Structural labor market changes, family behavior, and well-being in Europe

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A dissertation submitted to the University of Warsaw
for the degree of Doctor of Philosophy
under the supervision of prof. dr hab. Anna Matysiak and prof. dr Michaela Kreyenfeld

Warsaw, 2025–03–26

Acknowledgements

First, I would like to thank my advisors, Anna Matysiak and Michaela Kreyenfeld, for their counsel, guidance, and all the opportunities they have provided me. This research would not have been possible without the grant *Globalization- and Technology-Driven Labour Market Change and Fertility (LABFER, no. 866207)*, funded by the European Research Council and awarded to Anna Matysiak.

I am also grateful to the co-authors of my papers, both those included in this thesis and those that are not, as well as to my colleagues in my research network for the chance to learn from them. Special thanks go to my Master's thesis advisor, Piotr Wójcik, and my Bachelor's thesis advisor, Łukasz Byra, for helping me take my first steps in research when I approached them as an eager student.

Finally, I would like to express my gratitude to my family—especially my parents, Anna and Jacek, my brother, Hubert, and my partner, Radost—for their love and support in my scientific endeavors.

Summary

This dissertation examines the socio-economic consequences of technology- and globalization-driven structural labor market changes in Europe, focusing on fertility, return to work after childbirth, and workers' well-being. While labor economics has explored the impact of technology and globalization on employment, less attention has been given to their broader societal effects. Conversely, demographic and sociological studies have analyzed fertility and well-being without incorporating labor market transformations. By bridging these disciplines, this dissertation offers insights into how structural changes in labor shape family behavior and well-being.

The dissertation is based on four empirical papers, three published in international peer-reviewed journals. These studies use macro-level, survey-based, and administrative data, employing quantitative methods such as instrumental variable models and event history analysis. The research examines how structural labor market changes influence family-related decisions and subjective well-being, particularly in relation to socio-economic status and gender. The findings contribute to understanding how technological and economic transformations reinforce social inequalities.

The first paper examines how industrial robot adoption affects fertility rates at the regional level in Europe. It finds that automation's impact is stratified by regional development and education levels. Technologically advanced regions with a better-educated workforce see fertility increases, while less-developed regions with lower-educated populations experience declines.

The second paper explores the link between cognitive work and entry into parenthood in Germany, distinguishing between low- and high-intensity cognitive jobs. It finds that individuals in highly cognitive jobs—performing complex, non-routine tasks—are least likely to remain childless. Thus, cognitive skill demand facilitates family formation, while workers in non-cognitive jobs, more vulnerable to automation and offshoring, face greater economic uncertainty, discouraging parenthood.

The third paper investigates how job task content affects mothers' employment transitions after childbirth in Germany. It shows that mothers in highly cognitive jobs are most likely to return to work after their first child, while those in routine jobs face a higher risk of unemployment. Additionally, women in cognitive jobs are more likely to have a second child. These findings highlight the role of job stability and skill demand in shaping employment and fertility outcomes.

The fourth paper assesses the impact of industrial robot adoption on workers' subjective well-being in Europe. Using an instrumental variables approach, it finds that automation negatively affects medium-educated workers' well-being while benefiting low- and highly educated workers. These adverse effects are particularly strong for women. The well-being impact of automation is moderated by welfare state institutions, with stronger social policies mitigating the effects.

Two key conclusions emerge. First, structural labor market changes create disparities in family behavior and well-being. Automation increases fertility in high-tech regions while decreasing it in lower-educated areas. Workers in cognitive jobs are more likely to become parents than those in non-cognitive jobs. Mothers in highly cognitive jobs return to work more easily, while those in routine jobs face higher unemployment risks. Robot adoption negatively affects medium-educated workers' well-being but benefits both low- and highly educated individuals. These patterns suggest that labor market changes amplify socio-economic inequalities, favoring highly-skilled workers while disadvantaging those in lower-skilled jobs.

Second, the dissertation highlights the gendered effects of labor market transformations. The first paper finds that robot adoption has greater negative effects on fertility in regions where women are overrepresented in manufacturing. The second paper suggests that job characteristics, rather than gender, shape entry into parenthood in Germany. The fourth paper shows that automation has a stronger negative impact on women's well-being than on men's. These findings challenge the conventional view that automation primarily affects male-dominated manufacturing sectors, demonstrating that women's labor market outcomes and well-being may be disproportionately affected.

Given these stratified and gendered effects, the dissertation proposes two policy directions to reduce inequalities. One involves addressing labor market disparities, while the other focuses on lowering the costs of parenthood.

Overall, this dissertation provides new evidence on how technology and globalization affect not only labor markets but also private life, influencing fertility decisions, mothers' employment trajectories, and well-being. By integrating perspectives from labor economics, demography, and sociology, it highlights the broader social consequences of economic transformations and offers policy insights to mitigate their negative effects.

Keywords

structural labor market change, technology, family, fertility, well-being, task content of work, industrial robots, Europe

Streszczenie

Niniejsza rozprawa doktorska bada społeczno-ekonomiczne konsekwencje technologicznych i globalizacyjnych zmian strukturalnych na rynku pracy w Europie, koncentrując się na dzietności, powrocie do pracy po urodzeniu dziecka oraz dobrostanie (ang: *well-being*) pracowników. Podczas gdy ekonomia pracy analizowała wpływ technologii i globalizacji na zatrudnienie, mniej uwagi poświęcono ich szerszym skutkom społecznym. Jednocześnie badania demograficzne i socjologiczne zajmowały się dzietnością i dobrostanem, pomijając transformacje rynku pracy. Dysertacja łączy te perspektywy, dostarczając nowego wglądu w to, jak zmiany w zatrudnieniu kształtują zachowania rodzinne i dobrostan.

Rozprawa opiera się na czterech artykułach empirycznych, z których trzy zostały opublikowane w międzynarodowych recenzowanych czasopismach. Badania wykorzystują dane makroekonomiczne, ankietowe i administracyjne oraz metody ilościowe, takie jak modele zmiennych instrumentalnych i analiza historii zdarzeń. Analizują one wpływ strukturalnych zmian na rynku pracy na decyzje rodzinne i subiektywny dobrostan, ze szczególnym uwzględnieniem statusu społeczno-ekonomicznego i płci. Wyniki przyczyniają się do lepszego zrozumienia, jak transformacje technologiczne i gospodarcze pogłębiają nierówności społeczne.

Pierwszy artykuł bada wpływ wdrażania robotów przemysłowych na wskaźniki dzietności na poziomie regionalnym w Europie. Skutki automatyzacji zależą od rozwoju regionalnego i wykształcenia populacji. W regionach technologicznie zaawansowanych i lepiej wykształconych dzietność rośnie po wdrożeniu robotyzacji, natomiast w mniej rozwiniętych obszarach spada.

Drugi artykuł analizuje związek między pracą kognitywną a wejściem w rodzicielstwo w Niemczech, rozróżniając zawody o różnej intensywności kognitywnej. Wyniki wskazują, że osoby wykonujące złożone zadania kognitywne najrzadziej pozostają bezdzietne. Popyt na umiejętności kognitywne sprzyja zakładaniu rodziny, natomiast osoby w zawodach niekognitywnych, bardziej narażone na automatyzację i offshoring, doświadczają większej niepewności ekonomicznej, co ogranicza ich zdolność do posiadania dzieci.

Trzeci artykuł bada, jak charakter pracy wpływa na przejścia zawodowe matek po urodzeniu dziecka w Niemczech. Matki w zawodach kognitywnych najczęściej wracają do pracy po pierwszym dziecku, podczas gdy kobiety w zawodach rutynowych częściej tracą zatrudnienie. Dodatkowo, kobiety w zawodach kognitywnych częściej decydują się na drugie dziecko. Wyniki podkreślają rolę stabilności zatrudnienia i popytu na umiejętności w kształtowaniu decyzji rodzinnych i zawodowych.

Czwarty artykuł ocenia wpływ robotyzacji na dobrostan pracowników w Europie. Automatyzacja negatywnie wpływa na osoby ze średnim poziomem wykształcenia, przynosząc jednocześnie korzyści osobom o niskich i wysokich kwalifikacjach. Szczególnie dotkliwe skutki dotyczą kobiet. Ponadto, wpływ automatyzacji jest moderowany przez instytucje państwa opiekuńczego – silniejsze polityki społeczne łagodzą jej negatywne konsekwencje.

Z badań wynikają dwa kluczowe wnioski. Po pierwsze, zmiany strukturalne na rynku pracy prowadzą do różnic w zachowaniach rodzinnych i dobrostanie. Automatyzacja zwiększa dzietność w regionach technologicznie rozwiniętych, a zmniejsza ją w obszarach o niższym poziomie wykształcenia. Osoby w zawodach kognitywnych częściej decydują się na rodzicielstwo, a matki w tych zawodach łatwiej wracają na rynek pracy, podczas gdy kobiety w zawodach rutynowych częściej tracą zatrudnienie. Robotyzacja negatywnie wpływa na dobrostan pracowników o średnim poziomie wykształcenia, ale przynosi korzyści osobom o skrajnych kwalifikacjach. Wskazuje to, że zmiany na rynku pracy pogłębiają nierówności, faworyzując wysoko wykwalifikowanych pracowników kosztem osób na mniej wymagających stanowiskach.

Po drugie, dysertacja podkreśla genderowy wymiar transformacji rynku pracy. Pierwszy artykuł pokazuje, że robotyzacja silniej negatywnie wpływa na dzietność w regionach, gdzie kobiety są nadreprezentowane w przemyśle. Drugi artykuł wskazuje, że kluczową rolę w decyzjach o rodzicielstwie odgrywają cechy pracy, a nie płeć. Czwarty artykuł wykazuje, że automatyzacja ma bardziej negatywny wpływ na dobrostan kobiet niż mężczyzn. Wyniki te podważają przekonanie, że automatyzacja dotyka głównie męskie sektory przemysłowe, sugerując, że skutki dla kobiet mogą być równie istotne.

Biorąc pod uwagę te różnice i genderowe skutki, dysertacja proponuje dwa kierunki polityki publicznej w celu zmniejszenia nierówności: jeden skupiający się na eliminacji dysproporcji na rynku pracy, a drugi na obniżeniu kosztów rodzicielstwa.

Podsumowując, rozprawa dostarcza nowych dowodów na to, jak technologia i globalizacja wpływają nie tylko na rynki pracy, lecz także na życie prywatne, kształtując decyzje prokreacyjne, trajektorie zawodowe matek i dobrostan jednostek. Integrując perspektywy ekonomii pracy, demografii i socjologii, podkreśla szersze społeczne konsekwencje transformacji gospodarczych i sugeruje rozwiązania polityczne mające na celu złagodzenie ich negatywnych skutków.

Słowa kluczowe

strukturalne zmiany na rynku pracy, technologia, rodziny, dzietność, dobrostan, zadania wykonywane w pracy, roboty przemysłowe, Europa

Contents

Introduction

This dissertation examines the socio-economic consequences of technology- and globalization-driven structural labor market changes in Europe, with a focus on workers' family-related behavior and well-being[1]. Since the 1980s, technological change and globalization have substantially transformed labor markets in developed economies (OECD, 2019; World Bank, 2019), and they have done so in an age of particularly pronounced economic inequality (Piketty, 2014). Technologies like industrial robots or artificial intelligence, on one hand, and phenomena like offshoring or rising import competition, on the other hand, have caused certain job tasks or even jobs to disappear while creating entirely new tasks and occupations. In fact, a concern about the destabilizing effect progress might have on labor has been present at least since the Industrial Revolution (Mokyr et al., 2015). In recent years, the debate about the impact of contemporary technologies and globalization on labor has been fueled by a few influential studies predicting job losses (Arntz et al., 2017b; Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). Contrary to these studies, most empirical literature has reported mixed effects (Hötte et al., 2023; Hummels et al., 2018). It is clear, however, that technology and globalization destroy *some* jobs (Acemoglu & Restrepo, 2020; Autor et al., 2019; Dauth et al., 2021), in that they make routine skills redundant (Becker et al., 2013; de Vries et al., 2020). At the same time, highly skilled individuals might benefit as a result of these phenomena (Mandelman & Zlate, 2022). In a recently published book, economics Nobel Prize winners (2024) Acemoglu and Johnson (2023) argued that, over human history, technological progress has never led to a long-term increase in aggregate unemployment, but it also has not contributed to shared prosperity, benefiting those rather at the top of the wealth distribution. This reflection aligns with empirical studies showing that automation increases economic inequality (Acemoglu & Restrepo, 2022; Doorley et al., 2023; Prettner & Strulik, 2020).

It does so by modifying the conditions of participation in the labor market. Technology and globalization do not only affect employment but also a range of other labor market outcomes, including wages (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2022; Baumgarten et al., 2013), the gender wage gap (Aksoy et al., 2021; Anelli et al., 2024), working conditions (Antón et al., 2023), and contract type (Gallie, 2017; Rubery, 2015). Much research has focused on how technology and globalization affect socio-economic differences in labor market outcomes, but less is known about other social groups, such as women and their employment patterns in relation to childbearing, as well as workers' subjective well-being. Since work constitutes a major aspect of life, it is inherently tied to various outcomes in the private sphere, including fertility (Alderotti et al., 2021), return to the labor market after childbirth (Arntz et al., 2017b), and well-being (Green et al., 2024). For example, automation and trade competition have been known to cause unemployment in some contexts (Acemoglu & Restrepo, 2020; Autor et al., 2019), while men's unemployment is negatively related to fertility (Alderotti et al., 2021; Buh, 2023). Next, technology and globalization modify the demand for activities done at work. By promoting so-called cognitive tasks, which are associated with increased work intensity (Green et al., 2022), they might make paid work more challenging to combine with parenthood (Adda et al., 2017). Finally, these changes cause fear of job loss for workers (Dekker et al., 2017), which can adversely affect their well-being (Green et al., 2024) and thus the quality of their life. At the same time, however, technology- and globalization-driven labor market changes might have a more positive spillover on the private lives of other workers, for example by facilitating fertility or well-being of the highly-skilled, through increased economic resources. A hypothesis that these structural labor market changes contribute to the contemporary family behavior and well-being dynamics in Europe serves as the cornerstone of this dissertation, which represents a first step in shedding light on these issues. I posit that, by exacerbating a cleavage in work outcomes between higher-skilled and lower-skilled workers, these forces create uneven conditions

[1] This thesis does not cover technologies such as artificial intelligence (AI) or large language models (LLMs). As summarized briefly in Sections 1.1 and 3.2, research on the labor market consequences of these technologies is still in its early stages. At present, the future impact of AI and LLMs on work remains unclear.

for fertility, return to work after birth, and well-being for those two groups.

The focus on three different outcomes in this dissertation, fertility, return to work after the first childbirth, and well-being, is motivated by several considerations. First, these outcomes represent distinct but interconnected aspects of people's lives. Fertility decisions, return to work after childbirth, and well-being are all largely influenced by labor market dynamics and have feedback loops into the labor market. By analyzing them together[2], the dissertation can provide a more comprehensive insight into how structural labor market changes shape individuals' lives. This broadens the understanding of inequality beyond wages and employment, highlighting its far-reaching consequences. Second, policymakers are often interested in comprehensive strategies to address socio-economic challenges. By analyzing these outcomes together, the dissertation provides insights into how labor market changes create vulnerabilities or opportunities across different dimensions of life. This integrated approach could better inform policy interventions aimed at promoting work-life balance, reducing inequalities, and improving societal well-being. Finally, while the labor market impacts of technology and globalization have been widely studied, their ripple effects on fertility, return to work, and well-being remain underexplored. The dissertation can thus fill a timely research gap by providing insights into these less examined but highly socially significant areas. Even beyond the academic community, low fertility rates, gender equity in the workplace and private sphere, and mental health/well-being are pressing and hotly debated issues in Europe. Analyzing them as outcomes of structural labor market changes aligns the dissertation well with contemporary social and economic debates.

This interdisciplinary dissertation begins by linking four relevant strands of research together: economic literature on the impact of technology and globalization on labor (Section 1.1), demographic literature on labor market outcomes and fertility (Section 1.2), economic literature on the career cost of children and gendered labor market outcomes (Section 1.3), and socio-economic literature on labor market and well-being (Section 1.4). The literature review is followed by a description of the innovations and contributions of the thesis (Section 1.5). The core of the thesis comprises four empirical studies (Chapter 2), three of which have already been published in international journals (*European Journal of Population*, *Population Studies*, *Journal for Labour Market Research*). This collection of connected studies investigates the link between structural labor market changes, fertility, return to work after childbirth, and well-being in a relatively encompassing way in that it uses two different methodologies of assessing labor market changes (industrial robot adoption and task content of jobs; see Section 1.1), three types of data (macro, survey, and administrative), as well as several quantitative methods (econometric and demographic). While relatively broad, the paper series does not exhaust the topic.

Paper I, titled “Industrial Robots and Regional Fertility in European Countries” and co-authored by Anna Matysiak and Daniela Bellani, examines the effect of automation on age-specific and total fertility rates in several European countries representing different institutional settings—Czechia, France, Germany, Italy, Poland, and the United Kingdom (Matysiak et al., 2023). Industrial robot adoption can cause both a displacement effect, where workers are replaced by machines, and a productivity effect, where automation boosts economic activity and thus leads to job creation (Acemoglu & Restrepo, 2018). Whether one or both effects occur, and their magnitude, depends on regional characteristics such as the degree of industrialization or the educational attainment of the population. We expect that the widely documented effects of robots on employment (see a meta-analysis by Hötte et al., 2023) have a spillover effect on fertility. As a result of industrial robot adoption, fertility should decline in highly industrialized regions and those with lower-educated workers. At the same time, it might increase in more technologically developed regions with better-educated populations.

To verify these expectations, we link Eurostat regional data (NUTS-2) on fertility[3] and industry-specific employment with robot adoption data from the International Federation of Robotics[4]. We use fixed-effects linear panel models with instrumental variables to account for external shocks that could influence both fertility and robot adoption. Our results suggest that robot adoption may negatively affect fertility in highly industrialized regions, areas with lower-educated populations, and regions that are less technologically advanced. In contrast, regions with higher education levels and greater economic

[2]These outcomes are interconnected in a non-trivial way. Extensive evidence finds a spillover effect from work to life satisfaction (Green et al., 2024; Sirgy et al., 2001), making it unsurprising that subjective well-being moderates the relationship between job uncertainty and fertility intentions (Vignoli et al., 2020b). In low fertility settings, life satisfaction is also a strong predictor of actual fertility (Mencarini et al., 2018). On the other hand, subjective well-being is heavily influenced by experiences surrounding previous childbearing and is moderated by perceived work-family conflict (Luppi & Mencarini, 2018; Matysiak et al., 2016). Thus, well-being can be both a moderator between labor market outcomes and family formation, and an outcome influenced by previous fertility. While I do not analyze this mediation effect in this dissertation, I acknowledge its validity as a future research avenue in the limitations section.

[3]Eurostat, 2024d.

[4]International Federation of Robotics (IFR), 2020a.

prosperity may experience fertility increases due to automation. In summary, it appears that a region's focus on knowledge and technological innovation plays a significant role in how robots impact fertility, as some regions are better equipped than others to adapt to robot adoption.

In **Paper II**, titled "Structural labour market change, cognitive work, and entry to parenthood in Germany" and co-authored by Anna Matysiak and Michaela Kreyenfeld, we investigate the association between the spread of cognitive work and entry into parenthood in Germany (Bogusz et al., 2024). Over the last three decades, technology and globalization have vastly transformed labor markets in advanced economies, resulting in a growing disparity between workers in cognitive versus non-cognitive jobs. Labor demand for cognitive job tasks has consistently grown, along with a surging demand for non-cognitive tasks (Hardy et al., 2018; Rohrbach-Schmidt & Tiemann, 2013). This has led to increasing inequalities in earnings, job stability, and career opportunities between these two groups of workers. Since individuals' labor market situations are closely linked to their fertility decisions (Alderotti et al., 2021), we expect that this inequality affects entry into parenthood, with non-cognitive workers at a higher risk of remaining childless compared to cognitive workers.

To study this association, we link the cognitive task content of occupations, derived from data provided by the Employment Survey of the German Federal Institute for Vocational Education and Training[5], to individual life histories from the German Socio-Economic Panel, spanning 1984–2018[6]. We use event-history hazard models to analyze transitions into parenthood. Our findings show that both women and men in highly cognitive occupations tend to postpone parenthood initially but later accelerate it, resulting in the lowest probability of remaining childless by age 50. These patterns emerge only after 2000, with no significant differences observed in earlier periods. The findings suggest that structural changes in the labor market are amplifying inequalities not only in employment outcomes but also in family formation between low-skilled and highly skilled individuals.

In the single-authored **Paper III**, titled "Task content of jobs and mothers' employment transitions in Germany", I expand on the analysis from Paper II by examining the relationship between the task content of jobs and mothers' labor market reentry after their first childbirth (Bogusz, 2024). Cognitive jobs are generally less compatible with maternity-related career breaks (Adda et al., 2017), as they are characterized by greater work intensity than other types of jobs (Green et al., 2022). This leads to the expectation that mothers in cognitive jobs might be more inclined to return to work quickly after maternity leave. At the same time, routine jobs are at the highest risk of job displacement. Thus, recent mothers in routine jobs might face an elevated risk of technological unemployment after maternity leave.

I combine two data sources to verify these expectations. To quantify the task content of jobs, I again use data from the German Federal Institute for Vocational Education and Training's Employment Survey[7] and link these measures to individual employment and fertility records from the German Pension Fund, covering 2012–2020[8]. Using competing risks models, I estimate the probabilities of four post-birth outcomes: returning to employment, transitioning to unemployment, having a second child, or remaining inactive. The results indicate that women in occupations with high analytic and interactive task intensity—positions that are in high demand but less compatible with maternity breaks—are most likely to return to work after their first child. Conversely, women in routine-intensive jobs, which are more susceptible to automation and trade competition, are more likely to face unemployment. However, women in highly cognitive occupations are also more likely than women in routine-intensive jobs to transition directly to a second birth. All in all, structural labor market changes exacerbate both inequalities in family formation and the heterogeneous costs of motherhood by creating an advantageous position for women in cognitive jobs while disadvantaging women with routine jobs.

Finally, **Paper IV**, titled "Industrial robots and workers' well-being in Europe" and co-authored by Daniela Bellani, estimates the effect of automation (conceptualized again as industrial robot adoption) on workers' subjective well-being in Europe (Bogusz & Bellani, 2025). Industrial robots exert a heterogeneous impact on employment (Hötte et al., 2023). The debate on this topic is ongoing, but overwhelming evidence suggests that this effect might be polarized, with medium-skilled workers, often employed in manufacturing, being adversely affected (e.g. Autor & Handel, 2013; Goos et al., 2009; Oesch & Rodríguez Menés, 2010). At the same time, the productivity effect of automation creates new jobs for both low- and highly skilled individuals.

We expect that this inequality has a spillover effect on workers' well-being, which is generally closely

[5]Bundesinstitut für Berufsbildungsforschung (BIBB), Berlin, & Institut für Arbeitsmarkt- und Berufsforschung (IAB) der Bundesanstalt für Arbeit, Nürnberg, 1983, 1995, 2016; Hall and Tiemann, 2020; Hall et al., 2020b, 2020a; Rolf and Dostal, 2015.

