0.170 (0.177)
Education=Middle *Reference: In education*	0.625*** (0.167)	0.688*** (0.119)	0.119 (0.187)	0.156 (0.178)
Education=High *Reference: In education*	1.321*** (0.191)	1.411*** (0.126)	0.642*** (0.179)	0.684*** (0.142)
In union=1 *Reference: 0*	0.539*** (0.0638)	0.534*** (0.0847)	0.853*** (0.0626)	0.856*** (0.100)
Interactive=Not Working # Period=2000-2007 *Reference: Not Working # 1986-1999*	-	0.0901 (0.191)	-	0.443 (0.274)
Interactive=Not Working # Period=2008-2018 *Reference: Not Working # 1986-1999*	-	-0.0247 (0.130)	-	-0.266 (0.294)

Interactive=Low # Period=1986-1999 *Reference: Not Working # 1986-1999*	-	-0.689*** (0.133)	-	0.429** (0.200)
Interactive=Low # Period=2000-2007 *Reference: Not Working # 1986-1999*	-	-0.961* (0.496)	-	0.547** (0.218)
Interactive=Low # Period=2008-2018 *Reference: Not Working # 1986-1999*	-	-2.666** (1.208)	-	-0.322 (0.530)
Interactive=Medium # Period=1986-1999 *Reference: Not Working # 1986-1999*	-	-0.652*** (0.143)	-	0.511* (0.285)
Interactive=Medium # Period=2000-2007 *Reference: Not Working # 1986-1999*	-	-0.414*** (0.140)	-	0.539** (0.218)
Interactive=Medium # Period=2008-2018 *Reference: Not Working # 1986-1999*	-	-0.504*** (0.112)	-	0.513*** (0.198)
Interactive=High # Period=1986-1999 *Reference: Not Working # 1986-1999*	-	-1.064*** (0.181)	-	0.550* (0.311)
Interactive=High # Period=2000-2007 *Reference: Not Working # 1986-1999*	-	-0.514*** (0.124)	-	0.680*** (0.246)
Interactive=High # Period=2008-2018 *Reference: Not Working # 1986-1999*	-	-0.801*** (0.117)	-	0.570*** (0.204)
Constant	-4.173*** (0.144)	-4.238*** (0.169)	-5.523***	-5.556*** (0.216)
N	190428	190428	190428	190428
AIC	11281.6	11307.9	10243.0	10219.8
BIC	11515.2	11541.5	10476.6	10351.9

*Note: *** 1% ** 5% * 10%. Standard errors in parentheses. All variables except for baseline (person's age) and period are time-varying and are measured two years before the birth event.*

Table A5. Full results from first birth models with interaction of task measures with baseline (age). Odds ratios.

Covariate	(1) Women	(2) Women	(3) Men	(4) Men
	1st birth	1st birth	1st birth	1st birth
Age=25-29	0.653***	0.672***	1.150***	1.154***
Reference: 20-24	(0.0920)	(0.0868)	(0.149)	(0.145)
Age=30-33	0.192*	0.204**	1.158***	1.165***
Reference: 20-24	(0.114)	(0.0901)	(0.159)	(0.155)
Age=34-39	-0.938***	-0.926***	0.556***	0.566***
Reference: 20-24	(0.107)	(0.107)	(0.167)	(0.160)
Age=40-48	-2.841***	-2.818***	-1.642***	-1.634***
Reference: 20-24	(0.242)	(0.254)	(0.223)	(0.208)
Analytic=NA	-0.00453	-	0.145	-
Reference: Low	(0.345)		(0.218)	
Analytic=Not Working	0.785***	-	-0.278**	-
Reference: Low	(0.0993)		(0.127)	
Analytic=Medium	0.352***	-	0.233***	-
Reference: Low	(0.0963)		(0.0903)	
Analytic=High	-0.231**	-	0.191*	-
Reference: Low	(0.105)		(0.110)	
Period=2000-2007	0.117	0.186**	0.0315	0.0477
Reference: 1986-1999	(0.0821)	(0.0819)	(0.0861)	(0.0865)
Period=2008-2018	-0.0620	0.0272	-0.108	-0.0917
Reference: 1986-1999	(0.0785)	(0.0743)	(0.0892)	(0.105)
Number of siblings=1	0.183**	0.197**	0.0445	0.0478
Reference: 0	(0.0881)	(0.0816)	(0.102)	(0.0981)
Number of siblings=2 or more	0.0497	0.0516	0.0102	0.0101

Reference: 0	(0.0713)	(0.0841)	(0.0815)	(0.0944)
Residence=East Germany	-0.210***	-0.225***	-0.328***	-0.340***
Reference: West	(0.0649)	(0.0748)	(0.0801)	(0.0804)
In union=1	0.535***	0.528***	0.842***	0.845***
Reference: 0	(0.0648)	(0.0670)	(0.0789)	(0.0843)
Education=Low	0.118	0.161	0.147	0.180
Reference: In education	(0.169)	(0.150)	(0.176)	(0.161)
Education=Middle	0.631***	0.704***	0.153	0.199
Reference: In education	(0.129)	(0.130)	(0.164)	(0.160)
Education=High	1.332***	1.433***	0.663***	0.712***
Reference: In education	(0.147)	(0.149)	(0.166)	(0.173)
Interactive=NA	-	-0.0915	-	0.112
Reference: Low		(0.367)		(0.258)
Interactive=Not working	-	0.712***	-	-0.300**
Reference: Low		(0.0870)		(0.122)
Interactive=Medium	-	0.167	-	0.136
Reference: Low		(0.122)		(0.0890)
Interactive=High	-	-0.0621	-	0.233**
Reference: Low		(0.111)		(0.0940)
Constant	-4.949***	-5.002***	-5.137***	-5.165***
	(0.138)	(0.155)	(0.187)	(0.208)
N	190428	190428	190428	190428
AIC	11355.6	11387.4	10417.3	10419.7
BIC	11538.4	11570.2	10600.2	10602.5

*Note: *** 1% ** 5% * 10%. Standard errors in parentheses. All variables except for baseline (person's age) and period are time-varying and are measured two years before the birth event.*

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