[6]Socio-Economic Panel (SOEP), 2021.

[7]Hall and Tiemann, 2020.

[8]Forschungsdatenzentrum der Rentenversicherung (FDZ-RV), 2024a, 2024b.

associated with their employment situation (Green et al., 2024). To test this hypothesis, we compute a measure of robot density at the country-industry level by combining robot stock data from the International Federation of Robotics[9] with employment data from Eurostat[10]. This measure is merged with individual-level data from the European Social Survey (2002–2018)[11] to form a pseudo-panel. Using linear models with instrumental variables, we interact robot density with education to account for differences in skill level. Our evaluation of subjective well-being considers multiple aspects: life satisfaction, eudaimonic well-being, and affective well-being. A heterogeneity analysis is also conducted based on gender, age, and welfare state type. Our findings show that robot adoption adversely affects the well-being of medium-educated workers. Conversely, robots positively impact the well-being of both low- and highly educated workers. These effects are weaker in countries with relatively robust welfare states, such as Continental and Scandinavian countries, and are particularly pronounced among women. At the same time, we find minimal differences by age. Overall, our findings show that robots not only affect employment but also have far-reaching consequences for individual well-being and, thus, overall quality of life.

The four papers are followed by a conclusions section (Chapter 3) where I summarize the findings, discuss the limitations, and propose avenues for further research. I also consider the policy implications, although I recognize that this is a challenging task given the limited scope of current research on the topic.

1.1 Structural labor market changes

Adoption of new technologies has introduced permanent changes to the structure of labor demand and thus significantly influenced the ways we work (OECD, 2019; World Bank, 2019). Since the Industrial Revolution, workers have been continuously subject to coping with and producing new technologies, adjusting their skills to emerging innovations, or facing job displacement (Bellani & Bogusz, 2024; Gallie, 2017; Leontief, 1983; Mokyr et al., 2015). In a study on OECD countries, Arntz et al. (2017b) estimated that approximately 10% of occupations performed by humans will be fully automated in the next two decades, and in a further 25% of occupations, 50-70% of tasks will be automated. Globalization is another force that has been shown to affect labor markets in developed economies, e.g. by moving routine jobs to low-income countries ("offshoring"), lowering trade or immigration barriers, thereby creating competition for (especially manufacturing and low- and medium-skilled) workers (OECD, 2019; World Bank, 2019). This increased competition was argued to be a main source of the recent flexibilization of the Western labor markets, seen in the spread of unstable contracts, decreased access to social benefits, and an employer-oriented flexibility (Gallie, 2017; Rubery, 2015).

However, technological change does not only cause precarity and displacement, but it can also foster possibilities for some workers, e.g. by creating new occupations, needed to adjust production to emerging technologies. At the same time, globalization reinforces demand for skilled labor through increased competition. Labor demand is rising particularly strongly for highly educated workers with non-routine cognitive skills, especially in such sectors like engineering, high tech and IT but also for professionals in the service sector (Acemoglu & Autor, 2011; Deming, 2017). They enjoy steep career prospects with opportunities for professional advancement, greater work autonomy, and good pay (De La Rica et al., 2020). However, while the high-skilled workers may have greatly benefited from technological change, their work is becoming more demanding (Korunka & Kubicek, 2017). The so-called *effort-biased technical change* leads to intensification of work by improving the managerial control of the labor process and creating new forms of work (Green, 2004; Green et al., 2022), thereby pressuring workers to constantly improve their skills, adjust to new technologies and remain continuously connected to work, all of which can cause psychological distress and job strain (Mauno et al., 2023).

Two strands of literature have been offered to distinguish workers who gain and lose from these structural labor market changes. The first one advocates for *skill upgrading* or *skill-biased technological change*, namely a phenomenon, where, with the growing importance of knowledge to the production processes and the increased technological advancements, post-industrial societies will be characterized by steadily rising levels of skill (Gallie, 2017). In such a scenario, all workers are subject to a constant pressure to upgrade their skills and the highly-skilled gain, while everyone else loses. Using direct skill measures, and measures of occupational change, Handel (2012) found evidence of skill upgrading for most

[9] International Federation of Robotics (IFR), 2020a.

[10] Eurostat, 2023a.

[11] European Social Survey European Research Infrastructure (ESS ERIC), 2018a, 2018b, 2023a, 2023b, 2023c, 2023d, 2023e, 2023f, 2023g.

continental European countries. Fernández-Macías (2012) demonstrated an expansion of higher level skill categories in Europe. In the Anglosaxon countries, it was accompanied by polarization, whereas in others, the trend was unambiguous skill upgrading. More recently, Oesch and Piccitto (2019) analyzed occupational change for Germany, Spain, Sweden, and the United Kingdom from 1992 to 2015. They found clear occupational upgrading in Germany, Spain, and Sweden, as opposed to the UK, where some polarization in earnings could be identified.

The second line of research argues for *skill polarization* in the context of relative occupational wage position, i.e. it claims that demand is not only rising for the highly-skilled labor, but also for the low-skilled service workers, while the middle-skilled (mostly manufacturing) workers lose out as a result of decreased demand for routine jobs. However, even as demand for low-skilled jobs grows, low-skilled individuals must compete with displaced middle-skilled workers for those positions. This is sometimes referred to as the *routine-biased technological change* or the *routinization* hypothesis. There is an overwhelming empirical evidence of skill polarization in the U.S. (Autor & Dorn, 2013; Autor et al., 2003, 2006; Wright & Dwyer, 2003) and the UK (Goos & Manning, 2007) in earlier periods. These two countries have particularly high levels of wage and income inequality compared to most other developed nations (Piketty, 2014). However, more recent studies have shown that the skill polarization is occurring in Europe as well (Goos et al., 2009; Maarek & Moiteaux, 2021; Oesch & Rodríguez Menés, 2010; Peugny, 2019), which might be related to its rising income and wage inequalities (Blanchet et al., 2022). Overall, which approach, skill upgrading or polarization, explains labor market changes better remains unclear. In both models, however, the highly-skilled benefit, while low- and medium-skilled workers fall behind.

Past research on skill polarization has frequently used the *task content of jobs* framework to quantify the changing structure of demand for skills (Acemoglu & Autor, 2011; Autor et al., 2003; Hardy et al., 2018). This approach posits that occupations consist of a variety of tasks, and the composition of those tasks is modified with changes in labor demand. The literature proposed five task domains (Autor et al., 2003; Hardy et al., 2018; Spitz-Oener, 2006). The *analytic* category quantifies activities that require a complex analysis of data or concepts, such as programming or conducting statistical analyses. Next, *interactive* or interpersonal tasks rely on human interactions, such as counseling or negotiating. These latter two categories are currently the most difficult for machines to take over or to be moved to countries with lower labor costs, while the remaining three types are subject to automation and offshoring. The *non-routine manual* category comprises tasks done in a non-repetitive manner but using one's hands, such as massaging or hair styling. This is in contrast to *routine manual* tasks, defined as those performed with one's hands in a constant way, such as cleaning or sorting goods on a factory production line. The final category, *routine cognitive*, quantifies activities of a cognitive nature but performed in a routine fashion, such as measuring or bookkeeping.

It has been widely demonstrated that workers who perform analytic and interactive tasks, collectively referred to as non-routine cognitive tasks, are in high demand in the labor markets of advanced economies (Cortes et al., 2021; Deming, 2017; World Bank, 2019). They are more likely to secure and sustain employment (Deming, 2017; Deming & Kahn, 2018), experience upward occupational mobility (Fedorets, 2019), see increases in pay (Borghans et al., 2014; Deming, 2017), have higher occupational prestige and satisfaction (Oesch & Piccitto, 2019), and enjoy more stable contracts (Peugny, 2019). Simultaneously, the labor market opportunities for workers whose occupations involve routine and manual tasks have been deteriorating (Hardy et al., 2018; World Bank, 2019). Studies have shown that these workers are displaced and face unemployment as a consequence of automation (Acemoglu & Autor, 2011) or offshoring (Autor et al., 2013). On the other hand, there is an expansion of the labor demand for manual workers, employed in the small service economy (e.g., Uber drivers, delivery workers), whose jobs cannot be easily automated (Autor & Dorn, 2013; Goos et al., 2009). This expansion of jobs at the low end of the economy does not, however, go hand in hand with improvements in job quality, one of the fundamental determinants of individual well-being (Green et al., 2024).

The second approach is related to deroutinization, focusing on measuring workers' exposure to industrial robots and its impact on labor (as industrial robots predominantly replace routine tasks or entire jobs). According to the International Federation of Robotics, industrial robots are fully autonomous machines that do not require a human operator (Jurkat et al., 2022). Robot adoption reflects technological innovation and serves as an indicator of economic and labor market transformation (Dottori, 2021). In the EU alone, the stock of industrial robots per 10,000 manufacturing workers has tripled since the mid-1990s, reaching 114 in 2019, and it was not stalled by economic crises such as the Great Recession (International Federation of Robotics (IFR), 2020b). Studies have highlighted the destabilizing effect that robots have on labor. In the U.S., one robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42% (Acemoglu and Restrepo, 2020). In Germany, industrial robots lead to job loss in the manufacturing sector, but this is fully offset by productivity-induced job creation in other sectors (Dauth et al., 2021). Consistent with this finding, Graetz and Michaels (2018) demonstrated no aggregate displacement effect in 17 OECD countries; however, they documented a reduction in the employment share of low-skilled workers. Other papers identified a positive effect of robots on labor in France (Acemoglu et al., 2020) and the U.S. (Chung & Lee, 2023), in line with the argument that robots might cause job displacement at early stages of automation, but eventually reinstate it through the productivity effect of innovation at more advanced stages of the technological process (Acemoglu & Restrepo, 2018). Recently, a systematic review of 127 studies on technological change and employment has shown that technology affects adversely low-skilled and manufacturing workers, but, in aggregate terms, this displacement is more than offset by labor creation in other sectors (Hötte et al., 2023). Besides the effect on employment and wages, robotization has also been shown to affect related phenomena such as gender wage gap (Aksoy et al., 2021), family formation and dissolution (Anelli et al., 2024), mortality (O'Brien et al., 2022), voting (Anelli et al., 2021), workers' physical and mental health (Abeliansky et al., 2024; Gihleb et al., 2022), as well as alcohol abuse (Lu & Fan, 2024).

While the task content of jobs was designed to conceptualize structural labor market changes at the worker or occupation level, workers' exposure to robots is usually measured at the local labor market level, enabling a regional-level analysis (Acemoglu & Restrepo, 2020). Moreover, task content of jobs conveys both the impact of technology and globalization on labor, while the adoption of industrial robots focuses by definition on automation. Since this dissertation uses those two approaches, it is somewhat skewed towards the topic of automation. However, researchers have vastly examined the effects of offshoring and import competition on labor markets too. These forces move production to countries with lower costs of labor, thereby leading to a displacement of manufacturing jobs. This was shown empirically to be the case in manufacturing-savvy countries like the U.S. (Autor et al., 2019; Autor et al., 2013) and Germany (Baumgarten et al., 2013; Dauth et al., 2017; Huber & Winkler, 2019; Keller & Utar, 2023). Relatedly, the impact of offshoring on fertility has already been examined in two studies on Germany, which identified negative effects (Giuntella et al., 2022; Piriu, 2022). For that reason, offshoring and import competition are not tackled explicitly in this dissertation. The greater focus on automation is further motivated by the fact that technology is the most important factor in explaining the contemporary shift from routine to non-routine cognitive work observed in the developed world (Lewandowski et al., 2022).

In recent years, additional approaches to quantifying the impact of technology and globalization started to emerge. The central and currently most discussed one is workers' exposure to artificial intelligence (AI) (Brynjolfsson & Mitchell, 2017). Papers published before the development of Chat GPT and based on the U.S. context showed little evidence of a negative impact of AI on labor (Acemoglu et al., 2020; Brynjolfsson et al., 2018). Lately, papers forecasting the labor market implications of large language models have begun to appear (Eloundou et al., 2023; Felten et al., 2023; Gmyrek et al., 2023). For example, Eloundou et al. (2023) predicted that approximately 80% of the U.S. workforce could have at least 10% of their work tasks affected by large language models. However, since there is no strong evidence of a negative impact of AI on employment yet, it is too early to assess the influence of AI-driven employment uncertainty and its potential impact on family formation. While certainly being a worthwhile research avenue for the future, this topic is not addressed in this dissertation.

In addition to the issues discussed above, structural labor market changes is also reflected in phenomena such as the spread of information and communication technologies (ICT) or home-based work. Recent research shows that they can have an impact on various socio-economic outcomes such as fertility (Osiewalska et al., 2024), health (Hsu & Engelhardt, 2024), or the division of work between partners (Wang & Cheng, 2023). However, these developments change the way we work, rather than modify the structure of labor demand. While related, they are not the focus of this thesis.

1.2 Labor market and fertility

Interdisciplinary research in labor economics and family demography has provided substantial evidence on how labor market outcomes influence family formation, including fertility. Two key strands of literature are particularly relevant to this thesis: the theoretical literature linking individuals' labor market outcomes to fertility, and the empirical literature on economic uncertainty and fertility.

Theoretically, this issue was first addressed in economic research in the 1980s with the introduction of *new home economics* (Becker, 1993). Becker proposed a specialization framework in which one partner (typically the man) focuses on paid work, while the other (typically the woman) concentrates on household production. In this model, childbearing is positively linked to household income, as children represent a direct cost (*income effect*). However, parents can also choose to invest in the "quality" of children rather than having additional ones. Later, as female labor market participation in the U.S. grew, Becker noted that children impose an opportunity cost on women (*substitution effect*).

New home economics faced criticism from Ferber (1995), who argued that it assumes specialization maximizes the well-being of all family members, applies only to different-sex couples, and is unsuitable for the context of highly educated women in the marriage market, who might not want to specialize in household production. In parallel, Oppenheimer (1997) proposed a new theoretical framework, suggesting that an increase in women's educational attainment can lead to lower marriage rates on one hand, but higher union stability on the other. She argued that highly educated women with independent incomes are better able to choose suitable partners. Additionally, she posited that, in the face of male employment instability, women's income can positively influence childbearing. Thus, through higher union stability and the income effect, the growing female employment rate should lead to fertility increase. All in all, these critics of new home economics posited that women's labor force participation does not have to be conflict with family formation and its stability.

From an institutional perspective, McDonald (2000) observed that gender equity manifests in two distinct realms: individual-oriented institutions (such as education systems and the labor market) and family-oriented institutions. He noted that while women had made progress in accessing individual-oriented institutions, gender equity was still lacking in family-oriented institutions. In these contexts, women faced a double burden, balancing both paid employment and domestic responsibilities. This idea was further developed by Esping-Andersen and Billari (2015) and Goldscheider et al. (2015). The former developed a multiple equilibria model which posited that low fertility is a result of the lack of alignment between women's desire to combine paid work with care on equal terms with their partners and the actual division of paid labor within the couple. The latter introduced what demographers now call the *gender revolution theory*. In the first stage of the gender revolution, female labor market participation rises, but women continue to bear the primary responsibility for domestic work and child-rearing. As they face the opportunity costs of childbearing, fertility declines. In the second stage, men become more involved in household production, leading to a rebound in fertility as partners share paid and domestic work more equally.

This pattern is partially evident in Nordic countries, where policies promoting gender equality in employment and caregiving have been implemented. For instance, Duvander et al. (2019) and Lappegård and Kornstad (2020) found that couples in which fathers take parental leave after the birth of their first child are more likely to have a second child. The gender revolution theory has been used to explain the increase in total period fertility observed in the Nordic countries between 2000 and 2008 (Jalovaara et al., 2019), when fertility rates reached approximately 1.9—among the highest in Europe at the time. However, since the 2008 financial crisis, fertility in these countries has declined again, suggesting that factors beyond shifting gender roles may be influencing the trend. Nevertheless, the second stage of the gender revolution remains incomplete across Europe, including in the Nordic countries, where women still have lower labor market attachment than men (Eurostat, 2024b) and continue to shoulder a greater share of unpaid caregiving labor (Eurostat, 2019).

There is no consensus within the demographic community on which theory is the most salient or universal. In fact, each theory is heavily shaped by the time and context in which it was developed—such as the post-war U.S. in the case of Becker (1993) versus contemporary Scandinavian countries in the context of Esping-Andersen and Billari (2015) and Goldscheider et al. (2015). However, all of these theories (except for new home economics) highlight a key factor: normative gender roles. The impact of labor market outcomes on fertility is not universal, but gendered. While all three theories suggest that male labor market participation, employment, and income positively affect fertility, the role of female labor market outcomes is more ambiguous. This has often been addressed in empirical research on economic uncertainty (i.e., instability in employment or monetary outcomes) and fertility. A recent bibliometric analysis of papers published in the three leading demographic journals (*Demography*, *Population Studies*, *Population and Development Review*) between 1950 and 2020 found a significant increase in the proportion of studies on women's labor market participation, along with smaller increases in research on income and education—all linked to economic uncertainty (Merli et al., 2023). This trend has been accompanied by a decrease in the share of papers on demographic transitions, an older prominent narrative in demographic research. These findings underscore the relevance and timeliness of research that combines economic inequality and gender inequality. Contemporary studies on economic uncertainty and fertility, which I summarize below, fall within this scholarly tradition and are particularly relevant to this dissertation.

According to economic theory, childbearing involves both a direct, monetary cost (expenditures on children) and an indirect cost (lost opportunities) (Becker, 1993). When employment and income are uncertain, people may postpone having children until the uncertainty is resolved. This idea was first discussed by Ranjan (1999), who developed a theoretical model suggesting that fertility postponement is an optimal solution for individuals facing economic uncertainty, given that fertility decisions are irreversible and postponing fertility is possible, at least to some extent. While this model may explain fertility behaviors in couples where a man's economic situation is uncertain, the links between uncertainty surrounding female employment careers and fertility are less clear. According to Kreyenfeld (2009), these links depend on whether a woman is expected to be a caregiver or a household provider after childbirth.

The concept of economic uncertainty was further developed in the *narrative framework* (Vignoli et al., 2020a, 2022), which posits that uncertainty means the absence of clarity about one's future possibilities, making it difficult to make rational decisions about future events. In this context, individuals tend to consider not only past experiences and present status (the *shadow of the past*), but also future expectations (the *shadow of the future*), which are shaped by the available information. These ideas were tested experimentally, showing that a negative perception of future economic uncertainty is linked to lower fertility intentions (Lappegård et al., 2022; Vignoli et al., 2022). Conversely, a perception of resilience to job loss is a predictor of higher fertility intentions (Gatta et al., 2022).

Beyond experimental approaches, economic uncertainty has also been empirically assessed using objective measures such as unemployment, contract type, or income. A meta-analysis by Alderotti et al. (2021) demonstrated that male unemployment and temporary contracts depress fertility in Europe (Adserà, 2005; Andersen & Özcan, 2021). Meanwhile, male income is positively related to fertility (Hart, 2015; Vignoli et al., 2012). In contrast, women in various high-income countries often use employment instability as an opportunity to have children (Adserà, 2004; Andersen & Özcan, 2021; Kreyenfeld, 2009; Kreyenfeld & Andersson, 2014; Kristensen & Lappegård, 2022). Other studies show that fertility responds negatively to both male and female job loss, though the effect is smaller for women (Di Nallo & Lipps, 2023; Huttunen & Kellokumpu, 2016; Vignoli et al., 2012). Similarly, the meta-study by Alderotti et al. (2021) found that in countries with high gender equality, such as the Nordic countries, or in countries characterized by unstable male employment, such as Southern Europe, women no longer use unemployment as an opportunity to have children. The study also found that temporary contracts have a stronger negative effect on fertility when held by women than by men.

Two recent studies offer new insights into the relationship between women's labor market outcomes and fertility. In the Netherlands, van Wijk (2024) found that first birth probabilities are increasingly positively associated with both female and male income, though the income effect is stronger for men. In Germany, Kreyenfeld et al. (2023) reported that second birth probabilities are higher for both women and men in service classes. In a review of recent developments in the economic uncertainty-fertility literature, Matysiak and Vignoli (2024) concluded that the relationship between labor market outcomes and fertility has become less gendered, though more studies are needed.

To sum up, while men's labor market outcomes remain positively related to fertility, the effects of economic activity on family-related behaviors have likely become more similar across genders as women gain increasing economic independence. Although the debate on the relationship between socio-economic status and fertility remains active, it appears that highly educated workers and members of higher social classes now face better conditions for realizing their fertility intentions than their lower-educated counterparts and those from lower social classes.

Past research on economic uncertainty and fertility has primarily relied on unemployment or contract type to measure instability—factors strongly linked to the business cycle (Hoynes et al., 2012; Pissarides, 2013; Ravn & Sterk, 2017; Schaal, 2017). Recently, however, scholars have started to examine the role of labor market changes that occur over longer time scales, typically using a macro-level approach. Technology and globalization, which reshape labor demand and the nature of work, are key drivers of such changes (OECD, 2019; World Bank, 2019). These issues were first discussed in the context of fertility in a paper on the U.S. by Seltzer (2019) and a study on Europe by Matysiak et al. (2021). Both examined the fertility decline around the Great Recession and concluded that the economic downturn accounted for only a small portion of the fertility decline. Instead, they attributed a larger role to structural changes in labor market conditions, often measured by *long-term* unemployment rates. The authors of both studies suggested that technology and globalization might be driving these changes, leading to further research focused on these factors. Autor et al. (2019) showed that offshoring led to a loss of male manufacturing jobs in the U.S., which lowered their success on the marriage market and consequently, their birth rates. Anelli et al. (2024) demonstrated a similar mechanism with industrial robot adoption in the American context. In Germany, Giuntella et al. (2022) found that exposure to greater import competition from

Eastern Europe resulted in worse labor market outcomes and lower fertility rates. Piriu (2022) reported similar findings related to trade shocks from Chinese imports to Germany: these had a negative effect on male fertility and a positive effect on female fertility, driven by reduced opportunity costs of having children. Keller and Utar (2022) observed the same mechanism in Denmark: a gender-neutral import shock resulted in gendered outcomes, with women in their late 30s—towards the end of their biological clock—deciding to have children due to job displacement. Overall, this body of research suggests that technology- and globalization-driven structural labor market changes may negatively affect fertility, with medium-skilled male manufacturing workers being the most adversely affected.

1.3 Gendered labor market outcomes

Women in developed countries face numerous disadvantages in the labor market, a dynamic closely linked to family formation. Most notably, they have lower employment rates than men. In 2022, 66 percent of women aged 15-64 were employed in the European Union, compared to 75 percent of men (Eurostat, 2024b). Additionally, women are more likely to work part-time. In 2023, nearly 28 percent of employed women in the EU worked part-time, while only 8 percent of men did (Eurostat, 2024e). Women tend to be concentrated in occupations that offer more stability and compatibility with family life, such as those in the public sector (Matysiak & Cukrowska-Torzewska, 2021). At the same time, they remain underrepresented in STEM fields in most Western European countries as of 2022 (Eurostat, 2023b), and comprised only 34 percent of EU managers in 2021 (Eurostat, 2021).

These gendered patterns are mirrored in the effects of structural labor market changes on women and men. For a long time, European women were overrepresented in routine tasks (Brussevich et al., 2019; Piasna & Drahokoupil, 2017), although this pattern has recently been more evident among older workers (Brussevich et al., 2019). At the same time, low-skilled jobs involving manual tasks are predominantly held by men (Brussevich et al., 2019; Yamaguchi, 2018). However, men are more likely to occupy highly-skilled occupations that require analytical or managerial skills (Liu & Grusky, 2013; Matysiak et al., 2024a). In contrast, European women are overrepresented in occupations centered on interpersonal tasks such as caregiving and teaching, which are typically associated with lower wages (England, 2005; Matysiak et al., 2024a). Evidence suggests that women are transitioning away from routine-intensive jobs into non-routine, often cognitive, roles in the service sector more quickly than men (Black & Spitz-Oener, 2010; Cortes et al., 2021), with this shift occurring at a faster pace in countries that have more widely adopted new technologies (Aksoy et al., 2021). Simultaneously, male employment is more negatively affected by industrial robots and offshoring than female employment in the U.S. and Germany (Acemoglu & Restrepo, 2020; Anelli et al., 2024; Autor et al., 2019; Dauth et al., 2017; Deng et al., 2023; Huber & Winkler, 2019). In the U.S., robots exert a larger negative impact on men's income, which contributes to a smaller gender gap (Anelli et al., 2024). In Europe, however, robot adoption increases both male and female earnings, but also widens the gender pay gap, with highly-skilled men benefiting more from the productivity effects of automation (Aksoy et al., 2021).

The larger impact of automation on male than female employment and earnings may stem from men's greater attachment to the labor market and their overrepresentation in highly-skilled professional positions (Eurostat, 2021). In contrast, women's labor market attachment is more dependent on childbearing and child-rearing, with many women reducing their employment participation after becoming mothers (Arntz et al., 2017a; Waldfogel et al., 1999). In Europe, this is especially pronounced in countries where the division of paid and unpaid work between partners in heteronormative unions is highly gendered (Gustafsson et al., 1996; Gutiérrez-Domènech, 2005). Overall, the *work-family conflict* or *career cost of children* is particularly evident for women (Goldin, 2021; Matysiak & Cukrowska-Torzewska, 2021). Understanding the economic burden of maternity on women is essential for understanding contemporary family formation patterns in developed countries.

While women without children often see their earnings rise throughout their careers, new mothers typically experience reductions in earnings, income, employment, and hours worked—a phenomenon known as the *child penalty* (Blau & Kahn, 2017). These penalties are linked to the traditional gender roles in which women are expected to take on tasks related to childcare and homemaking, while men focus on paid work (Andresen & Nix, 2022; Cukrowska-Torzewska & Matysiak, 2020; Dominguez-Folgueras, 2022; Kleven, 2022). Explanations based on differences in human capital or fathers' labor market advantages (specialization in paid work measured by productivity), as well as biological costs of giving birth have been disproven (Andresen & Nix, 2022; Kleven et al., 2021), while the role of work-family reconciliation policies remains less clear. A meta-analysis by Cukrowska-Torzewska and Matysiak (2020) found that the residual motherhood wage gap is smallest in countries with public policies that actively support gender equality. However, Kleven et al. (2024b) quasi-causally identified the impact of 60 years of policy experimentation in Austria (expansions of parental leave and childcare), concluding that these policies had virtually no impact on gender convergence in labor market outcomes. Recent research shows that child penalties intensify with a country's wealth and development, suggesting that as economic necessity decreases, women may reduce workforce participation when dual-income households are no longer essential (Kleven et al., 2024a). In contrast, fathers often experience a *child premium*, with increased earnings driven by longer hours, additional jobs, or career advancements (Baranowska-Rataj & Matysiak, 2022; Cukrowska-Torzewska & Matysiak, 2020). This premium, initially explained by Becker's specialization hypothesis (Becker, 1965), may now reflect evolving gender norms and perceptions of fatherhood, with fathers being seen as more willing to work long hours with fewer family-related interruptions (Baranowska-Rataj & Matysiak, 2022; Hodges & Budig, 2010). Additionally, the fatherhood premium may also result from a selection effect, where more successful men with greater resources are more likely to become parents (Waszkiewicz & Bogusz, 2023).

Taken together, parenthood explains much of the gender gap in employment in high-income countries, with marriage contributing to the remaining gap (Kleven et al., 2024a). The shift from routine to non-routine cognitive jobs has likely exacerbated these gaps, as the greater work intensity associated with cognitive labor (Green et al., 2022), combined with the decline of routine jobs (de Vries et al., 2020), has intensified the career cost of children. This was examined empirically only by Adda et al. (2017) in a study on Germany from 1972 to 2001. Supporting the argument that jobs requiring cognitive tasks might be less compatible with maternity than those with routine or manual tasks, they found that women in jobs involving abstract tasks were more likely to remain childless or have only one child compared to their peers in routine and manual jobs. Furthermore, women who were more family-oriented tended to sort into routine occupations early in their careers. Overall, structural labor market changes not only create economic inequalities that may influence fertility, but also affect the expected work-family conflict, which is a key factor in individuals' decisions to become parents or have additional children (Begall & Mills, 2011).

1.4 Labor market and well-being

Subjective well-being encompasses three interconnected dimensions: evaluative well-being, which involves an overall assessment of one's life (life satisfaction); the eudaimonic dimension, related to a sense of purpose; and affective well-being, which pertains to emotions typically tied to short-term experiences (happiness) (Diener, 2009; Layard, 2010; Nikolova & Graham, 2020).

As work is a major aspect of life, it influences all three dimensions of subjective well-being (Green et al., 2024; Sirgy et al., 2001). These impacts can be disaggregated into objective and subjective dimensions (Nikolova & Cnossen, 2020). In the objective approach, worker well-being is evaluated based on whether the job provides workers with the capabilities and material security needed to achieve their goals and fulfill their needs. In contrast, the subjective well-being approach assumes that individuals are the best judges of their working and living environments, with typical measures including self-reported feelings and evaluations of overall working conditions. These feelings can be influenced by factors such as the meaningfulness derived from a job, a sense of work autonomy, expectations, norms, values, alternatives, and the outcomes and rewards of work (Nikolova & Cnossen, 2020). The objective and subjective approaches are not mutually exclusive and are often used in complementary ways (Green, 2006).

A substantial body of literature shows that labor market outcomes strongly affect life satisfaction and happiness, both in terms of objective measures such as employment status and income (Diener, 2009; Nikolova & Graham, 2020; Peiró, 2006), and subjective measures like perceptions of income or financial satisfaction (Ngamaba et al., 2020; Zhao & Chen, 2023). Most studies find stronger associations with life satisfaction than with happiness (Diener, 2009; Kahneman & Deaton, 2010; Peiró, 2006).

Less is known about how labor-replacing technologies impact subjective well-being[12]. These technologies may reduce work meaningfulness (fulfillment derived from work) by affecting workers' autonomy and discretion over tasks, and by shaping perceptions of choice and authority (Nikolova & Cnossen, 2020). Simultaneously, they can increase work intensity, job insecurity, and limit wage growth (Abeliansky et al., 2024; Acemoglu & Restrepo, 2020; Antón et al., 2023). They may also require skill changes and cause unwanted job mobility (Blasco et al., 2024). Additionally, even without immediate job loss, workers

[12]To my knowledge, little is known about the perceptions of mechanisms related to globalization, such as trade competition.

may fear the disruptive potential of technological advances (Innocenti & Golin, 2022; Yam et al., 2021), especially those in routine jobs, which can negatively impact their well-being (Nikolova et al., 2024).

On the other hand, automation can improve working conditions by reducing repetitive tasks, eliminating dangerous jobs, and decreasing physically demanding work and job intensity (Autor, 2015; Gihleb et al., 2022; Maurin & Thesmar, 2004). These improvements may enhance subjective health, which is linked to happiness (Spencer, 2018). Thus, the hedonic dimension, along with perceived health, can significantly influence workers' well-being, especially among those more exposed to robotization.

The potential effects of structural labor market changes on workers' well-being—across its three dimensions—remain complex. However, empirical research shows negative impacts. In the U.S., workers exposed to higher levels of automation report declines in health and job satisfaction (Nazareno & Schiff, 2021). Industrial robots, by increasing economic insecurity, are associated with higher substance abuse and elevated mortality rates (Gihleb et al., 2022; O'Brien et al., 2022). Even in more egalitarian countries like Norway, 40% of workers fear being replaced by machines, negatively impacting job satisfaction (Schwabe & Castellacci, 2020). Similarly, in 20 European countries, Dekker et al. (2017) found that fears of job loss to robots are especially pronounced among economically vulnerable, blue-collar workers, and those in regions with weaker employment protections.

The impact of technology on well-being can differ by gender. The so-called *female happiness paradox* persists in well-being research: while women are generally more satisfied with their lives and happier than men, they fare worse in terms of negative affect and mental health (Blanchflower & Bryson, 2024a; Blanchflower & Bryson, 2024b). These gaps remain largely unchanged despite the gradual convergence towards gender equality in the labor market (Blanchflower & Bryson, 2024a). In terms of work, women report higher levels of job satisfaction than men, even in identical jobs (Clark, 1997). Clark (1997) argues that this finding may be due to women having lower expectations regarding their jobs compared to men. Whether automation affects women's well-being more than men's may depend on two additional factors. As discussed in Section 1.3, research suggests that women's employment may be more adversely affected by structural labor market changes than men's in Europe. This could result in a greater spillover effect on women's well-being. Following this reasoning, Nikolova et al. (2024) predict that women may experience reduced autonomy and a diminished sense of self-determination amid automation, while men's perceptions of their work's meaningfulness and their competencies may improve. Men may perceive their competencies more highly than women due to greater exposure or access to robots, or because they have more confidence or self-efficacy in using them. Alternatively, women may perceive their competencies less strongly due to more barriers or challenges in using robots, or because they have more negative or fearful attitudes toward them. This has been further explored by Borwein et al. (2024), who argue that women, being more sensitive to economic volatility and labor market shocks, tend to have a less positive view of workplace automation. Empirically, they show that, across 10 developed countries, women perceive the fairness of automation more negatively than men.

1.5 Innovations and contributions

This dissertation makes four significant contributions. First, it represents an ambitious attempt to integrate literature and concepts from economics, demography, and sociology to provide comprehensive evidence on unexplored contemporary social phenomena. The impact of technology and globalization on labor markets has typically been studied within labor economics, while the drivers of fertility and well-being have been addressed within demography and sociology. By combining these perspectives, my research broadens the scope and offers new insights into established scientific paradigms, such as how labor market outcomes influence fertility and well-being. In particular, my work demonstrates that these impacts extend beyond cyclical factors, such as unemployment, and that long-term changes in labor demand can affect personal life, regardless of whether they result in actual job loss. My thesis underscores the importance of adopting an interdisciplinary perspective when studying complex social phenomena. I believe this approach is essential for advancing contemporary social science, which has reached its limits when confined to strict disciplinary boundaries.

Second, my dissertation explores previously unaddressed consequences of structural labor market changes. As mentioned earlier, research in labor economics has typically focused on the economic outcomes of technology and globalization, such as wages, employment, and economic growth. My thesis demonstrates that these impacts can have ripple effects on more personal phenomena, such as decisions about childbearing and individual well-being. Thus, my work addresses the often-overlooked issue of social inequalities, which is frequently neglected in economic studies.

Third, my dissertation incorporates a gender perspective, with the exception of Paper III, where data limitations prevent an analysis of men. Despite significant advances in women's participation in public life over recent decades (Goldin, 2014), substantial gender inequalities persist in areas of power, such as the labor market, politics, and wealth. Research that accounts for gender is crucial for identifying and understanding these disparities, which in turn allows us to work toward solutions that promote equality and fairness. As I illustrated in Sections 1.2 and 1.3, gender is a crucial factor in discussions of the interactions between labor market outcomes and fertility. In particular, my research uncovers interdependencies that challenge established ideas. For example, Paper I finds that robot adoption has larger negative effects on fertility rates in European regions where a higher share of women, compared to men, is employed in manufacturing. Paper II shows almost no gender differences in the relationship between individual task content at work and entry to parenthood in Germany. Paper IV demonstrates that industrial robot adoption has a larger negative impact on women's well-being than on men's. Contrary to the commonly held view that automation predominantly harms men's employment in manufacturing (e.g. Acemoglu & Restrepo, 2020; Anelli et al., 2024), my findings suggest that, in terms of social inequality, women may be more affected (at least in Europe).

Fourth, my thesis contributes to the demographic literature on the causes of ultra-low fertility in Europe (Kreyenfeld & Konietzka, 2017; Zeman et al., 2018). In 2022, the total fertility rate in the European Union stood at 1.46 live births per woman, nearly half of what it was in the 1960s (Eurostat, 2024c). For much of this period, fertility fluctuated with the economic cycle: declining during recessions and increasing during economic booms (Adserà, 2005; Matysiak et al., 2021; Neels et al., 2024). Economic uncertainty, alongside the second demographic transition and ideational changes, has been a central narrative in demographic research (Blossfeld et al., 2005). However, European fertility rates did not recover after the Great Recession (Matysiak et al., 2021), suggesting that other factors may be at play (Matysiak & Vignoli, 2024). The *gender revolution theory* (Esping-Andersen & Billari, 2015; Goldscheider et al., 2015) posited that a lack of gender equality in the domestic sphere might explain low fertility rates, a view supported by selected studies from Nordic countries (Duvander et al., 2019; Jalovaara et al., 2019; Lappegård & Kornstad, 2020). Yet, even Nordic fertility rates have declined since 2010, despite being generally higher than in the rest of Europe (Comolli et al., 2021). Additionally, proponents of the narrative framework have suggested that subjective economic uncertainty, conceptualized as concerns about an unstable future, might contribute to low fertility in Europe (e.g. Lappegård et al., 2022; Vignoli et al., 2022). My dissertation contributes to this literature by demonstrating that technology and globalization, which drive changes in labor demand over long time scales (decades), can have positive effects on fertility for some social groups, while negatively affecting others. For example, Paper I shows that more technologically advanced and better-educated regions experience fertility increase as a result of robotization, while the impact is negative in lower-educated regions. Paper II shows that women and men with cognitive jobs (those in highest labor demand) delay entry into parenthood, but are overall the least likely to remain childless by the end of their reproductive life, with no such differences evident before 2000. My thesis also engages with the topic of gender and subjective well-being, aligning it with the broader discussions on low fertility outlined above.

Finally, my dissertation emphasizes practical considerations when studying interdisciplinary topics. It discusses measures of structural labor market changes that can be used in research on family outcomes and demonstrates the utility of various data types: regional data in Paper I, panel survey data in Paper II, administrative data in Paper III, and cross-sectional survey data in Paper IV. This integrated approach shows that research on complex interdisciplinary topics often requires combining multiple data sources and methodologies. It also demonstrates my ability to integrate diverse perspectives in research, work with complex datasets, and apply econometric and statistical methods appropriately within the conceptual framework. Thus, it highlights my proficiency and maturity in quantitative social science.

This dissertation has limitations, which I outline in Section 3.2. For example, while I study the impact of structural labor market changes on family outcomes and well-being, I do not explore the interdependencies between these issues. This work represents an initial attempt to shed light on an unexplored issue. However, further research should follow. I outline promising avenues for future research in Section 3.2.

Collection of research papers

The main results of this thesis are a series of four research papers, three of which already published in international academic journals.

- Matysiak, A., Bellani, D., & Bogusz, H. (2023). Industrial Robots and Regional Fertility in European Countries. *European Journal of Population*, **39**. https://doi.org/10.1007/s10680-023-09657-4
- Bogusz, H., Matysiak, A., & Kreyenfeld, M. (2024). Structural labour market change, cognitive work, and entry to parenthood in Germany. *Population Studies*, 1–27. https://doi.org/10.1080/00324728.2024.2372018
- Bogusz, H. (2024). Task content of jobs and mothers' employment transitions in Germany. *Journal for Labour Market Research*, **58**. https://doi.org/10.1186/s12651-024-00384-9
- Bogusz, H., & Bellani, D. (2025). Industrial robots and workers' well-being in Europe. *WNE Working Papers*, **464**. https://www.wne.uw.edu.pl/application/files/6317/3980/6548/WNE_WP464.pdf

2.1 Paper I: *Industrial Robots and Regional Fertility in European Countries*

Paper I

"*Industrial Robots and Regional Fertility in European Countries*"

A. Matysiak, D. Bellani, and H. Bogusz

Commentary

Over recent decades, the adoption of industrial robots has significantly transformed labor markets in advanced economies, leading to job loss for some workers and new employment opportunities for others. The debate about the impact of this technology on employment and wages is ongoing, with different studies showing negative (Acemoglu & Restrepo, 2020), mixed (Acemoglu et al., 2020; Dauth et al., 2021; Goos et al., 2009), or even positive effects (Chung & Lee, 2023; Deng et al., 2023). It is, however, clear that these effects are stratified across demographic groups such as gender (Aksoy et al., 2021; Anelli et al., 2021; Autor et al., 2019), education (Acemoglu & Restrepo, 2020), or sector, with manufacturing workers being the most adversely affected (Acemoglu & Restrepo, 2020; Autor et al., 2019; Dauth et al., 2021). Building on these studies, scholars have begun exploring whether these labor market effects extend to other domains of human life, such as demographic behavior (Anelli et al., 2024; O'Brien et al., 2022), voting (Anelli et al., 2021), or health (Gihleb et al., 2022).

In this study, we contribute to the literature by examining the effects of industrial robot adoption on fertility in selected European countries. Prior to our paper, this issue had been addressed only in the context of the U.S. (Anelli et al., 2024), where robots are adopted to a much smaller extent than in most of Europe (International Federation of Robotics (IFR), 2020b). To investigate this issue, we combine regional data on fertility and employment structures from Eurostat[1] with data on robot stocks from the International Federation of Robots[2]. We construct a Bartik instrument, called *exposure to robots*, which uses pre-robotization employment structures to allow for the endogeneity of robot stocks only (Acemoglu & Restrepo, 2020). We estimate fixed-effects panel models with instrumental variables to account for global shocks that might simultaneously affect robot adoption and fertility.

Our findings are mixed and suggest that robots tend to exert a negative impact on fertility in highly industrialized regions, regions with relatively low-educated populations, and those that are technologically less advanced. At the same time, better-educated and more prosperous regions may even experience fertility improvements as a result of technological change.

In this study, I suggested and developed the causal analytical strategy based on panel models and the Bartik instrument. I contributed to developing the conceptual framework, prepared and analyzed the data, and created all plots and tables shown in the paper. I also participated in the preparation of the manuscript (especially the parts related to the analytical strategy, data, and results). In addition, I presented the paper at the Population Association America Annual Meeting (2021). The codes employed for the analysis are publicly available on Github.

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[1]Eurostat, 2024d.
[2]International Federation of Robotics (IFR), 2020a.

European Journal of Population (2023) 39:11
https://doi.org/10.1007/s10680-023-09657-4

ORIGINAL RESEARCH

Industrial Robots and Regional Fertility in European Countries

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Received: 17 October 2022 / Accepted: 15 January 2023 / Published online: 28 March 2023

Abstract
In this study, we examine whether the long-term structural changes in the labour market, driven by automation, affect fertility. The adoption of industrial robots is used as a proxy for these changes. It has tripled since the mid-1990s in the EU, tremendously changing the conditions of participating in the labour market. On the one hand, new jobs are created, benefitting largely the highly skilled workers. On the other hand, the growing turnover in the labour market and changing content of jobs induce fears of job displacement and make workers continuously adjust to new requirements (reskill, upskill, increase work efforts). The consequences of these changes are particularly strong for the employment and earning prospects of low and middle-educated workers. Our focus is on six European countries: Czechia, France, Germany, Italy, Poland and the UK. We link regional data on fertility and employment structures by industry from Eurostat (NUTS-2) with data on robot adoption from the International Federation of Robotics. We estimate fixed effects linear models with instrumental variables in order to account for the external shocks which may affect fertility and robot adoption in parallel. Our findings suggest robots tend to exert a negative impact on fertility in highly industrialised regions, regions with relatively low educated populations and those which are technologically less advanced. At the same time, better educated and prospering regions may even experience fertility improvements as a result of technological change. The family and labour market institutions of the country may further moderate these effects.

Keywords Fertility · Employment · Industrial robots · Technological change · Europe

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1 Introduction

Over the last two decades, technological advancements in production, including cutting-edge industrial robots, have tremendously transformed the labour markets in advanced market economies, creating new career opportunities, but also inducing fears of job displacement (OECD, 2019). Only in the EU, the stock of industrial robots per 10.000 manufacturing workers has tripled since the mid-1990s reaching 114 in 2019 (International Federation of Robotics, 2020). Because of the scale and speed of automation and its possible consequences for workers, there has been an explosion of studies on how technological advancements in production affect employment (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018), wages (Dauth et al., 2021), social and economic inequalities (Aksoy et al., 2021; de Vries et al., 2020) and more recently workers' physical and mental health (Abeliansky and Beulman, 2019; Gihleb et al., 2022). With this study, we contribute to this discussion by examining how automation, and more specifically the adoption of industrial robots, influences fertility, an outcome which so far has been largely neglected in the scientific debate.

In our view, automation may affect fertility since it alters the conditions of participating in the labour market and with it the economic well-being of the family and the strategies of its adult members adopted to combine paid work with care. Past research has clearly demonstrated that individuals tend to postpone or even abstain from having children during economic downturns (Cherlin et al., 2013; Sobotka et al., 2011), usually in response to an increase in unemployment and growing instability of employment (Adsera, 2004; Bellani, 2020; Matysiak et al., 2021; Schneider, 2015). The feeling of economic uncertainty may also hinder fertility decisions irrespective of the real economic conditions (Vignoli et al., 2020). Notably, fertility usually declines more strongly in response to worsening of employment prospects for men and young workers as well as in countries offering weaker social protection in case of a job loss (Alderotti et al., 2021; Comolli, 2017).

Past research has largely concentrated on examining fertility consequences of short-term changes in labour market conditions, caused by cyclical swings in the economy and reflected in upward and downward moves in (un)employment or work conditions. Much less has been done on how fertility reacts to long-term structural changes in the labour markets, driven, for instance, by globalisation or technological change. These changes may not necessarily affect (un)employment, but rather change the demand for workers' skills. They may increase uncertainty, push workers into poorly paid low quality jobs or increase workers' effort to catch up with quickly changing work guidelines and skill requirements (Autor et al., 2006; Green et al., 2022). In fact, Seltzer (2019) demonstrated that the cyclical approach performed very well in predicting a decline in fertility rates during the Great Recession in the USA, but completely failed in its aftermath when envisioning a fertility rebound.

This study contributes to the discussion on labour markets and fertility by investigating how the long-term structural changes in the labour market, driven by robot adoption, affect regional fertility. Robot adoption mirrors technological innovation and is a marker of economic and labour market transformation (Dottori, 2021). Following the International Federation of Robotics, we define industrial robots as fully autonomous machines that do not require a human operator (Jurkat et al., 2022). So far, little attention has been paid to this topic in fertility research. A notable exception among the published papers is the study by Anelli et al. (2021) who investigated the effects of the adoption of industrial robots on marriage and fertility in the USA. Our focus is on Europe, where, despite large cross-country diversity, workers are much better protected against job loss or poverty (Esping Andersen, 1990). By exploiting variation in robot penetration across NUTS-2 regions, we examine how robotisation influenced fertility in six European countries, namely Czechia, Germany, France, Italy, Poland and the UK. These countries differ in the penetration of automation, labour market and family policy regimes and gender norms. They also constitute good cases for examination as they provide a reasonable number of NUTS-2 regions for obtaining robust empirical findings (with Czechia pooled together with Poland).

2 Literature Review

2.1 Automation, Employment and Economic Uncertainty

The fear that automation will lead to a massive job destruction has been a concern for at least two centuries since the first industrial revolution began (OECD, 2019). Even though the industrial revolution didn't, in the end, lead to unemployment, but to an expansion of job opportunities and improvement in living standards, fear of automation persisted. In the twenty-first century, we are facing a new wave of anxiety that robots will take over our jobs—this time it is about cutting-edge industrial robots (Dekker et al., 2017).

The adoption of robots and machines will indeed change the ways we work and change the demand for skills. Some jobs, in particular those which require performing routine tasks, will likely be destroyed or substantially changed (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2020). In the OECD countries, it was estimated that around 10–14% of jobs will be fully replaced by robots and for 25%—32% around 50–70% of tasks will be automated in the next two decades (Arntz et al., 2017; Nedelkoska & Quintini, 2018). Yet, automation does not only destroy jobs but also increases productivity and thereby facilitates job creation. The newly created jobs often require different skills, however. Most often there are non-routine highly cognitive skills which can be implemented in the expanding high tech sector, education or highly specialised customer service (Acemoglu & Autor, 2011). New jobs are also created in the lower-skill service sector (e.g. delivery workers, drivers), but they often offer poor social protection, are low paid and/or unstable (Autor, 2019).

Empirical research demonstrated the effects of automation on labour market outcomes to be unequivocal and clearly depend on workers' education and skills, the sector they are employed in and the overall economic and institutional environment. Automation seems to exert particularly negative effects on employment and/

or earning opportunities of low-and-middle educated workers, both in the USA (Acemoglu & Restrepo, 2020) and in Europe, though in the latter to a lower extent (Graetz & Michaels, 2018). Robots usually destroy jobs in manufacturing (Jung & Lim, 2020) but create new jobs in the service sector (for the US case see Acemoglu & Restrepo, 2020; for the UK see Kariel, 2021). As companies which adopt robots increase their productivity, they can invest more resources into product development, sales and marketing. Robots are thus indirectly increasing demand for workers who can fill in the jobs in highly specialised customer service and product development, not even mentioning the high tech workers who are able to design and operate industrial robots. Indeed, it was demonstrated that highly educated workers, performing nonroutine cognitive tasks, usually benefit from the ongoing changes (de Vries et al., 2020). Automation is also more likely to bring increases in employment in companies and regions which are more technologically advanced and better prepared to embrace the benefits brought about by technological progress. It was demonstrated, for instance, that regions with higher shares of knowledge and creative workers are better able to adapt to changes driven by digitalisation and thus are less vulnerable to automation shocks (Crowley et al., 2021). Last but not least, the effects of robotisation on employment and earnings may differ across countries and depend on their institutional settings. The labour substituting effect of robots tends to be stronger in countries with higher labour costs (Bachmann et al., 2022; Jung & Lim, 2020) and is argued to increase with a decline in employment protection legislation (Traverso et al., 2022).

Much less is known about how automation affects men's versus women's employment and earning opportunities, with few empirical findings suggesting mixed results. While Acemoglu and Restrepo (2020) find no gender differences in automation effects in the USA, Brussevich et al. (2019) argue that women in OECD countries may be more exposed to automation as they are more often employed in jobs which involve routine tasks (see also Piasna & Drahokoupil, 2017 for the same conclusions for the EU). Robotisation also seems to increase gender wage inequalities in Europe by disproportionately benefiting men in medium- and high-skill occupations (Aksoy et al., 2021). At the same time, however, there is evidence that young generations of women are moving away from the routine-intense jobs more quickly than men and take non-routine jobs in the service sector (Black & Spitz-Oener, 2010; Cortes et al., 2021) and that the pace of such job reallocation is faster in countries more advanced in robotisation (Aksoy et al., 2021).

Overall, whether the new wave of automation will indeed lead to declines in employment is not yet clear. There is evidence, however, that it increases turnover in the labour market, requires readjustment from workers and increases uncertainty. The aforementioned studies by Arntz et al (2017) and Nedelkoska and Quinitni (2018) demonstrate that robots substantially change the task content of jobs, modifying the demand for skills and requiring employees to acquire new qualifications and follow new guidelines. A study from Norway found that around 40% of workers fear being replaced by a machine, which lowers their job satisfaction (Schwabe & Castellacci, 2020). Abeliansky and Beulman (2019) demonstrated negative effects of robot adoption on workers' mental health in Germany. Robot adoption was also found to increase death rates due to substance and alcohol abuse (Gihleb et al., 2022;

O'Brien et al., 2022). Finally, the fear of robots was found to be particularly pronounced among the blue collar workers, most exposed to negative effects of automation, and in countries with weaker safety nets (Dekker et al., 2017).

2.2 Automation and Fertility

A large body of the literature has provided evidence that weakening employment prospects, increase in unemployment and economic uncertainty lead to postponement of fertility or even lower fertility rates (Adsera, 2004; Comolli, 2017; Matysiak et al., 2021; Schneider, 2015). This is particularly true in countries offering weak safety nets for the unemployed (Mills et al., 2005). Growing instability of employment has also more negative consequences on fertility when it concerns men than women who, instead, may treat unemployment as an opportunity window for childbearing (Kreyenfeld & Andersson, 2014; Schmitt, 2012). These gender differences in the role of unemployment or precarious employment for fertility are, however, gradually in decline with an increase in women's education, changing gender roles and growing instability of men's employment (Oppenheimer, 1997). In a meta-study Alderotti et al. (2021) showed that in countries with high gender equality, such as Nordic Europe, or countries characterised by strongly unstable employment patterns among men, such as Southern Europe, women no longer use unemployment in order to have children. The same study showed that temporary contracts depress fertility more strongly if they are held by women than men.

Past research on labour market and fertility has, however, largely relied on such labour market indicators, such as (un)employment rate, wages or proportion of persons on specific contracts (e.g. temporary or part time). These indicators excel in identifying short-term cyclical economic conditions, but are less able to capture long-term structural changes in the labour markets, driven for instance by globalisation or technological change. These changes may not necessarily affect (un)employment, but may require workers to adjust to the changing demand for skills. They may thus increase uncertainty and workers' effort to adapt new work guidelines and protocols or undertake training. New employment opportunities may open in front of some workers, while others may be pushed into poorly paid low quality jobs (Autor et al., 2006; Green et al., 2022). In particular, Seltzer (2019) showed that the cyclical approach performed very well in predicting a decline in fertility rates during the Great Recession in the USA, but failed when envisioning a fertility rebound in its aftermath. Instead, fertility continued to fall despite a steep decline in unemployment in the post-crisis period (until the breakdown of the Covid-19 pandemic). This phenomenon was apparently driven by long-term structural changes in the labour market, caused by globalisation and technological change. These changes started already before the Great Recession but accelerated throughout it as companies which implemented labour replacing technologies during the economic crisis were most likely to survive it (Hershbein & Kahn, 2018). With time, the displaced workers found employment in the lower-skill service sector, which resulted in a decline in unemployment, but these jobs were of lower quality, at least in the USA (Seltzer, 2019).

So far few studies have looked at how these long-term structural transformations in the labour market affect fertility. Among them the majority concentrated on changes caused by globalisation, in particular the detrimental role of import competition with China for employment opportunities of middle-skilled workers, mostly male, in goods-producing industries. Studies consistently showed that increased import competition led to a decline in fertility, largely by a declining marriage value of men (Autor et al., 2019; Giuntella et al., 2022; Piriu, 2022). Researchers' interest in how technology-driven labour market changes affect fertility has been even scarcer. On one hand, it has been shown that technological complexity, that reflects the capacity to innovate, develop and create job opportunities, is positively associated with fertility (Innocenti et al., 2021). This is because it fosters a fertility-friendly context characterised by better employment prospects. On the other hand, however, technological upgrading driven by automation is likely to increase turnover in the labour market, increase uncertainty and force workers to re-skill, which, in turn, may decrease fertility. In the only published empirical study on the effect of robotisation on fertility, Anelli et al. (2021) demonstrate that an increase in the adoption of industrial robots in the USA led to an increase in cohabitation and divorce and a decline—though not significant—in the number of marriages. Their findings also point to a decline in marital fertility and an increase in out-of-wedlock births.

3 Country Context

Our study is situated in six European countries, namely Czechia, Germany, France, Italy, Poland and the UK. This country choice is driven by the desire to cover European countries which represent different labour market and family policy regimes and which also differ in the advancement of robot adoption. At the same time, we faced data restrictions. Conducting a regional level analysis, we were restricted to the choice of only bigger European countries with a large number of NUTS-2 regions. Furthermore, due to the choice of the IV strategy (for details, see Sect. 5.2) we were not able to pool European countries into groups (except for Czechia and Poland).

Among the selected countries France and UK have had the highest fertility for about four decades (with TFR oscillating between 1.7 and 2.0), though on a slow but gradual decline since the onset of the Great Recession. Germany and Italy had been the lowest low fertility countries (with TFR below 1.35) since the mid-1980s and Czechia and Poland since the late 1990s/early 2000s. However, while Germany and in particular Czechia experienced some increase in fertility over the last 15 years, Italy and Poland remained at the fairly low levels with TFR oscillating between 1.25 and 1.45 (Eurostat, 2022).

The analysed countries also represent different welfare regimes which define the extent to which workers are protected against a job loss and supported in case of unemployment, all of which may matter for their fertility decisions (Adsera, 2005; Bastianelli et al., 2022). Germany and France are typically classified into the conservative/employment-centred regimes (Amable, 2003; Esping-Andersen, 1990; Walther, 2006), based on strong employment protection and coordinated bargaining systems which allow for a "solidaristic wage setting" (Amable, 2003: 15). The two countries tend to offer generous income support for the unemployed and institutional support in job search (Tamesberger, 2017). Employment protection is also high in Italy, but is strictly directed at protecting workers on permanent contracts, leaving workers on temporary contracts often trapped in the secondary labour market (Pinelli et al., 2017). The UK, instead, is an example of liberal welfare state (Esping-Andersen, 1990), with a very low employment protection and low public support for the unemployed, offered only to those in the highest need (Caroleo & Pastore, 2007). Finally, Czechia and Poland belong to the post-socialist transitional regime with strong market orientation, low levels of state intervention, weak unions and limited support for the unemployed (Visser, 2011), providing rather low support for the unemployed (Tamesberger, 2017). They also display much lower labour costs than the remaining countries (Eurostat, 2022).

Family policies and the gender norms represent another element of the country context which may affect fertility responses to the changing labour market conditions. Whereas France stands out for its very good childcare coverage, Germany for a long time adhered to a modernised male breadwinner policy and only recently started to invest in childcare (Fagnani, 2012). Consequently, while it is common for mothers in France to work full time, many women in Germany switch to part-time jobs after they become mothers (Fagnani, 2007). In Italy, childcare is seen as a private issue, which results in strong gender inequalities both in paid and unpaid work (Menniti et al., 2015). Childcare provision in the UK is also weak and care usually has to be purchased on the market (Yerkes & Javornik, 2019). Mothers usually work part-time or make use of flexible work arrangements which are available in the UK on a wider scale than in other studied countries (Chung & Horst, 2018). Poland and Czechia also display low childcare provision (Szelewa & Polakowski, 2008). Interestingly, mothers usually return to full-time employment after birth though in Czechia much later than in Poland (Matysiak, 2011).

Finally, the analysed countries differ in the robot penetration. The process of robot adoption in the old EU member states (Germany, France and Italy) and the UK started in the early 1990s (see Fig. 1). In all these countries, robots are predominantly employed in the automotive industry, apart from Italy where the allocation of robots across industries is more balanced with 26% in the metal, 17% in the automotive and 12% in the plastic and chemical industry (International Federation of Robotics, 2020). Germany is a clear leader in robot adoption worldwide (Dauth et al., 2021). It is followed by France and Italy where the robot penetration, measured by the number of robots per 10,000 employees, in 2019 was around half of that in Germany. Even lower penetration is observed in the UK which is an example of the Western European country with relatively slow adoption of industrial robots. The two post-socialist countries, Czechia and Poland, also display lower levels of robotisation, but the process of robot adoption started much later there, in the late 2000s. Robotisation in Czechia was very dynamic, due to the rapid development of its automotive industry, with the penetration rate surpassing the French one in 2017. The process in Poland was slower though gradual. Interestingly, in none of the studied countries did an increase in robot adoption go hand in hand with an increase in unemployment (see Fig. 2). Neither

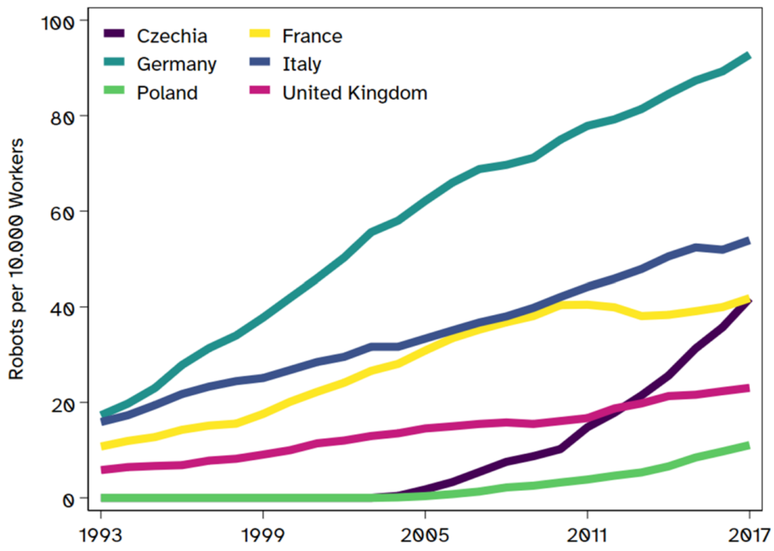

Fig. 1 Industrial robot penetration in 6 European countries by calendar year. *Sources: International Federation of Robotics (IFR) and Eurostat. Calculated by summing robot stocks and employment for the following 1 digit industries: manufacturing, mining and quarrying, electricity, gas, water supply, and construction. Time series are constrained by data availability, as IFR publishes robot stock from 1993 onwards. Figure prepared by the authors in Stata*

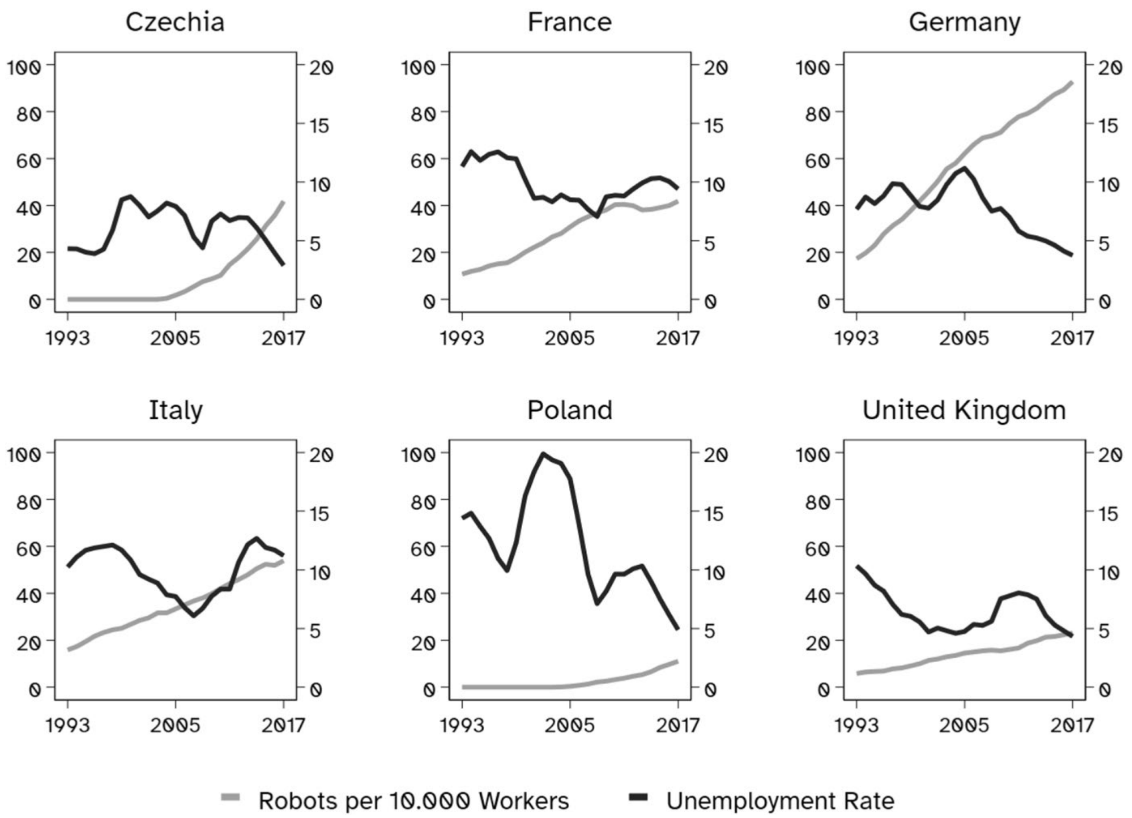

Fig. 2 Robot penetration (left y axis) vs unemployment (right y axis) by country in time. Note: Robot stocks are summed up for the following 1 digit industries: Manufacturing, Mining and quarrying, Electricity, gas, water supply, and Construction. Source: International Federation of Robotics and Eurostat. Figure prepared by authors in Stata

did robot penetration change during the Great Recession. Instead, we observed a gradual increase in robot adoption in all analysed countries alongside cyclical movements in unemployment. This observation confirms that robotisation does not necessarily reflect the same phenomenon as unemployment.

4 Research Objectives and Hypotheses

In this study, we extend the work by Anelli et al. (2021) and examine the effects of long-term structural changes in the labour market, driven by adoption of industrial robots, on regional fertility rates in six European countries—Czechia, France, Germany, Italy, Poland and the UK. As we demonstrated in Sect. 2.1, automation may benefit certain groups of workers (e.g. highly educated, working in the service sector) and diminish the earning/employment opportunities of the others (e.g. low and middle educated workers in the manufacturing sector). We thus do not expect it to affect regional fertility rates in any uniform way. Instead, we anticipate the fertility effects of robot adoption to depend on the structural conditions of the regional labour markets. First, we expect robot adoption to exert more negative/less positive effects on fertility in those regions which used to have large employment in manufacturing before the onset of robotisation **(H1).** This expectation is formed due to the fact that industrial robots are largely employed in manufacturing, leading to a larger job destruction, turnover and uncertainty there rather than in the service sector. Second, we hypothesise that the negative (positive) fertility effects of robot adoption will be more (less) evident in regions where the proportion of men employed in manufacturing at early stages of automation was larger, making men more exposed to robotisation **(H2)**. This is because fertility is less likely to decline in a reaction to a deterioration in women's than men's employment conditions. Next, we expect stronger fertility declines/weaker fertility increases in response to robot adoption in regions with a larger proportion of low and middle educated workers **(H3)** since they are the ones which are mainly negatively affected by automation, either by being at risk of job displacement or having to compete with displaced workers for jobs. Last but not least, we anticipate that fertility effects of robot adoption depend on the region's capacity to embrace technological change. Consistently with past research showing that employment effects of robot adoption are weaker or even positive in regions which invest in modern technologies, we expect that fertility will be less likely to decline/more likely to increase in response to automation in technology- and knowledge-intensive regions **(H4)**. Finally, fertility effects of robot adoption may also vary across the studied countries since they display substantial differences in welfare regimes, the gender normative context and penetration of automation. We abstain, however, from formulating specific hypotheses on the role of the specific cross-country differences for our findings since a comparison of only six countries which vary in numerous important dimensions precludes testing such hypotheses. We rather discuss our findings from the perspective of the cross-country differences presented in Sect. 3.

5 Methodology

5.1 Data

Our study is based on regional NUTS-2 data. The nomenclature of territorial units for statistics (NUTS) is a hierarchical system for dividing up the economic territory of the European Economic Area, the UK, and Switzerland for the purpose of data collection and socio-economic analyses. NUTS-2 regions are roughly equally populated, with population ranging from 0.8—3 million, and these are the smallest geographical units for which employment data are available in Eurostat for all 6 countries of our interest. We observe the countries fairly since the start of the robotisation till 2017. This means we cover the years 1997–2017 for the old EU member states and the UK and 2007–2017 for Czechia and Poland. Covering fully the 1990s for the old EU member states was not possible due to data availability.

To measure fertility, we use TFR and the age-specific fertility rates for the following age groups: 20–24, 25–29, 30–34, 35–39, 40–44, 45 + . These data have been provided by Eurostat at the NUTS-2 level since 1990. They are computed by combining national statistics on births by mother's age and population of women by age. They are fairly complete with some missing data in fertility of women aged 45 + (around 10% of all observations). We use simple linear interpolation to supply them.

To measure worker's exposure to automation we use data on industrial robot stocks provided by the International Federation of Robotics (henceforth: IFR). Industrial robots are defined by IFR as fully autonomous machines that do not require a human operator. Their main tasks are handling operations and machine tending (55% of all European robots fall into this category) and welding and soldering (22% of all European robots) (Jurkat et al., 2022). IFR provides annual data on the operational stock of industrial robots by country and industry since 1993. The industries are coded according to the International Standard Industrial Classification of all economic activities (ISIC, UN, 2008). The stocks of robots are provided by IFR at 1 digit level for all ISIC industries, and max 3 digits for manufacturing industries. The IFR data is complete. We utilise records at 1 digit for three following 'heavy' industries: mining and quarrying, electricity, gas, water supply, and construction. We utilise records at 2 digits for the remaining 13 manufacturing industries[1] to match our regional employment structure data, which is also coded in 2-digit industry categories. We don't include non-industrial categories such as Services, Public Administration, or Education, as those industries employ predominantly service, not manufacturing robots, and at a much smaller scale than robots operating in manufacturing or 'heavy' industries (Hajduk and Koukolova, 2015).

[1] Automotive/Other vehicles, basic metals, electrical/electronics, food and beverages, glass, ceramics, stone, mineral products (non-automotive), industrial machinery, metal products (non-automotive), paper, pharmaceuticals, cosmetics, rubber and plastic products (non-automotive), textiles, wood and furniture, all other manufacturing branches/other chemical products not elsewhere classified.

The data on robots are linked to data on regional employment structures by industry using the methodology developed by Acemoglu and Restrepo (2020) and described in detail in Sect. 5.2. Eurostat has provided NUTS-2 regional employment structures by 2-digit industry codes classified according to Nomenclature of Economic Activities (NACE Rev. 1.2 before 2008, NACE Rev. 2 after 2008) since 1986. We reclassify these data to the ISIC classification to match them to robot stocks. Moreover, since our main covariate (explained in detail in Sect. 5.2) relies on summation of employment numbers over time, we impute missing records of the regional employment structure. Finally, changes in the past NUTS classifications require reclassifying regional codes to one, consistent version. Both reclassifications and the imputation are described in detail in the Appendix in Tables 6 and 7.

Besides fertility rates, Eurostat online database provides us also with NUTS-2 level controls by calendar year, as well as potential moderators, which we interact with our main explanatory variable in order to test our research hypotheses. We include the following set of controls at the regional level: share of population aged 15–24, share of population aged 25–49, share of population aged 50+, share of highly educated (ISCED levels 5–8), ratio of share of highly educated women to share of highly educated men, the square of the latter and women's economic activity rate. The variables denoting population structure by age are introduced to control for any variation in population exposed to childbearing. We also account for the population education level given the educational gradient in fertility (Wood et al., 2014). The share of highly educated women relative to highly educated men and the square of this ratio aim at capturing the difficulties to find a partner in regions with better educated female population (Bellani et al., 2017) given that partners tend to form unions if they have similar education levels (de Hauw et al., 2017). Finally, women's economic activity rate is also tightly linked to fertility.

The potential moderating variables are settled at the regional level as well. They are the initial (measured around the onset of robot adoption) proportion of workers employed outside of manufacturing (used to test H1), the initial proportion of women employed in manufacturing over the proportion of men in manufacturing (H2), proportion of highly educated persons (time-varying) (H3) and the proportion of workers employed in technology- and knowledge-intensive sectors (time-varying) (H4). The control and moderating variables are fairly complete. Any missing values were imputed via linear interpolation. This was done in 14% of cases for population structure by education, and max. 25% for employment data. There are no cases when the entire time series for specific regions are missing.

After accounting for the NUTS reclassifications and excluding foreign territories (see Table 7 in the Appendix), we have data for 34 NUTS 2 regions in Germany, 22 in France, 20 in Italy, 35 in the UK, 16 in Poland, and 8 in Czechia. We pool the data for Czechia and Poland due to the smaller number of regions in the two post-socialist countries and their similarities when it comes to labour market and family policy institutions, economic developments and delayed start of automation in comparison with Western Europe. In total, we have 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK and 240 for Czechia and Poland jointly.

5.2 Methods

Our methodology relies on regressing fertility rates against workers' exposure to robotisation as well as a set of control variables mentioned in Sect. 5.1, separately for Germany, Italy, France, the UK and the group formed by Czechia and Poland.

We quantify workers' exposure to robotisation following the methodology developed by Acemoglu and Restrepo (2020) and used, among others, in Dauth et al. (2021), Anelli et al. (2021), and O'Brien et al. (2022):

$$Exposure\ to\ robots_{r,t} = \sum_{i=1}^{N} \frac{empl_{r,i,t_0}}{empl_{r,t_0}} \left(\frac{robots^{C}_{i,t}}{empl_{i,t_0}} \right) \tag{1}$$

where $robots^{C}_{i,t}$ is the country-level stock of robots across industries in year t; $empl_{i,t_0}$ identifies the total number of workers (in 10 thousands) employed in sector i in t_0, i.e. at the start of the robotisation (hereafter initial) and $\frac{empl_{r,i,t_0}}{empl_{r,t_0}}$ denotes the initial distribution of employment in industry i across regions. Effectively, $\frac{robots^{C}_{i,t}}{empl_{i,t_0}}$ captures robots adopted in industry i and country c replacing its initial employment, while $\frac{empl_{r,i,t_0}}{empl_{r,t_0}}$ disaggregates it onto regions. We set t_0 to 1994 for Western European countries and to 2004 for Czechia and Poland, as those are years when robotisation started in those respective countries (see Sect. 3). The measure defined in *Eq. 1* is known as "shift-share instrument" or "Bartik instrument" (Goldsmith-Pinkham et al., 2020).

While exposure to robots is already considered exogenous, as its variation relies on employment shares before robotisation had started, concerns about endogeneity of $robots^{C}_{i,t}$ might still appear, i.e. when external factors affect both the robot adoption and fertility. These may be domestic or sector-specific shocks, such as policy changes. To address this issue, we follow Acemoglu and Restrepo (2020) and instrument the industry-specific stock of robots in country c $robots^{C}_{i,t}$ with industry-specific stock of robots in other countries, which serve as a proxy for advancements in robotisation in developed economies.Choosing the right country for instrumenting robot adoption in Western European countries turned out to be challenging, however. The US' industry-specific stocks of robots could not be used for this purpose since robots (relative to workforce) in that country were used on a smaller scale than in Western Europe (International Federation of Robotics, 2020)—thus the USA cannot be considered as a pioneer of robotisation which the Western European countries would follow. Some of the East Asian economies are more advanced in robotisation than Western Europe (e.g. South Korea), but they adopt robots in other industries than European countries. We are thus uncertain about whether Europe will follow their path. We adopt the strategy suggested by Dauth et al. (2021) who used industry-specific stocks of robots from several advanced economies as instruments of robot stocks in Germany (overidentified IV model). We thus build an overidentified model for each country with k ={Germany, France, UK, Italy, Spain, Sweden, Norway, Finland, United States of America} instruments. In models for Germany, France, UK, and Italy, we exclude the country of interest and the USA, and thus apply 7 instruments. In models for Poland and Czechia, all 9 instruments are applied. Those external instruments are likely relevant, as industrial robots are manufactured by only a few international companies, which set global trends in industrial robot adoption. Thus, robot adoption in one developed economy is a good proxy for robot adoption in another one, with a similar socio-economic context. The proposed set of instruments should also be valid, as there is no reason to expect that robot adoption in one developed economy has a direct influence on fertility rates in another one. To test the instruments' relevance and validity of the overidentifying restrictions, we compute Kleibergen-Paap rk Wald F statistic, and Hansen J statistic (Kleibergen & Paap, 2006; Sargan, 1958; Wooldridge, 2010) and report it along with full model results in the Appendix (Tables 8, 9, 10, 11, 12). Even though this strategy for instrumenting our variable of interest resulted in relevant and valid instruments, it also has a drawback. Namely, we were not able to pool all European countries and estimate one model as that would leave us with collinear sets of instruments, which would be endogeneous and thus of little use.

Our model takes the following form:

$$fertility_{r,t} = \alpha Exposure\ to\ robots_{r,t-2} + \beta Controls_{r,t-1} + \eta_r + v_t + \varepsilon_{r,t} \tag{2}$$

where $fertility_{r,t}$ denotes regional total and age-specific fertility rates, α is our parameter of interest capturing the effect of workers' exposure to robotisation on fertility in region r, η_r corresponds to region individual effects and v_t are time dummies. In order to test hypotheses H1-H4, we interact $Exposuretorobots_{r,t-2}$ with the potential moderators listed in Sect. 5.1. In all models, we control for a set of demographic and socioeconomic characteristics of a region, $Controls_{r,t-1}$, enumerated in Sect. 5.1, which may confound the effects of robot penetration on fertility. They are lagged by 1 year to avoid simultaneity issues. At the same time, we lag the exposure to robots by 2 years to account for the pregnancy and the fact that, once exposed to labour market changes, workers might take some time to decide whether to have a child or not. *Equation 2* is estimated using the two-stage least squares approach with a fixed effects "within" estimator (Wooldridge, 2010). Standard errors are clustered at the region level to acknowledge for within-region dependence of the observations and robustify the model to serial correlation.

6 Results

Our full model estimates along with the IV tests are displayed in Tables 8, 9, 10, 11, 12 in the Appendix (basic models as expressed by Eq. 2) and Tables 1–20 in the Online Supplementary Material (models with interactions). In all 175 regressions for the different countries and fertility rates, the instrument was relevant (as indicated by the Kleibergen-Paap rk Wald F statistic) and the overidentifying restrictions were valid with the Hansen J p-value exceeding the 5% significance level in

153 regressions, and the 1% in 8 cases. In 14 cases, it was not possible to conduct the Hansen J test, due to the fact that the number of clusters (regions) was smaller than the sum of the number of exogenous regressors and the number of excluded instruments (Baum et al., 2002; Frisch & Waugh, 1933). Those 14 cases correspond to the models for Italy and Czechia with Poland in which we introduced two interactions at once to test the H2. However, given that the overidentifying restrictions were valid in all other cases for those country samples, it is reasonable to assume that they are valid also in the remaining 14 cases.

6.1 Overall Effects of Robot Adoption on Fertility

We find few rather small effects of robot adoption on fertility (Table 1). Total fertility is affected significantly only in Italy. This effect is negative: An increase in workers' exposure to robots by 1 robot per 10.000 workers reduces the total fertility rate by 0.00118. This effect is entirely driven by the negative effect of automation on fertility at young ages, in particular in the 25–29 group. Apart from Italy, we also find negative fertility effects in Germany, the leader of robot adoption worldwide, for certain age-specific fertility rates. These effects are weaker and, in contrast to Italy, emerge only at older ages (i.e. for age groups 35–39 and 40–44). We do not find significant negative effects on fertility in other countries of our interest. In some of them, we even identify a significant positive influence of robots on fertility at higher ages. For instance, an increase in exposure to robots by 1 robot per 10.000 workers results in an increase in 35–39 fertility rate 0.00025 in Czechia and Poland and a gain in the 40–44 fertility rate by 0.00039 in the UK. We don't observe any statistically significant findings for France.

6.2 Workforce Sectoral Composition

Since robots are mostly employed in manufacturing, we hypothesised that the negative fertility effects will be most likely to emerge in regions with large manufacturing sectors (H1). The respective findings are presented in Table 2. The coefficients in rows entitled 'Exposure to robots' show the main fertility effects of robotization in regions with high initial employment in manufacturing and the interaction

Table 1 Exposure to robots (α) coefficients from basic 2SLS models (Eq. 2)

Country	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45+
Germany	−0.00016	0.00004	0.00002	−0.00002	−0.00011***	−0.00005***	−0.000001
France	0.00003	−0.00010	0.00009	0.00012	−0.00001	−0.00004	0.000003
Italy	−0.00118*	−0.00020	−0.00090***	−0.00012	0.00014	−0.00005	0.00001
UK	0.00168	−0.00087	0.00079	0.00133	0.00109	0.00039*	−0.000002
Czechia & Poland	0.00053	0.00010	−0.00044	0.00050	0.00025*	−0.00005	−0.00001

***1% **5% *10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

Table 2 Exposure to robots (α) and its interaction with the initial (start of observation period) share of workers employed in manufacturing

Country	Measure	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45+
Germany	Exposure to robots	−0.0022*	−0.0012***	−0.00137***	0.00037	0.00009	−0.000029	−0.00000
	Exposure to robots # Initial share of workers out of manufacturing	0.00003**	0.00002***	0.00002***	−0.00001	−0.00000	−0.00000	0.00000
France	Exposure to robots	0.00163	0.00062	0.00212	0.00013	−0.00082	−0.00045**	−0.00008*
	Exposure to robots # Initial share of workers out of manufacturing	−0.00002	−0.00001	−0.00003	−0.00000	0.00001	0.000006*	0.000001*
Italy	Exposure to robots	−0.00264	−0.00051	−0.00201	−0.00085	0.00069	0.00039**	−0.00013**
	Exposure to robots # Initial share of workers out of manufacturing	0.00002	0.000005	0.00002	0.00001	−0.000007	−0.00001**	0.000002***
UK	Exposure to robots	−0.0223**	−0.00584	−0.00094	−0.00088	−0.00384	−0.00155	0.00012
	Exposure to robots # Initial share of workers out of manufacturing	0.00031**	0.000065	0.00002	0.00003	0.00006	0.00003	−0.00000
Czechia & Poland	Exposure to robots	0.00627	0.00295***	−0.00337**	0.00275	0.00251***	0.00004	0.00001
	Exposure to robots # Initial share of workers out of manufacturing	−0.00009*	−0.00005***	0.00005**	−0.00004	−0.00004***	−0.00000	−0.00000

***1% **5% *10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

term beneath informs us about the extent to which the effect of robotization differs from the main effect in regions where the initial proportion of persons employed in manufacturing in the region was 1 pp lower.

With few exceptions, our findings are largely consistent with our hypothesis H1. We observe a clearly negative effect of robot adoption on total fertility in those German regions which were initially highly industrialised. It is strongly driven by fertility reduction at young ages (20–24 and 25–29). This negative effect is significantly weaker in regions with a smaller initial proportion of workers employed in manufacturing. We also detect some negative fertility effects of robots in the French and British regions with initially large manufacturing sectors. In the UK, the negative effects on age-specific fertility in those regions are not significant but the negative effect on total fertility is significant. In France, they emerge at the highest reproductive ages: 40–44 and 45 +. In Italy, most of the effects in highly industrialised regions are insignificant except for those at higher reproductive ages where the pattern is unclear (positive effect of robot adoption in highly industrialised regions at ages 40–44 and negative at ages 45 +). Some inconsistency is also detected in Czechia and Poland though it seems that the effects of robot adoption there tend to be rather positive in highly industrialised regions: The main effects at all reproductive ages, but for 25–29, are positive though significant only at ages 20–24 and 35–39.

6.3 Gender Composition of Manufacturing Workers

Next, we expected that fertility effects of robot adoption will be more negative in regions where men were more exposed to automation than women (H2). The findings which allow to verify this hypothesis are presented in Table 3. The coefficients in rows entitled "Exposure to robots' display fertility effects of robotisations in regions with high initial employment in manufacturing where in addition employment in manufacturing was dominated by men. The following interaction terms inform us to what extent the effect of robotization differs from the main effect in regions where the initial proportion of persons employed in manufacturing in the region was 1 pp lower/initial ratio of women over men employed in manufacturing was by 1 pp. higher.

Apart from the UK and the cluster built by Czechia and Poland, we do not find evidence for hypothesis H2. Our findings even suggest the reverse, namely that robot adoption in Germany, France and Italy leads to stronger fertility decline in regions where the initial ratio of women's to men's employment share in manufacturing was larger. These negative effects, obtained net of the regional employment in manufacturing and women's activity rate, are largely significant at young reproductive ages. Interestingly, in Italy and to some extent in France we even find traces of positive effects of robot adoption in regions with initially large manufacturing sectors which are dominated by men.

The findings for the UK and Czechia and Poland are more consistent with our expectations. In the UK, the interaction between exposure to robotisation and the ratio of women's and men's employment in manufacturing is positive at all

Table 3 Exposure to robots (α), interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing

Country	Measure	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Germany	Exposure to robots	0.00079	−0.00041	−0.00018	0.00064	0.00053	0.00000	0.00001
	Exposure to robots # Initial share of workers out of manufacturing	0.00001	0.00001**	0.00001**	−0.00001	−0.00001	−0.00000	−0.00000
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	−0.0035***	−0.00093*	−0.00141***	−0.00031	−0.00052**	−0.00004	−0.00001
France	Exposure to robots	0.0049	0.00188*	0.00352**	0.0008	−0.00098*	−0.00056**	−0.00012**
	Exposure to robots # Initial share of workers out of manufacturing	−0.00002	−0.00000	−0.00003	−0.00000	0.00001	0.000005*	0.000001*
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	−0.00681**	−0.00307***	−0.00292*	−0.00122	0.00049	0.00036	0.00011**
Italy	Exposure to robots	0.0144***	0.00535***	0.0067***	−0.00056	0.00038	0.00116***	−0.00014*
	Exposure to robots # Initial share of workers out of manufacturing	−0.00011**	−0.00004**	−0.00005***	0.00001	−0.00000	−0.00001***	0.000002**
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	−0.0137***	−0.00462***	−0.00693***	−0.00039	0.00025	−0.0006***	0.00002
UK	Exposure to robots	−0.0378***	−0.0103	−0.00187	−0.00319	−0.00486	−0.00202	−0.00024
	Exposure to robots # Initial share of workers out of manufacturing	0.00042***	0.0001	0.00003	0.00004	0.000069	0.000028	0.000001
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.0187*	0.00487	0.00091	0.00303	0.00177	0.00073	0.00043**
Czechia & Poland	Exposure to robots	0.00195	0.00041	−0.00436	0.00246	0.00178**	−0.00013	−0.000023
	Exposure to robots # Initial share of workers out of manufacturing	−0.00007	−0.00003*	0.00005*	−0.00004	−0.00003***	0.000000	−0.00000
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.00402	0.00228***	0.00099	0.0003	0.00063	0.00014	0.00002

***1% **5% *10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

Table 4 Exposure to robots (α) and its interaction with the share of the highly educated population (ISCED 5–8)

Country	Measure	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Germany	Exposure to robots	−0.00161***	−0.00027*	−0.00011	−0.00045**	−0.00044***	−0.00014***	−0.00001**
	Exposure to robots # Share of highly educated	0.00005***	0.00001**	0.00001	0.00002**	0.00001***	0.000003**	0.0000003**
France	Exposure to robots	0.0015**	0.00058**	0.00105***	0.00019	−0.00027	−0.00015**	−0.00001
	Exposure to robots # Share of highly educated	−0.000054**	−0.00002***	−0.00003**	−0.00000	0.00001	0.000004*	0.000000
Italy	Exposure to robots	−0.00292*	−0.00102	−0.00124**	0.0002	−0.00016	−0.0002*	0.00001
	Exposure to robots # Share of highly educated	0.0001	0.00004*	0.00002	−0.00001	0.00002	0.00001**	−0.00000
UK	Exposure to robots	0.00026	−0.00049	0.00171*	0.00063	0.00008	−0.00016	−0.00009**
	Exposure to robots # Share of highly educated	0.00003	−0.000009	−0.00002	0.00001	0.00002	0.00001	0.000002***
Czechia & Poland	Exposure to robots	−0.00018	0.00039	−0.00182***	0.00023	0.00066***	0.00002	−0.00003***
	Exposure to robots # Share of highly educated	0.000021	−0.00002	0.00007**	0.00001	−0.00002**	−0.00000	0.000001**

***1% **5% *10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

Table 5 Exposure to robots (α) and its interaction with the share of workers employed in technology- and knowledge-intensive sectors

Country	Measure	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Germany	Exposure to robots	−0.00006	0.0001	0.00015**	−0.00003	−0.00015***	−0.00005***	−0.000003*
	Exposure to robots # Share employed in technology and knowledge sectors	−0.00002	−0.00001	−0.00005***	0.00001	0.00002*	0.00001	0.000001**
France	Exposure to robots	−0.00015	−0.00019*	0.00006	0.00013	−0.00004	−0.00007***	−0.000002
	Exposure to robots # Share employed in technology and knowledge sectors	0.00007	0.00003	0.00002	−0.00000	0.00001	0.00001*	0.000002
Italy	Exposure to robots	−0.00116*	−0.00013	−0.00117***	−0.00017	0.00037***	−0.00001	0.000002
	Exposure to robots # Share employed in technology and knowledge sectors	0.000005	−0.00002	0.0001	0.00002	−0.00008	−0.00001	0.000002
UK	Exposure to robots	0.00161	−0.0008	0.00122	0.00151	0.00071	0.00016	−0.00001
	Exposure to robots # Share employed in technology and knowledge sectors	0.00001	0.00000	−0.00020*	−0.00005	0.00012	0.00007*	−0.00000
Czechia & Poland	Exposure to robots	0.00119	0.00025	−0.00047	0.00096	0.00039*	−0.00009**	−0.00003***
	Exposure to robots # Share employed in technology and knowledge sectors	−0.00031	−0.00004	−0.00003	−0.00022	−0.00006	0.00002	0.000006**

***1% **5% *10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

reproductive ages and significant in the models for the total fertility. At the same time, the effect of robot adoption on fertility in highly industrialised regions where employment in manufacturing is dominated by men is negative, suggesting that robotisation reduces fertility in such regions. In Czechia and Poland, the interaction between exposure to robotisation and ratio of women's and men's employment in manufacturing is positive at all reproductive ages (like in the UK), but significant only at ages 20–24.

6.4 Educational Attainment of the Population

Subsequently, we test the hypothesis that robots exert a more negative impact on fertility in lower educated regions (H3). We present our findings in Table 4 where the rows 'Exposure to robots' denote the fertility effects of robotisation in regions with low educated populations and the interaction term demonstrates how these effects differ across regions with an increase in the proportion of educated persons by 1 pp.

We find clear support for hypothesis H3 in Germany and Italy. There is some evidence for this hypothesis also in the remaining countries but for France where our findings suggest the opposite.

In Germany, we identify a significantly negative effect of exposure to robots on fertility in regions characterised by lower educational attainment of the population: An increase in the exposure to robotisation by 1 robot per 10,000 workers leads to a decline in total fertility by 0.0016 there. Negative and mostly significant fertility effects are found at all reproductive ages. They clearly weaken with an increase in the proportion of highly educated individuals in a region. We find some traces of a similar pattern in Italy and Czechia and Poland, but the estimated effects are significant only at some ages and in Czechia and Poland some reversed findings are also obtained for the age group 35–39. The educational attainment of the regional population does not seem to matter for the effects of robotisation on fertility in the UK (except for highest reproductive ages where the findings are consistent with our expectations). Finally, in France we find that robotisation has a positive influence on fertility in regions with fairly low educated populations, which is in contrast to our hypothesis H3.

6.5 Region's Orientation at Investments in Knowledge and Technology

Finally, we expected the fertility effects of robotisation to be less negative or more positive in regions which are better able to embrace technological change. We operationalise this ability with the regional investment in technology- and knowledge-intensive sectors, measured by its employment. Only a few findings are consistent with this hypothesis (Table 5).

On the one hand, we find the interaction term between exposure to robotisation and employment in technology- and knowledge-intensive sectors to be significantly negative at lower reproductive ages (25–29) in Germany and the UK. On the other hand, however, the interaction term turns often positive and significant at high reproductive ages. This latter finding emerges clearly in Germany, but also to a lower extent in France, UK and Czechia and Poland, suggesting fertility recuperation (or higher-order fertility) encouraged by increasing employment/earning opportunities and growing prosperity of the region.

7 Discussion

Industrial robots substantially change the conditions of participating in the labour markets and thereby may also affect fertility. On the one hand, there is evidence that robots destroy jobs, increase turnover in the labour market and make workers adjust to the new demands in the labour markets (reskill, upskill or increase work effort to follow the new work guidelines or even keep the job). On the other hand, however, robots may also increase productivity and thereby contribute to the expansion of new jobs, in particular in regions with highly educated workforce open to technological innovations. In this study, we examined whether these long-term structural changes, driven by adoption of industrial robots, affect regional fertility rates in six European countries. We find that fertility effects of robot adoption are rather small and vary across regions, depending on workforce education, employment structure and region's capacity to embrace technological change. Briefly, our findings suggest that robots tend to exert a negative influence on fertility in regions where substantial numbers of workers are exposed to losing their jobs due to automation, i.e. highly industrialised regions (except for Czechia and Poland) and regions with relatively low educated populations (except for France). We also find the fertility effects to be more negative in less technologically advanced regions where robotisation is unlikely to boost productivity and create new jobs. The negative fertility effects are clearly most evident at young ages, especially in regions with large manufacturing sectors and to some extent in regions with lower educated populations. This finding may suggest postponement of fertility to higher ages, though fertility recuperation at older ages does not emerge clearly from our study, except for regions which are strongly oriented at knowledge and technological innovations. These findings are consistent with past research, showing that highly educated individuals, whose skills are valued in the labour market, tend to postpone childbearing into higher ages (Kantorova, 2004; Neels & De Wachter, 2010), but tend to recuperate it so that educational differences in cohort fertility tend to be smaller or even disappear in better developed regions (Nisen et al. 2021).

We also observe some country differences in fertility effects of robot adoption, but the pattern is not very clear. We see the negative effects of robots on fertility to be most pronounced in Germany, which is most advanced in automation among the studied countries. This is despite the strong employment protection in the country. We also observe some negative effects in Italy and less so in the UK. Robotisation in these two countries has progressed more slowly than in Germany, but employment protection is weaker there (in Italy low protection concerns disproportionately the young workers) and support for the unemployed is more limited. We also find the effects of robot adoption to be less disruptive for fertility and even to encourage it in Czechia and Poland. This finding is seemingly striking, but we explain it by the fact that robots are less likely to replace labour in countries with lower labour costs (Bachmann et al., 2022; Jung & Lim, 2020), which Czechia and Poland undoubtedly are in comparison with the Western European states. Moreover, we are puzzled by the fact that consistently with hypothesis H2 we find less negative effects of robot adoption in those British, Polish and Czech regions—where the ratio of women's to men's initial employment in manufacturing was higher—but not in Germany, France or Italy, even though the division of paid work between partners in Germany or Italy is not less asymmetric than in Poland or the UK (Matysiak & Steinmetz, 2008; Matysiak & Vignoli, 2013). One possible explanation for this finding might be related to the fact that women working in manufacturing moved out into the service sector much more quickly than men. Such a phenomenon was indeed observed in countries most advanced in automation (Black & Spitz-Oener, 2010; Cortes et al., 2021), which Germany, Italy and France indeed are. At the same time, the new jobs in the service sector turned out to be characterised by high insecurity and precarity with employers requiring from workers great deal of flexibility (Allen & Henry, 1997; Reimer, 1998). Finally, we find robotisation to exert most negative impact on fertility in regions with low-educated population in all analysed countries except for France. Past studies indeed showed that education is a weaker predictor of the realisation of fertility intentions in France than in Italy (Régnier-Loilier and Vignoli 2011) and that economic uncertainty is less disruptive for fertility in France than in Germany (Salles et al., 2016), likely because of the strong two-child family norm in France, less pronounced specialisation of partners in paid and unpaid labour and generous financial transfers to families, including the unemployment schemes (Pailhé and Solaz 2012). For these reasons, the French may be less sensitive to the risks resulting from long-term developments in the labour markets than other nations we studied. There is no doubt, however, that more in-depth insights are needed into the topic to corroborate our interpretations.

Our study is not without limitations. Due to the anonymisation procedures at Eurostat, some of our data were missing and had to be imputed. As a result our main measure, exposure to robots, contains measurement error, which causes its increased variance in comparison with a perfect measurement. Thus, we expect all regression lines that we fitted to be biased towards 0 (regression dilution/attenuation; Fuller, 1987). Our measure of exposure to robotisation faces other problems as well. Although it is at the forefront of economic research on automation and employment (Acemoglu & Restrepo, 2020; Dauth et al., 2021), it assumes that regional employment structure by sector remains unchanged over time. This assumption is needed in order to keep exposure to robots exogeneous, as the regional employment shares by sector are measured before the start of robotisation. Furthermore, we were not able to include more countries into our study. The adopted instrumental variable strategy, which implied instrumenting robotisation in one European country with robot adoption in other European countries, left us with no possibility to pool all European countries. Comparing a greater number of countries was not feasible since we had to choose countries with a reasonably large number of NUTS-2 regions. Last but not least, our analytical strategy did not allow us to account for possible spatial spillovers which may take place if workers commute to jobs outside of the regions of their residence (Monte et al., 2018). According to our best knowledge, in econometric literature exploiting sectoral composition as a source of local labour demand shocks (Bartik shocks) and in particular discussing the exposure to robots, no solutions to the two above-mentioned issues have been offered so far. We underline them as important areas for future research.

Despite these limitations and some inconsistencies, our findings suggest that long-term structural changes, driven by automation, can indeed affect fertility as it was proposed by Seltzer (2019). Nonetheless, it does not seem robotisation is primarily responsible for fertility declines observed in the aftermath of the Great Recession in most advanced countries. It exerts a negative influence on fertility in certain regions (highly industrialised or low/middle educated), but these effects are compensated by fertility increases in better educated and dynamically developing regions. It is likely that fertility is also affected by other components of structural labour market changes, driven by digitalisation, such as implementation of digital automats which also replace workers but are not classified as industrial robots, spread of remote work or increasingly widespread use of AI. Another possibility is that our study, conducted at the macro level, masks some important nuances such as differential effects of automation on workers' fertility. These effects may certainly differ by workers' gender and socio-economic status (education or occupation) or firm characteristics (firm's capacity to retrain and retain workers). Fertility effects of automation may also depend on the labour market situation of the other partner and whether he or she is affected by automation as well. Future research should thus account for other aspects of long-term structural changes in the labour market, besides automation, and involve individual-level data in order to look more closely into specific circumstances of workers. More research is also needed to unravel the mechanisms which underlie these relationships. Several mechanisms are possible, among them certainly job displacement, job-related uncertainty or pressure to reskill and adapt to new work guidelines and ways of working. Finally, future research should more closely explore the cross-country differences in fertility effects of long-term labour market changes caused, among others, by automation. In particular, it is of vital importance to understand which specific public policies and other institutional factors may mitigate the negative consequences of automation on fertility. Being one of the first attempts to investigate the role of labour market changes, driven by automation, for fertility this single study is not able to address all these questions but certainly aims at stimulating future research on the topic.

Appendix

Reclassifying Industry

The regional employment structure data are aggregates obtained from the European Union Labour Force Survey microdata. We reclassify them to 16 ISIS categories that we operationalise for the robot data using the correspondence table available through the online resources of the United Nations Statistics Division (see Table 6). As can be seen in the table, in some cases, it involves summing employment for 2 or 3 NACE categories to match the ISIC category.

Imputing Regional Employment Structures

Eurostat anonymises records where employment in a specific region, industry, and year was above zero but below 1,000 people, i.e. information is missing for such records. As a result, 50% of employment records were initially missing in the data. In the cases when only observations for specific years for a given region-industry are missing, we impute it by drawing a number between 0 and 1000 from a uniform distribution. In the cases when the entire time series for a given region-industry is missing, we impute it with median employment for that industry in the country, normalised to a 0–1000 range. Since our main explanatory measure (described in detail in the Sect. 5.2 in the main text) relies on a sum of employment over industries, it would be impossible to construct it without assumptions about the missing data. We decided to choose the imputation with median instead of the mean, to robustify the imputed data to extreme values in existing data. One should bear in mind that, after imputation, there is a measurement error in our regional employment data. Thus, the regression coefficient corresponding to our main measure will be downward-biased (regression dilution bias; Fuller, 1987).

Reclassifying NUTS 2 Codes

The NUTS classification of regions underwent a few reclassifications in its history. Eurostat usually publishes regional data for specific years for regions which were operative depending on then-current NUTS classification. To obtain a balanced panel, we reclassify all regional codes, which simply changed name, to the NUTS 2016 classification, using crosswalks available on the Eurostat web page. For the countries and time frame we consider in our analysis, there are eight cases when two or three regions split or merged resulting in changes in the NUTS classification (see Table 7). In those instances, we sum up/average (depending on a variable) data for the smaller regions to obtain consistent data for the larger region. We exclude 5 French overseas territories with distinct socioeconomic setups, not directly comparable to European regions (Guadeloupe, Martinique, French Guiana, La Reunion, and Mayotte).

Table 6 ISIC-NACE industry codes crosswalk for sectors used in our analysis

Category	IFR (ISIC)	Regional employment (na112d)	Regional employment (nace2d)
All other manufacturing branches/other chemical products n.e.c	91, 20–21	30, 37, 23	32, 33, 19
Automotive/other vehicles	29–30	34, 35	29, 30
Basic metals	24	27	24
Construction	F	45	41, 42, 43
Electrical/electronics	26–27	31, 32, 33	26, 27
Electricity, gas, water supply	E	40, 41	35, 36
Food and beverages	10–12	15, 16	10, 11, 12
Glass, ceramics, stone, mineral products (non-automotive)	23	26	23
Industrial machinery	28	29	28
Metal products (non-automotive)	25	28	25
Mining and quarrying	C	10, 11, 12, 13, 14	05, 06, 07, 08, 09
Paper	17–18	21, 22	17, 18
Pharmaceuticals, cosmetics	19	24	20, 21
Rubber and plastic products (non-automotive)	22	25	22
Textiles	13–15	17, 18, 19	13, 14, 15
Wood and furniture	16	20, 36	16, 31

Table 7 NUTS-2 region splits/merges over years (1994–2017)

1994–1998	1999	2000–2001	2002–2003	2004	2005–2010	2011–2012	2013–2017	Action
DE40	DE40	DE40	DE40	DE41	DE40	DE40	DE40	sum DE41 and DE42 to DE40
				DE42				
DEB1	DEB1	DEB0	DEB1	DEB1	DEB1	DEB1	DEB1	sum DEB1, DEB2, and DEB3 to DEB0
DEB2	DEB2		DEB2	DEB2	DEB2	DEB2	DEB2	
DEB3	DEB3		DEB3	DEB3	DEB3	DEB3	DEB3	
DED0	DED0	DED2	DED2	DED2	DED2	DED2	DED2	sum DED2, DED4, and DED5 to DED0
		DED4	DED4	DED4	DED4	DED4	DED4	
		DED5	DED5	DED5	DED5	DED5	DED5	
DEE1	DEE1	DEE1	DEE1	DEE1	DEE0	DEE0	DEE0	sum DEE1, DEE2, and DEE3 to DEE0
DEE2	DEE2	DEE2	DEE2	DEE2				
DEE3	DEE3	DEE3	DEE3	DEE3				
IT31	ITH1	ITH1	ITH1	ITH1	ITH1	ITH1	ITH1	sum ITH1 and ITH2 to IT31
	ITH2	ITH2	ITH2	ITH2	ITH2	ITH2	ITH2	
UKI1	UKI1	UKI1	UKI1	UKI1	UKI1	UKI3	UKI3	sum UKI3 and UKI4 to UKI1
						UKI4	UKI4	
UKI2	UKI2	UKI2	UKI2	UKI2	UKI2	UKI5	UKI5	sum UKI5, UKI6, and UKI7 to UKI2
						UKI6	UKI6	
						UKI7	UKI7	
PL12	PL12	PL12	PL12	PL12	PL12	PL12	PL91	sum PL91 and PL92 to PL12
							PL92	

Table 8 Full basic model results for Germany (see Table 1 in Sect. 6.1)

Covariate	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Exposure to robots	−0.000159	0.0000438	0.0000217	−0.0000215	−0.000110***	−0.0000484***	−0.00000125
Share of population aged 15–24	−1.141**	−0.821***	−0.424***	0.710***	−0.179**	−0.164***	−0.0135***
Share of population aged 25–49	2.184*	−0.0586	−0.579	1.537***	0.978***	0.0514	−0.0156
Share of population aged 50 +	0.522	−0.257*	−0.430**	1.106***	0.141	−0.167***	−0.0225***
Share of highly educated population	−0.00173	−0.00133**	−0.00335***	0.000463	0.00182***	0.000682***	0.0000721***
Ratio of share of highly educated women to share of highly educated men	−0.651***	−0.0780**	−0.140**	−0.223***	−0.127***	−0.021	−0.00263*
Square of ratio of share of highly educated women to highly educated men	0.522***	0.0711***	0.124***	0.161***	0.0980***	0.0183***	0.00183**
Share of economically active women	−0.000723	−0.000145	0.00125*	−0.000427	−0.000933*	−0.000450**	−0.0000538***
Kleibergen-Paap rk Wald F statistic	347.778	347.778	347.778	347.778	347.778	347.778	347.778
Hansen J p-value	0.4002	0.3592	0.4523	0.0432	0.0281	0.2845	0.2264

***1% **5% *10%. $N = 680$, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level

Table 9 Full basic model results for France (see Table 1 in Sect. 6.1)

Covariate	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45+
Exposure to robots	0.000026	−0.000102	0.0000935	0.000118	−0.0000115	−0.0000356	0.00000348
Share of population aged 15–24	−3.278	−3.082***	−0.0862	0.299	0.34	0.0384	0.026
Share of population aged 25–49	−7.505***	−3.952***	−1.944**	−0.307	−0.212	−0.189	0.00224
Share of population aged 50+	−6.268***	−2.929***	−1.067*	−0.579	−0.645***	−0.336***	−0.0457***
Share of highly educated population	0.00187	0.000263	0.00035	0.000389	0.000697**	0.000121	0.0000129
Ratio of share of highly educated women to share of highly educated men	0.223	−0.0326	−0.106	0.17	0.147**	0.0642**	0.00710**
Square of ratio of share of highly educated women to highly educated men	−0.109	0.0116	0.0409	−0.0771*	−0.0637***	−0.0274**	−0.00259**
Share of economically active women	−0.00113	0.000105	0.000387	−0.000880*	−0.000793***	−0.000354***	−0.00000468
Kleibergen-Paap rk Wald F statistic	1042.809	1042.809	1042.809	1042.809	1042.809	1042.809	1042.809
Hansen J p-value	0.6166	0.2884	0.3651	0.4868	0.4660	0.1540	0.8730

***1% **5% *10%. $N=440$, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level

Table 10 Full basic model results for Italy (see Table 1 in Sect. 6.1)

Covariate	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Exposure to robots	−0.00118*	−0.000196	−0.000898***	−0.000116	0.00014	−0.0000473	0.00000823
Share of population aged 15–24	−9.167***	−4.185***	−3.894***	0.368	−0.686	−0.461***	−0.0355*
Share of population aged 25–49	−7.001***	−1.823***	−4.355***	−0.810***	0.14	−0.167*	−0.02
Share of population aged 50 +	−6.623***	−2.395***	−3.063***	−0.321*	−0.373**	−0.264***	−0.0108
Share of highly educated population	−0.00181	−0.000107	−0.00257**	−0.00181*	0.000255	0.00118***	0.000136*
Ratio of share of highly educated women to highly educated men	−0.0448	−0.109	−0.0746	0.105	0.0448	−0.0258	−0.00212
Square of ratio of share of highly educated women to highly educated men	0.0536	0.0511*	0.0308	−0.0308	−0.00361	0.0113	0.000552
Share of economically active women	0.00296	0.00197***	0.000202	−0.000201	0.00083	0.0000921	0.0000639
Kleibergen-Paap rk Wald F statistic	175.284	175.284	175.284	175.284	175.284	175.284	175.284
Hansen J p-value	0.2683	0.3285	0.1599	0.7500	0.1742	0.5438	0.3200

***1% **5% *10%. $N = 400$, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level

Table 11 Full basic model results for the UK (see Table 1 in Sect. 6.1)

Covariate	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45+
Exposure to robots	0.00168	−0.000872	0.000793	0.00133	0.00109	0.000386*	−0.00000172
Share of population aged 15–24	0.555	−2.063***	0.595	2.364***	1.35	0.16	−0.0840***
Share of population aged 25–49	−0.491	−1.086*	−0.437	1.422	0.803	−0.0106	−0.0516*
Share of population aged 50+	2.041	0.0326	0.372	1.462**	0.918	0.032	−0.0430*
Share of highly educated population	0.000193	0.000994	−0.000392	−0.00058	−0.000765**	−0.000104	0.0000304*
Ratio of share of highly educated women to share of highly educated men	1.032***	0.213*	0.241*	0.367***	0.224**	0.0436	-0.000287
Square of ratio of share of highly educated women to highly educated men	−0.490***	−0.107*	−0.105	−0.169***	−0.110***	−0.0223	−0.0000613
Share of economically active women	−0.00260*	−0.000123	−0.000653	−0.000624	−0.000863**	−0.000277**	−0.0000203
Kleibergen-Paap rk Wald F statistic	137.303	137.303	137.303	137.303	137.303	137.303	137.303
Hansen J p-value	0.0363	0.0847	0.6383	0.0140	0.0815	0.1513	0.0684

***1% **5% *10%. $N=700$, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level

Table 12 Full basic model results for Poland and Czechia (see Table 1 in Sect. 6.1)

Covariate	TFR	FR 20–24	FR 25–29	FR 30–34	FR 35–39	FR 40–44	FR 45 +
Exposure to robots	0.000530	0.000104	−0.000436	0.000501	0.000253*	−0.0000469	−0.0000119
Share of population aged 15–24	−1.043	−0.893	0.506	2.092***	−1.640***	−0.801***	−0.0889***
Share of population aged 25–49	−6.482**	−2.873***	−1.501	1.013	−1.432***	−0.683***	−0.0819***
Share of population aged 50 +	−3.253***	−1.658***	−0.478	1.379**	−1.273***	−0.616***	−0.0698***
Share of highly educated population	0.00325	−0.00108	0.000824	0.00320***	0.000581	−0.000123	0.0000267
Ratio of share of highly educated women to share of highly educated men	0.151	0.0122	−0.263***	0.166	0.171**	0.0228	0.00496*
Square of ratio of share of highly−educated women to highly educated men	−0.0445	−0.00413	0.104***	−0.0581	−0.0580**	−0.00915	−0.00182*
Share of economically active women	0.00692**	0.00185	0.00518***	0.000411	−0.000553	0.0000953	−0.0000223
Kleibergen-Paap rk Wald F statistic	45.992	45.992	45.992	45.992	45.992	45.992	45.992
Hansen J p-value	0.1429	0.0456	0.0299	0.2654	0.1859	0.1341	0.1430

***1% **5% *10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10680-023-09657-4.

Acknowledgements This research was possible thanks to financial supported granted by the Polish National Agency for Academic Exchange (Polish Returns Programme 2019) and two ERC Consolidators Grants "Globalisation- and Technology-Driven Labour Market Change and Fertility" (LABFER, grant agreement no 866207) "Economic Uncertainty and Fertility in Europe" (EU-FER, grant agreement no DLV-725961). We also acknowledge very useful comments and suggestions we received at various stages of this research from Wolfgang Dauth, Lucas van der Velde and Daniele Vignoli as well as the researchers from the Interdisciplinary Centre for Labour Market and Family Dynamics (LABFAM, University of Warsaw).

Funding Anna Matysiak is a co-editor of the special issue "Families in the Changing World of Work", a member of the Editorial Board of the European Journal of Population and Secretary-General and Treasurer of the European Association for Population Studies. All funding sources of the research were listed in the Acknowledgments and none of them has influenced the outcomes presented in this publication.

Declarations

Conflict of interests The authors declare no conflicts of interest associated with this publication.

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2.2 Paper II: *Structural labour market change, cognitive work, and entry to parenthood in Germany*

Paper II

"Structural labour market change, cognitive work, and entry to parenthood in Germany"

H. Bogusz, A. Matysiak, and M. Kreyenfeld

Commentary

Technological change and globalization have transformed the structure of labor demand in developed countries, and the *task content of jobs* methodology has been the most common approach to describe and quantify these changes (Acemoglu & Autor, 2011; Autor et al., 2003; Hardy et al., 2018; Spitz-Oener, 2006). This approach posits that occupations consist of different tasks, some of which are easier to automate or offshore than others. More specifically, there appears to be a growing divide in work prospects between workers who perform cognitive tasks (which are in high demand) and those engaged in non-cognitive (i.e., routine or manual) tasks, which are in decreasing demand. These task indicators arguably capture the long-term labor market situations of individuals more effectively than traditional indicators like education. Thus, they can be used to examine whether the structural labor market changes driven by technology and globalization influence family formation—a salient question given the ultra-low fertility rates in contemporary Europe.

In this study, we focus on entry into parenthood, specifically the first birth. We link the cognitive task content of occupations, constructed using data from the Employment Survey of the German Federal Institute for Vocational Education and Training[3], to individual histories from the German Socio-Economic Panel, 1984–2018[4]. We employ event-history hazard models to analyze the transition to parenthood, with task content as the main time-varying variable. For easier interpretation of the results, we estimate predicted cumulative first-birth probabilities for certain "ideal types" of workers. This approach allows us to disentangle birth quantum from timing.

We find that both women and men in highly cognitive jobs delay entering parenthood but eventually accelerate it, making them the least likely to remain childless by age 50. These differences emerge after 2000, with no such disparities visible in earlier periods. These findings suggest that structural shifts in the labor market are exacerbating disparities between low-skilled and highly-skilled individuals, not only within the labor market but also in family formation.

The idea for the study emerged during my discussions with Anna Matysiak. I actively contributed to developing the conceptual framework, suggested and prepared the data, developed the analytical strategy, and conducted the statistical analysis. I prepared all plots and tables presented in the paper. I participated in the literature review, wrote the first version of the paper and edited all subsequent versions. In addition, I presented the paper at several conferences, including Population Association America Annual Meeting (2022) and European Population Conference (2022), and am the corresponding author. The codes employed for the analysis are publicly available on Github.

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[4]Socio-Economic Panel (SOEP), 2021.

Population Studies
A Journal of Demography

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rpst20

Structural labour market change, cognitive work, and entry to parenthood in Germany

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Population Studies, 2024
https://doi.org/10.1080/00324728.2024.2372018

Structural labour market change, cognitive work, and entry to parenthood in Germany

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Technological change and globalization have caused unprecedented transformations of labour markets, resulting in a growing division between workers who perform cognitive vs non-cognitive tasks. To date, only few studies have addressed the fertility effects of these long-term structural changes. This study fills that gap. We measure the cognitive task content of occupations using data from the Employment Survey of the German Federal Institute for Vocational Education and Training, which we link to individual histories from the German Socio-Economic Panel 1984–2018. We find that women and men with non-cognitive jobs are increasingly less likely to enter parenthood; this is reflected in lower first-birth intensities but also in higher probabilities of childlessness compared with workers in highly cognitive jobs. These findings imply that structural shifts in the labour market are exacerbating disparities between low-skilled and highly skilled individuals, not only within the labour market but also in the realm of family formation.

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

[Submitted April 2023; Final version accepted February 2024]

Introduction

Over the last three decades, technological change and globalization have led to substantial transformations of labour markets in advanced economies (World Bank 2019). These structural labour market changes have also created new divisions in the sphere of work, resulting in growing inequalities in earnings, job stability, job flexibility, and career opportunities among workers. The new demarcation line seems to run between workers who perform mainly cognitive tasks and those who perform mainly non-cognitive tasks. The labour demand for the former has been on the rise, as cognitive skills —either analytic or social/interpersonal—are increasingly sought after in the rapidly expanding high-tech sectors and in specialized consumer service, business, and education (Acemoglu and Autor 2011; Cortes et al. 2023). As a result of the development of information and communication technologies, cognitive workers increasingly enjoy higher flexibility in where and when they work, although often at the price of greater responsibility for their work outcomes (Van Echtelt et al. 2009; Kvande 2017). At the same time, the demand for workers who perform non-cognitive tasks, in particular routine manual tasks, has been on the decline, as these sorts of tasks can be easily automated or offshored to countries with lower labour costs (Acemoglu and Autor 2011; World Bank 2019).

These developments may not only increase labour market disparities between more highly skilled and lower-skilled workers but may also affect family behaviour, including the decision whether and when to become a parent. There has been broad consensus among demographers that earnings prospects (Oppenheimer 1997; Hart 2015), job stability (Adsera 2011; Hofmann et al. 2017; Alderotti et al. 2021), and the compatibility of paid work with family life (Begall et al. 2015; Wood et al. 2020; Osiewalska et al. 2024) are important determinants of family formation. Growing demand for highly skilled workers and increasing flexibility of work schedules provide cognitive workers with better opportunities for earning income and combining paid work with family life, thereby improving their conditions for having children. The same structural developments in the labour market, however, worsen low-skilled workers' conditions for having children by making certain non-cognitive job tasks and occupations redundant (Arntz et al. 2016; Nedelkoska and Quintini 2018) and by depriving these workers of employee-oriented flexibility (Chung 2018). As structural changes in the labour market are permanent in nature (in contrast to economic recessions, which are cyclical and temporary), they may lead to long-term changes and divergences in the fertility behaviour of workers in occupations requiring non-cognitive vs cognitive tasks. It is thus imperative to understand how these labour market changes affect childbearing, not only for explaining past trends in fertility but also to provide insights about its future developments.

In this study, we take a first step in that direction. In particular, we examine how long-term structural changes in the labour market are associated with the process of entering parenthood and whether they lead to different patterns of first births between workers with jobs that are in high demand on the labour market, as opposed to those in jobs exposed to automation or offshoring. To date, this question has not been addressed. Past demographic research has provided rich evidence on how unemployment, income, type of work contract, and subjective measures of employment and financial uncertainty relate to birth behaviour, including entry to parenthood (Kreyenfeld 2010; Adsera 2011; Vignoli et al. 2012; Alderotti et al. 2021). Further, scholars have examined how the process of becoming a parent is influenced by non-standard or flexible work schedules or the opportunity to work from home (Begall et al. 2015; Matysiak and Mynarska 2020; Osiewalska et al. 2024). By drawing on established measures of employment and economic vulnerability, these studies have shown how economic uncertainty and difficulties with combining paid work and care affect the transition to parenthood and that patterns differ by context and sex. In this study, we add to those findings by examining how first-birth behaviour is related to the digitalization- and globalization-induced changes in labour markets.

To capture the recent structural changes in the labour market, we follow the *task-based approach*, which has recently been adopted in labour market economics (e.g. Autor et al. 2003; Arntz et al. 2016; De La Rica et al. 2020). This approach presupposes that jobs consist of a variety of tasks that require certain skills. Since technology and globalization 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. In contrast to occupations with low cognitive task content, those with high cognitive task intensity offer better long-term labour market opportunities for earning income and flexible organization of the workplace and working time, although sometimes at the price of blurred boundaries between paid work and family life and also high work intensity (Van Echtelt et al. 2009; Kvande 2017).

The great benefit of the task-based approach is that it not only describes the relationship between the task content of work and labour market change but it also offers a toolkit for measuring the task intensity of work by relying on occupational codes. We measure the task content of occupations using data from the Employment Survey run by the German Federal Institute for Vocational Education and Training (see Bundesinstitut für Berufsbildung (BIBB), Berlin, and Institut für Arbeitsmarkt- und Berufsforschung (IAB) der Bundesanstalt für Arbeit, Nürnberg 1983, 1995, 2016; Jansen and Dostal 2015; Hall et al. 2020a, 2020b; 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. 2019) for the years 1984–2018. We use event-history models to model transition to parenthood, with task content as the main time-varying variable. For easier interpretation of the results, we estimate predicted cumulative first-birth probabilities for certain 'ideal types' of workers. Because the GSOEP data (Release 37) provide us with information from 1984 to 2018, this gives us the opportunity to examine a 35-year period that encompasses both the early and advanced stages of digitalization- and globalization-driven labour market change, allowing us to examine how structural labour market changes have been associated with first-birth patterns over time.

Background

Changing demand for job tasks and rising work autonomy

Globalization and the adoption of new technologies have led to tremendous changes in the structure of tasks demanded in the labour market (Autor et al. 2003; Acemoglu and Autor 2011). It has been widely demonstrated that workers who can perform abstract tasks (also called non-routine cognitive tasks) are in the greatest demand (Autor et al. 2006; World Bank 2019; Cortes et al. 2023). Abstract tasks require creativity, problem-solving, and complex organization and communication, and they are not easy to automate or offshore. These tasks can be *analytic* (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 carry out non-cognitive routine tasks (which are repetitive and involve following easily programmable rules) and non-cognitive manual tasks (which require motor skills or physical strength).

Workers who are able to perform abstract tasks are increasingly likely to find and maintain employment (Autor et al. 2006; Deming 2017) 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 for workers whose skill levels do not enable them to perform abstract tasks have been deteriorating sharply (Hardy et al. 2018; World Bank 2019). These processes have resulted in growing inequalities between workers in cognitive and non-cognitive jobs 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.

Workers who can perform abstract tasks have not only benefited from the increased demand for their skills but have also been granted greater work autonomy. Closely related to the rise of information and communication technologies, opportunities to work flexible hours or engage in home-based teleworking have increased rapidly in recent years (Rubery 2015; Arntz et al. 2022), mostly benefiting workers with cognitive skills, for example managers and professionals (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). However, empirical research has also pointed out some potential negative consequences of work schedule and workplace location flexibility—such as longer working hours (Felstead and Henseke 2017; Kvande 2017), round-the-clock availability (Presser 2003), more fragmented working time, and blurred boundaries between paid work and family life (Lott and Abendroth 2023)—all of which can ultimately lead to intensification of work–family conflict.

These changes in the labour market have affected both women and men. However, women have 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 taken mainly by women, this pattern is currently observed only among earlier birth cohorts (Brussevich et al. 2019). Meanwhile, low-skilled jobs that involve manual tasks continue to be taken mainly by men (Yamaguchi 2018; Brussevich et al. 2019). At the same time, men are more likely than women to work in highly skilled occupations that involve performing intensive analytic tasks or social/interpersonal tasks that require managerial skills (Liu and Grusky 2013; Matysiak et al. 2024). These kinds of jobs usually give workers high autonomy in how, where, and when work is carried out (Golden 2008; Cukrowska-Torzewska et al. 2023). By contrast, in most European countries, women are over-represented in occupations that involve social/interpersonal tasks oriented towards providing interactive services to others (e.g. healthcare, teaching, nursing), and these occupations are often associated with lower wage returns (England 2005; Liu and Grusky 2013; Matysiak et al. 2024) and less flexibility (Golden 2008; Cukrowska-Torzewska et al. 2023).

Structural labour market changes and parenthood

The structural labour market transformations will likely have had serious implications for fertility behaviour, including transition to first child, as they have greatly altered the conditions for earning income and combining paid work with childcare, conditions that have been shown to be important determinants of family formation (Hofmann et al. 2017; Greulich et al. 2018; Marynissen et al. 2020; Alderotti et al. 2021). Scholars have posited that patterns are gendered and context specific. In (modernized) male breadwinner societies such as Germany, men's earnings and their stable employment are crucial for entering parenthood (Kreyenfeld et al. 2012; Andersson et al. 2014). In line with this argument, empirical research has shown that couples in which the male partner is employed and has high earnings are more likely to transition to first birth, whereas couples in which the male partner is unemployed or has a time-limited working contract are more likely to postpone parenthood until the uncertainty around the man's labour market position is resolved (Kreyenfeld et al. 2012). It is thus highly likely that structural labour market changes have created better conditions for parenthood for men employed in cognitive jobs, by improving their earning opportunities. At the same time, they have led to a worsening of employment and earning conditions for non-cognitive workers, thereby lowering their chances of family formation.

The impact of women's economic activity on transition to first birth is more ambiguous. Conventional theoretical approaches have argued that due to the combination of gendered care patterns and incompatibility of employment with care obligations, having children is associated with high opportunity costs for women. Therefore, women who are on a promising career track are likely to postpone the transition to motherhood or remain childless altogether (e.g. Gustafsson 2001). More recent theoretical approaches have challenged this view, however, pointing to the expansion of policies that facilitate work–family reconciliation by increasing access to childcare and income-related parental leave, the spread of more egalitarian gender role attitudes, and greater involvement by men in childcare and housework (McDonald 2000; Esping-Andersen and Billari 2015; Goldscheider et al. 2015).

Structural labour market changes may further erode the role of the traditional family model for childbearing in future. Growing economic uncertainties create a need for both partners to participate in the labour market to diversify the risks of a job loss for the household income. At the same time, the increasing flexibility to choose when and where to work may improve the reconciliation of paid work and childcare, making it easier for working women to have children than in the past. However, this increase in work autonomy does not affect all women but rather those in cognitive jobs and, more often, jobs involving analytic work. Structural labour market changes may thus improve the conditions for having children for women in cognitive jobs but not necessarily for women in non-cognitive jobs, for which the increasing pressure to work for pay is not accompanied by higher flexibility in work schedules and work location. In other words, structural labour market changes may improve the conditions for becoming a mother among women in cognitive occupations but not for women in non-cognitive jobs.

Country context

This study is conducted on Germany. Germany's labour market is known for its heavy demand for highly skilled labour (Spitz-Oener 2006; Rohrbach-Schmidt and Tiemann 2013). The transformation of Germany's economy into a knowledge economy began in the late 1960s. Germany maintained its manufacturing traditions but invested strongly in modernization and digitalization of manufacturing (Thelen 2019). Like other countries, it also experienced a substantial increase in occupational complexity, with abstract job tasks, both analytic 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 among men (Black and Spitz-Oener 2010).

The structure of the labour market makes Germany an ideal test case for examining the consequences of digital transformation on family behaviour. It is also ideal for showcasing the role of sex differences in this transformation due to its strongly gendered care patterns. Germany used to be classified as a conservative welfare state model (Esping-Andersen 1990; Amable 2003) that was based on strong employment protections and coordinated bargaining systems (Amable 2003). The sole breadwinner model was supported by the tax and transfer system, and the limited availability of full-time day care inhibited mothers' labour market integration. In 2007, a parental leave reform was enacted, introducing an income-related parental leave that reserved two months of leave for each parent (often referred to as the '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 day-care slot was introduced for all children aged one year and older. The large majority of couple households with children are organized as dual-worker households. In 2019, for example, 65 per cent of couple households with children were dual-earner households, only 29 per cent were single-earner households, and in 6 per cent of cases neither of the partners worked (BMFSFJ 2023). While large fractions of mothers work, most work only part-time (Boll and Lagemann 2019; Müller and Wrohlich 2020), especially in West Germany (Stahl and Schober 2018).

With respect to birth patterns, West Germany has experienced a steady postponement of first childbirth in recent decades. While age at first childbearing was around age 24 in the 1960s (Kreyenfeld 2002), it had increased to around age 30 by 2020 (DESTATIS 2023). Cohort fertility rates used to be the lowest and childlessness among the highest of all European countries (Sobotka 2017). For example, cohort fertility declined from 1.72 for women born in 1950 to only 1.56 for those born in 1965 (Human Fertility Database 2023). Further, birth patterns differed radically by women's education. For the 1950s cohorts, around 20 per cent of (West) German women remained childless overall, whereas among university-educated women ultimate childlessness was around 30 per cent (Kreyenfeld and Konietzka 2017, p. 30). In more recent years, educational differences in childlessness among women have narrowed (Kreyenfeld and Konietzka 2017, p. 105). At the same time the association between employment characteristics and fertility has become less gendered than in the past. Thus, not only men's but also women's unemployment and low wages have been reducing first-birth rates (Lambert and Kreyenfeld 2023). Important to note is that East–West differences in fertility behaviour have largely converged since unification, but some small differences in ages at first birth have persisted, however (e.g. Goldstein and Kreyenfeld 2011).

Hypotheses

Given that women's and men's labour market opportunities affect the process of becoming a parent, it is likely that these ongoing structural labour market changes will be manifested in first-birth patterns. Thus, a first guiding hypothesis is that work with a low cognitive task intensity will be reducing first-birth probabilities relative to work with a medium or high cognitive task intensity (*Hypothesis 1a*). We also anticipate that the structural changes in the labour market will be increasing employment, earnings, and flexible work opportunities disproportionally strongly for workers in jobs with high cognitive task intensity. As a result, first-birth patterns should be increasingly diverging over time between workers in occupations characterized by low and high cognitive task intensity (*Hypothesis 1b*).

Fertility and employment patterns may have been gendered in the past, but as women's participation in the labour market and men's participation in childcare have increased, we expect that the transition to parenthood will be becoming more similar for men and women over time (*Hypothesis 2a*). We may assume that this convergence applies to both analytic and interactive cognitive occupations, although some sex differences may emerge for occupations which require high interactive task content. As mentioned earlier, occupations with high interactive task content requiring managerial skills are more often chosen by men, while women more often choose interactive occupations that involve providing services to others (e.g. healthcare, teaching, nursing) (Liu and Grusky 2013; Matysiak et al. 2024). The former occupations are usually better paid and provide more flexibility. We thus expect the convergence among women and men in transition to first birth to be stronger for analytic than for interactive tasks (*Hypothesis 2b*).

Data and measures

Data sources

In our study we make use of two data sources. The main data set is the GSOEP (Release 37), which we use to model the relationship between men's and women's occupational histories and first-birth transitions. The GSOEP is longitudinal panel survey, ongoing since 1984. These data are well suited to our investigation as the survey collects complete fertility histories from both men and women and includes three-digit occupational codes for the employed (Goebel et al. 2019). It is worth noting that several subsamples have been included in the GSOEP across time (e.g. a sample that included the East German population in 1990 and several migration and refreshment samples).

We limit our sample to childless individuals of childbearing age (20–49). We do not include respondents below age 20, because these individuals are predominantly in education; thus, their current labour market situation is unlikely to be a determinant of their fertility. We also limit the sample to individuals with German citizenship and to respondents who provided valid information in the birth biographies (around 2 per cent had missing information). We include all data for the years 1984–2018, but as we lag the main covariates by two years, we observe fertility in the period 1986–2018. By doing so, we cover a large part of the period when Germany was undergoing the transition to becoming a knowledge economy, including the structural labour market changes caused by globalization and digitalization (Thelen 2019; Dauth et al. 2021). It should, however, be noted that East Germany is included only from 1990. Finally, very specialized subsamples, such as the refugee sample, the high-income sample, and the LGBTQ+ sample are excluded from the analysis. We organize our data in long format, with each survey year contributing one entry to our sample. Thus, individuals are right-censored when they drop out of the survey or when they reach age 49. They are left-truncated if they enter the survey at over 20 years old. The total number of person-years in the sample is 101,440, and the number of events (first births) is 3,989.

To construct the task measures at the occupational level, we use the BIBB Employment Survey. These measures are next linked to our analytical sample from the GSOEP via the three-digit occupation codes included in the employment biographies. The BIBB Employment Survey is a repeated cross-sectional survey that has been conducted every six to seven years since 1979, with seven waves so far (1979, 1986, 1992, 1999, 2006, 2012, and 2018). It contains detailed information on job characteristics, such as tasks performed at work (e.g. programming, cleaning, teaching), work location, work schedules, working hours, contract types, and wages. These data allow us to identify which occupations involve mainly abstract tasks and to differentiate between analytic and interactive task content. Using the three-digit occupational codes, this information is merged with the GSOEP data.

Independent variables

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 adapted to the German context by Spitz-Oener (2006) and Rohrbach-Schmidt and Tiemann (2013). We classify tasks as 'analytic' or 'interactive' following the criterion validation method suggested in Rohrbach-Schmidt and Tiemann (2013). The analytic domain quantifies activities that are non-manual and non-routine (e.g. programming, researching), while the interactive domain quantifies non-repetitive tasks that require human interaction (e.g. consulting, managing). The exact task items that we measure and their availability in consecutive waves are displayed in Table 1.

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

$$j\,\text{task measure}_{ot} = \frac{\sum_{i=1}^{N} j\,\text{task measure}_{oit}}{N} \tag{1}$$

where:

$$j\,\text{task measure}_{oit} = \frac{\text{number of items in category } j \text{ performed by } i \text{ in time } t}{\text{total number of items in category } j \text{ in time } t} \tag{2}$$

and o = occupation, i = individual, $j \in$ {analytic, interactive}, and $t \in$ {1979, 1986, 1992, 1999, 2006, 2012, 2018}. Equation (2) corresponds to the measure first developed in Spitz-Oener (2006) and applied in (among others) Black and Spitz-Oener (2010) and Rohrbach-Schmidt and Tiemann (2013). Its values range from zero to 100, and it 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 the five analytic task items considered (see Table 1). Then, their analytic task measure is $(4/5) \times 100 = 80$. We average Equation (2) over individuals to obtain Equation (1): a measure at occupation level that can then be merged with individual data from the GSOEP by three-digit occupational code. We interpret this as reflecting the extent to which an occupation has high analytic or interactive task intensity. Since we have measures for seven points in time, we use a simple linear interpolation to obtain observations between the available time points.

The continuous task measures are transferred into the following five categories: low [0, 33), medium [33, 66), high [66, 100], in education, and the residual category (inactive, unemployed, occupation missing). We do not use them as continuous variables, to account for individuals without valid task measures in the sample. Individuals who were not

Table 1 Availability and classification of the task items in the BIBB Employment Survey, Germany

Number	*Task item*	*Waves available*	*Task category*
1	Investigating	1999, 2006, 2012, 2018	Analytic
2	Organizing	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

Note: Waves to date were conducted in 1979, 1986, 1992, 1999, 2006, 2012, and 2018.
Source: BIBB Employment Survey; Rohrbach-Schmidt and Tiemann (2013).

working (inactive, unemployed, in education) have no valid occupational codes.

Besides the respondent's age, we control for the following individual characteristics: region of residence (West/East Germany), number of siblings (zero, one, two or more), and calendar period. Task measures and residence are time-varying and lagged by two years to account for the duration of pregnancy (one year in year-based analysis) and the fact that an individual might take some time to decide whether to have children, given their labour market situation.

Method and analytical strategy

This analysis is conducted separately for women and men. With annual data at our disposal, we model the transition to first birth using hazard models with a complementary log–log function of form:

$$\log\left[-\log\left(1-\lambda\right)\right] = \beta' x \tag{3}$$

where the fitted probability $\hat{\lambda}$ can be expressed:

$$\hat{\lambda} = 1 - \exp[-\exp(\beta' x)] \tag{4}$$

The function from Equation (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 Equation (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 t is the respondent's biological age divided into five intervals: 20–24, 25–29, 30–34, 35–39, and 40–49.

The models just specified allow for an assessment of the general relationship between the cognitive content of women's and men's work and their entry to parenthood (Model 1). We are, however, also interested in investigating how these relationships have changed over time. To this end, we interact individuals' task measures with time period (Model 2).

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 individuals 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 would lead them to accelerate childbearing (Impicciatore and Tomatis 2020). This aspect is relevant for us, as our event-history model relies on the proportionality assumption, which 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. To test for this possibility, we interact individuals' task measures with age (Model 3). This model is first estimated on the full sample, covering the years 1984–2018. However, to be able to trace changes in the relationship between task content of occupations and first-birth probabilities over time and to account for differences in birth timing across different task categories, we also estimate Model 3 on two subsamples, for the periods 1984–99 and 2000–18 (Models 4a–b). While the findings from Models 1–3 are displayed as average predicted probabilities, we use the estimates from Models 4a–b to generate cumulative incidence curves for some specific covariate constellations. Cumulative incidence curves are presented to better understand and illustrate the differences in the timing and probability of having a first child between workers with high and low cognitive task intensity. The cumulative incidence curves require us to select specific covariate constellations. We compute cumulative incidence for three cases (ideal types):

- Case 1: A person who enters the labour market before age 20 and works in an occupation characterized by low task intensity.
- Case 2: A person who finishes education at age 24 and then works in an occupation characterized by medium task intensity.
- Case 3: A person who stays in education until age 29 and then works in an occupation characterized by high task intensity.

We choose these cases based on descriptive analysis of lifetime employment patterns, where we plot mean analytic and interactive task measures (respectively) across age by highest task measure ever achieved at age 35+ (Appendix Figure A1).

Results

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 construct are indeed associated with higher wage returns, more flexibility (in terms of time schedule and work location), greater work demands and higher work pressure, as past research on cognitive work has suggested. In this way we check whether our measures reflect the phenomena we discussed earlier. Second, we study the developments in cognitive task measures over time to see whether our measures indicate an increase in the cognitive task content of work, as might be expected based on the past literature.

First, to examine if the measures of cognitive task content of work are indeed related to higher wage returns, greater flexibility, and also higher work intensity, we pool two waves of the BIBB Employment Survey (2006, 2018). We next regress 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), and monthly gross wages, and also time dummies and two socio-demographic characteristics (age, education). The findings from these models are presented in Appendix Table A1, by sex and task measure. 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 between the analytic task measure and wages, although there is no association between wages and the interactive measure for women. This finding is supported by the work of Matysiak et al. (2024) who showed that women are over-represented in 'outward oriented' interpersonal tasks (e.g. care, teaching), which are associated with lower wage returns than the 'inward oriented' social tasks (e.g. managerial) exercised largely by men.

Second, we examine whether our measures point to an increase in the cognitive task content of work in our sample over time, as would be expected on the basis of past research. Figure 1 displays the distribution of our main independent variables for our first-birth sample (comprising nulliparous women and men). It points to a dramatic decline in occupations with low cognitive task intensity and an increase in occupations with medium cognitive task intensity among childless women and men. It also shows that childless individuals hardly ever worked in highly cognitive occupations in the 1980s and early 1990s, with such roles starting gradually only later. Finally, the figures indicate that childless men in our sample take on occupations characterized by high analytic task intensity more often than women, whereas women are more often in occupations that display high social/interactive task intensity. This observation is expected, as women are over-represented in professions that require human interactions (Matysiak et al. 2024) but under-represented in STEM occupations (those involving science, technology, engineering, and mathematics; Eurostat 2022).

Cognitive work and first birth: Overall association

We now move to a discussion of the relationships between cognitive work and first-birth transitions. Figure 2 presents the average predicted probabilities of first birth by respondents' cognitive task intensity from Model 1 (full results are presented in Appendix

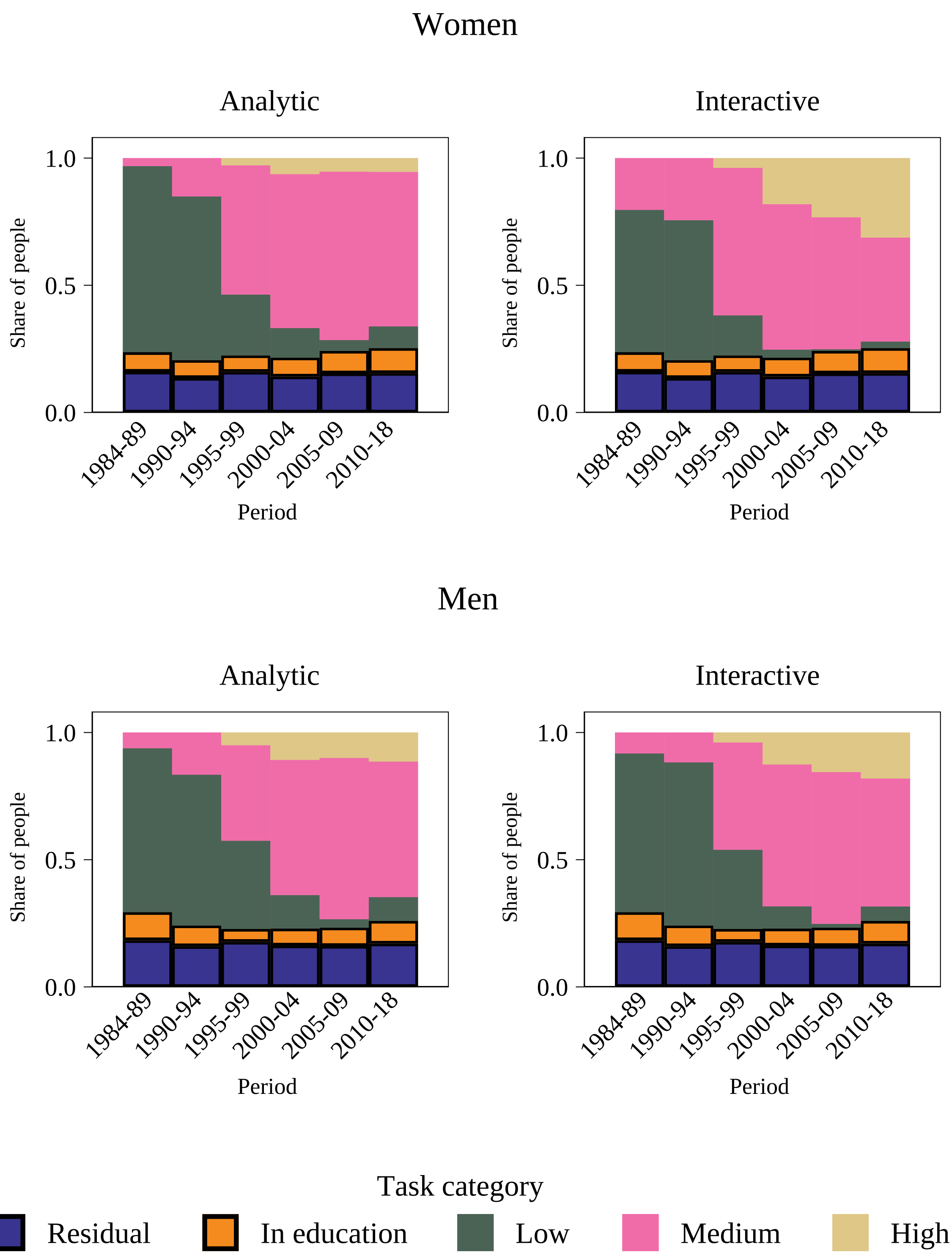

Figure 1 Share of nulliparous GSOEP respondents by task category, sex, and calendar period, Germany
Note: Person-years = 45,177 for women, 56,263 for men. The residual category is composed of inactive, unemployed, and individuals with missing occupation. Low, medium, and high refer to intensity of cognitive tasks.
Source: Authors' analysis of data from BIBB Employment Survey and GSOEP.

Table A2). The figure shows low first-birth rates for women and men who are in education. First-birth rates are also low for the residual category (composed of individuals who are not in the labour market for reasons other than being in education). Our main interest is the effect of the analytic and

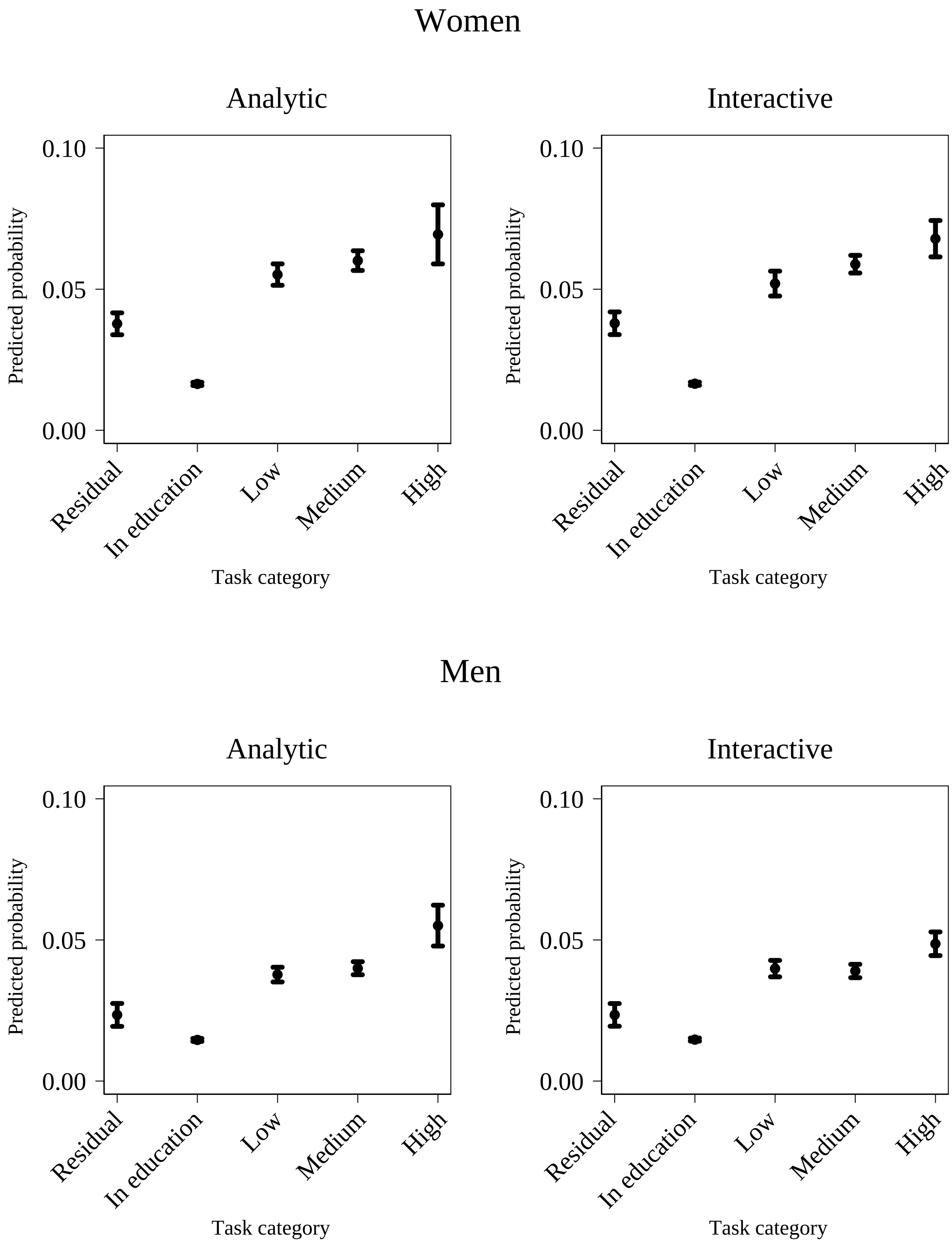

Figure 2 Average predicted probabilities from first-birth models (with 83 per cent confidence intervals), Germany

Notes: Further controls in the model are age (time-varying), period, residence (West vs East Germany), and number of siblings. Reference category = low task measure [0, 33). Person-years = 36,075 for women, 45,100 for men. Low, medium, and high refer to intensity of cognitive tasks.

Source: As for Figure 1.

interactive task measures. We observe a positive gradient for women: that is, the higher the cognitive task intensity (analytic and interactive), the higher the first-birth probability. Men in jobs with high analytic or interactive task intensity exhibit significantly higher first-birth probabilities than men in jobs with low or medium task intensity. There is no difference in first-birth probabilities between men in jobs with low and medium task intensity.

Developments over time

In the second step of our analysis, we interact the task measures with calendar period to study how first-birth probabilities have evolved over time for people with different levels of cognitive task intensity (Model 2). Figure 3 presents the average predicted annual probabilities from those estimations. The findings are similar for both task measures. We note a decline over time in first-birth probabilities for women and men in jobs with low cognitive task intensity (both analytic and social/interactive), for women and men in education, and for non-working women. At the same time, we see that first-birth probabilities have hardly changed over time for women and men in jobs with medium or higher levels of cognitive task intensity. The only exception is for women in jobs with high social/interactive task intensity, among whom first-birth probabilities increased somewhat between 2000–07 and 2008–18.

Interaction with age

Next, we interact task measures with age (Model 3) as we expect that, among respondents in jobs with high task intensities, transition to first birth will be accelerated at higher ages, as such respondents enter the labour market later and may postpone 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 4 support this view. The first-birth schedules for women and men in jobs with medium and high task intensities are different from those for other men and women. We see that the birth probabilities for these groups peak at later ages. For women who perform tasks with low cognitive intensity, first-birth probabilities peak at ages 25–29, and for those who perform tasks of medium cognitive intensity the peak is at ages 30–34, whereas for women in jobs with high cognitive task intensity it extends to ages 35–39. The overall pattern is similar for men with the difference that first births are even more delayed.

Cumulative incidence

So far, we have demonstrated that individuals with highly cognitive jobs exhibit higher first-birth probabilities than those whose jobs require low cognitive task intensity and that the differences in first-birth probabilities between the two categories have increased over time. We have also seen that individuals who eventually work in jobs high in cognitive task intensity tend to postpone childbearing until they acquire the necessary skills to take on such jobs and accelerate their entry to parenthood afterwards. A question which emerges here is whether the raised first-birth intensities among workers with highly cognitive jobs can be attributed only to these shifts in first-birth timing or whether these individuals are also becoming less likely to be childless than those in jobs with low cognitive task intensity.

The results from the standard event-history models do not readily answer this question. However, using the event-history model results to calculate cumulative incidence curves helps to display the results in a manner that enables us to gauge differences in timing and quantum. To this end, we first estimate Models 4a–b, in which task intensity is interacted with respondents' age. Further, the models are estimated on two subsamples (for the periods 1984–99 and 2000–18). We next compute the cumulative incidence, which is defined as 1 – survivor function (calculated from the predicted hazard). Unlike the hazard rate, which is often less accessible, it provides a straightforward indicator: the proportion of respondents who have experienced the event of interest by each age.

The cumulative incidence curves for the three ideal type cases are presented in Figure 5 (analytic tasks) and Figure 6 (interactive tasks). We start by interpreting the findings from the more recent period (2000–18). We find that men who eventually reach high cognitive task intensity (either analytic or social/interactive) initially display lower first-birth probabilities than men with low cognitive task intensity (Case 3 vs Case 1). This situation reverses, however, as they age: men who eventually achieve high cognitive task intensity display higher first-birth probabilities at ages 35+ and are less likely to remain childless than those who work in occupations with low cognitive task intensity. For women the

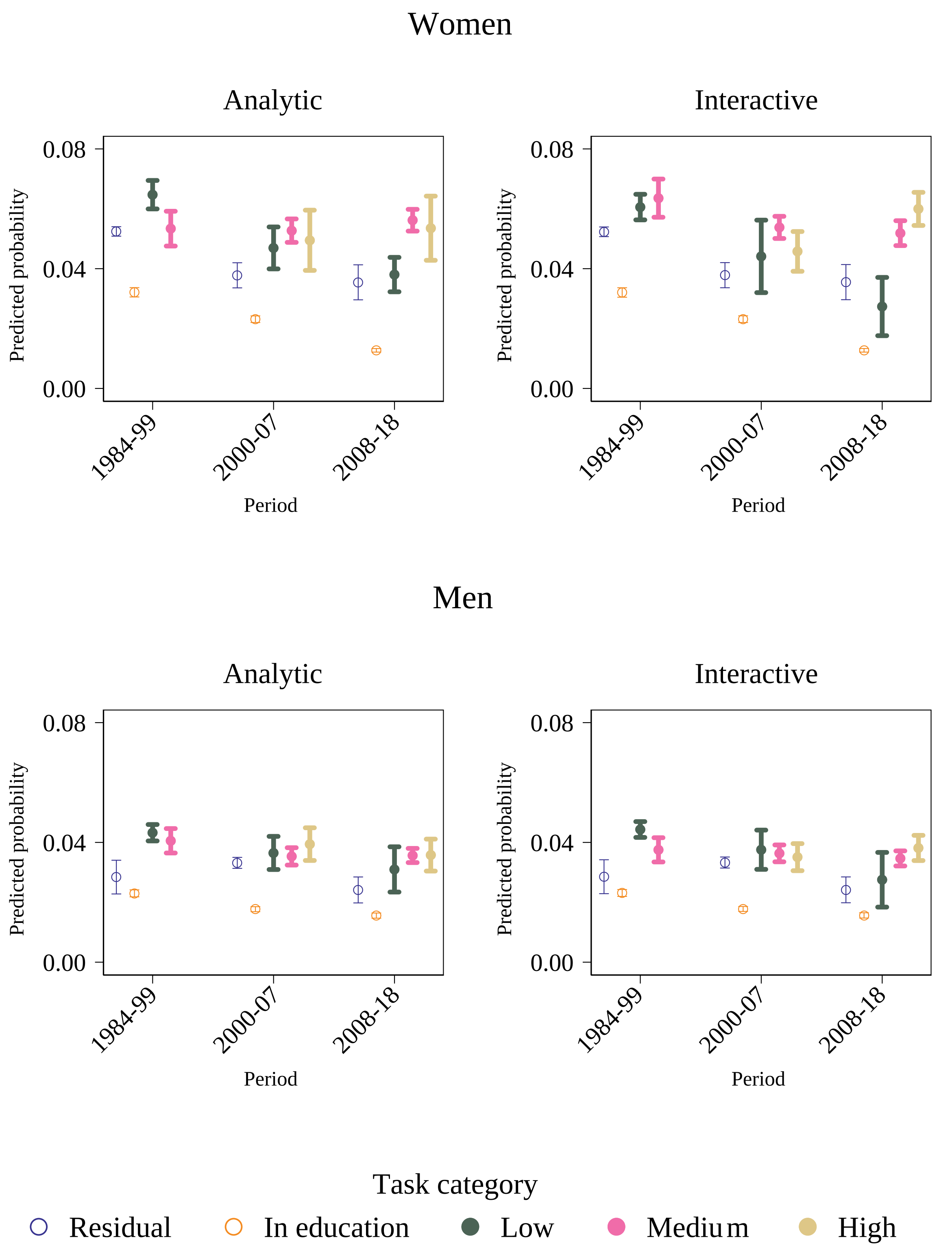

Figure 3 Average predicted probabilities from first-birth models (with 83 per cent confidence intervals): Interaction of respondents' task measures with period, Germany

Note: Further controls in the model are age (time-varying), residence (West vs East Germany), and number of siblings. Person-years = 36,039 for women, 44,990 for men. Low, medium, and high refer to intensity of cognitive tasks. We do not observe workers with high cognitive task intensity before 2000.

Source: As for Figure 1.

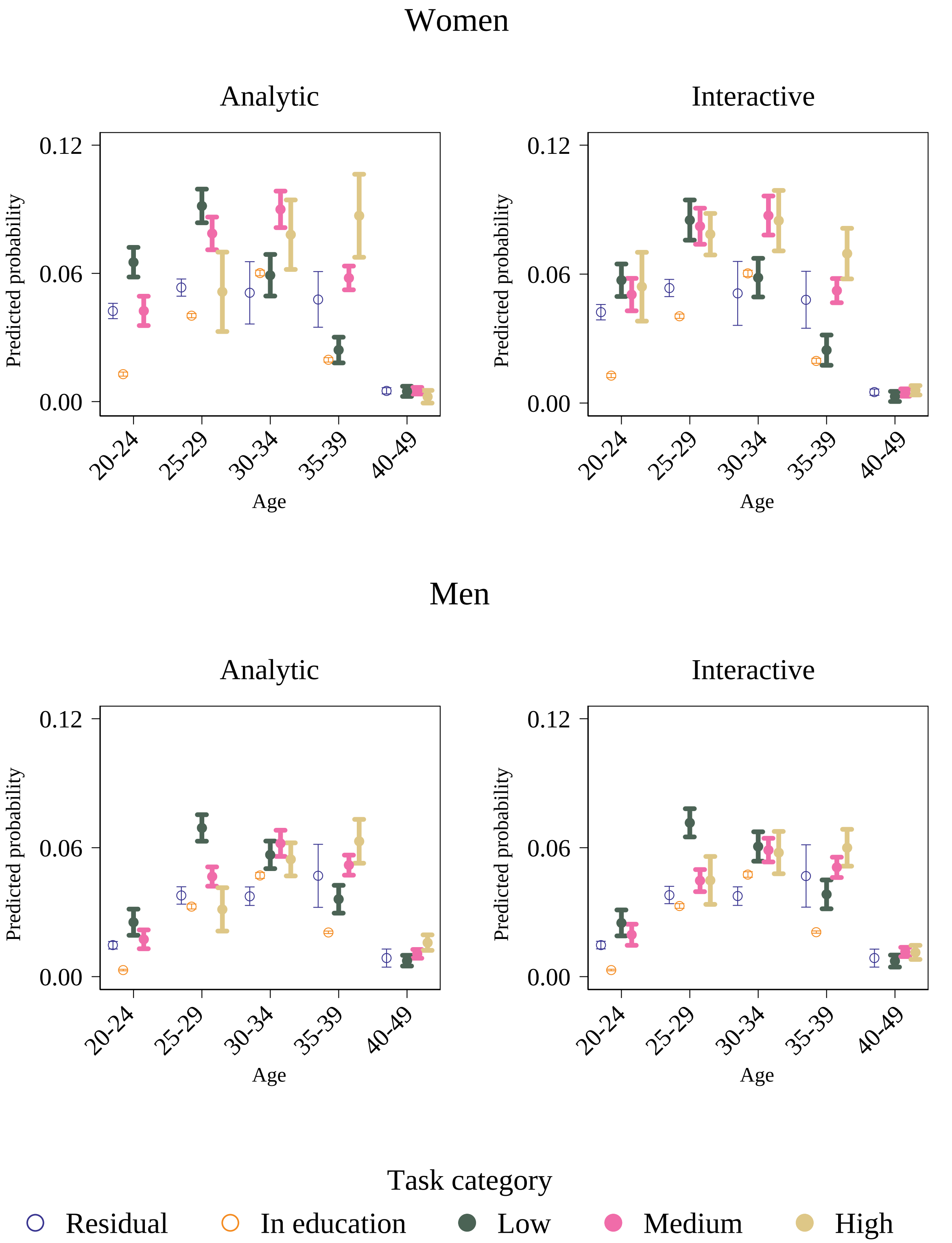

Figure 4 Average predicted probabilities from first-birth models (with 83 per cent confidence intervals): Interaction of respondents' task measures with age (time-varying), Germany

Notes: Further controls in the model are period, residence (West vs East Germany), and number of siblings. Person-years = 35,964 for women, 44,883 for men. Low, medium, and high refer to intensity of cognitive tasks.

Source: As for Figure 1.

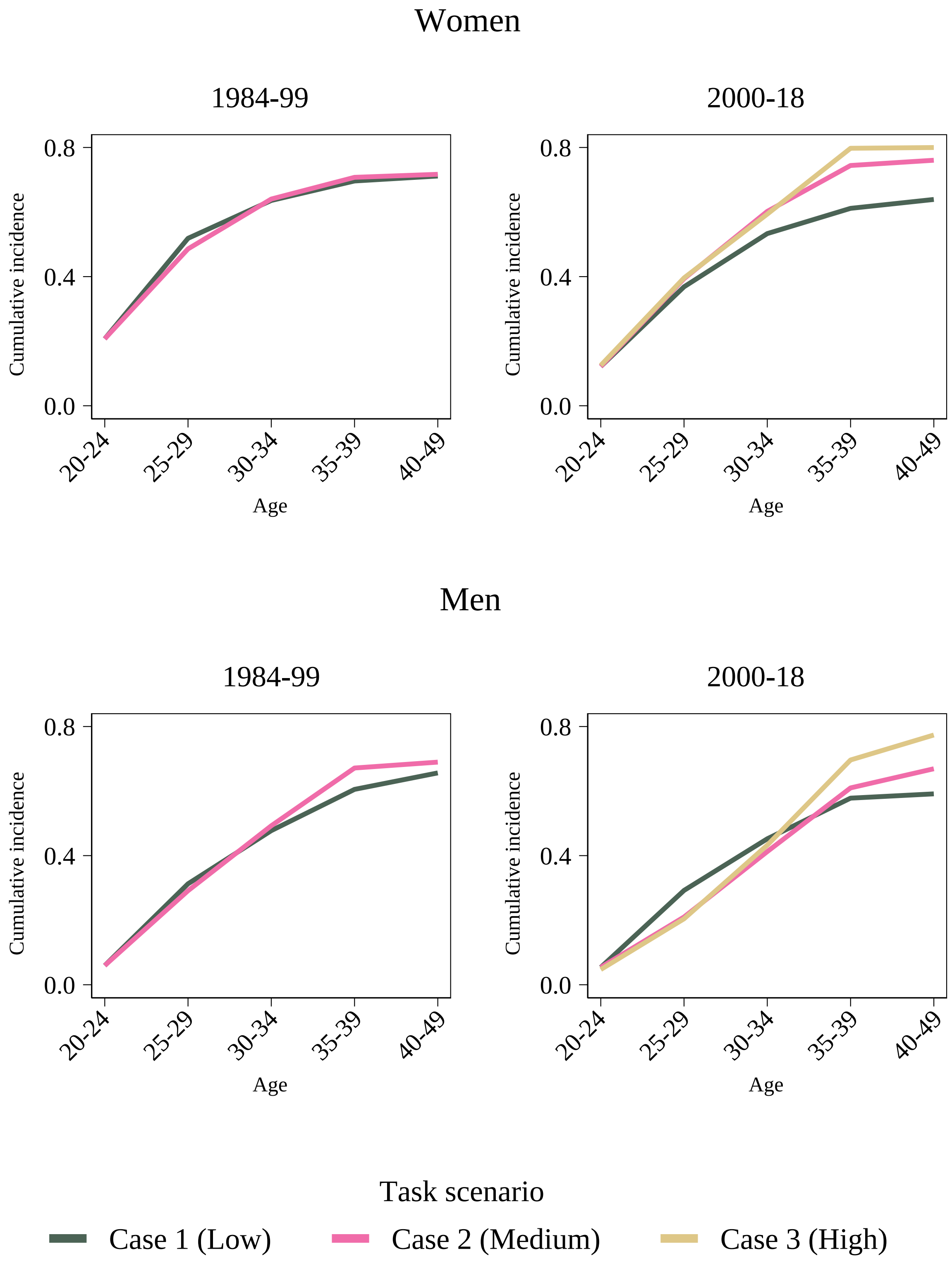

Figure 5 Cumulative incidence of first birth calculated from models with an interaction of *analytic* task measure and respondent age, Germany

Notes: For model results, see Figure 4. Case 1: a person who enters the labour market before age 20 and then has a job with low analytic task intensity. Case 2: a person who is in education until age 24 and then has a job with medium analytic task intensity. Case 3: a person is in education until age 29 and then has a job with high analytic task intensity. Other covariates are set to: residence = West Germany; number of siblings = one. We do not observe workers with high cognitive task intensity before 2000. For 1984–99: person-years = 10,917 for women, 15,113 for men. For 2000–18: person-years = 25,273 for women, 30,044 for men.
Source: As for Figure 1.

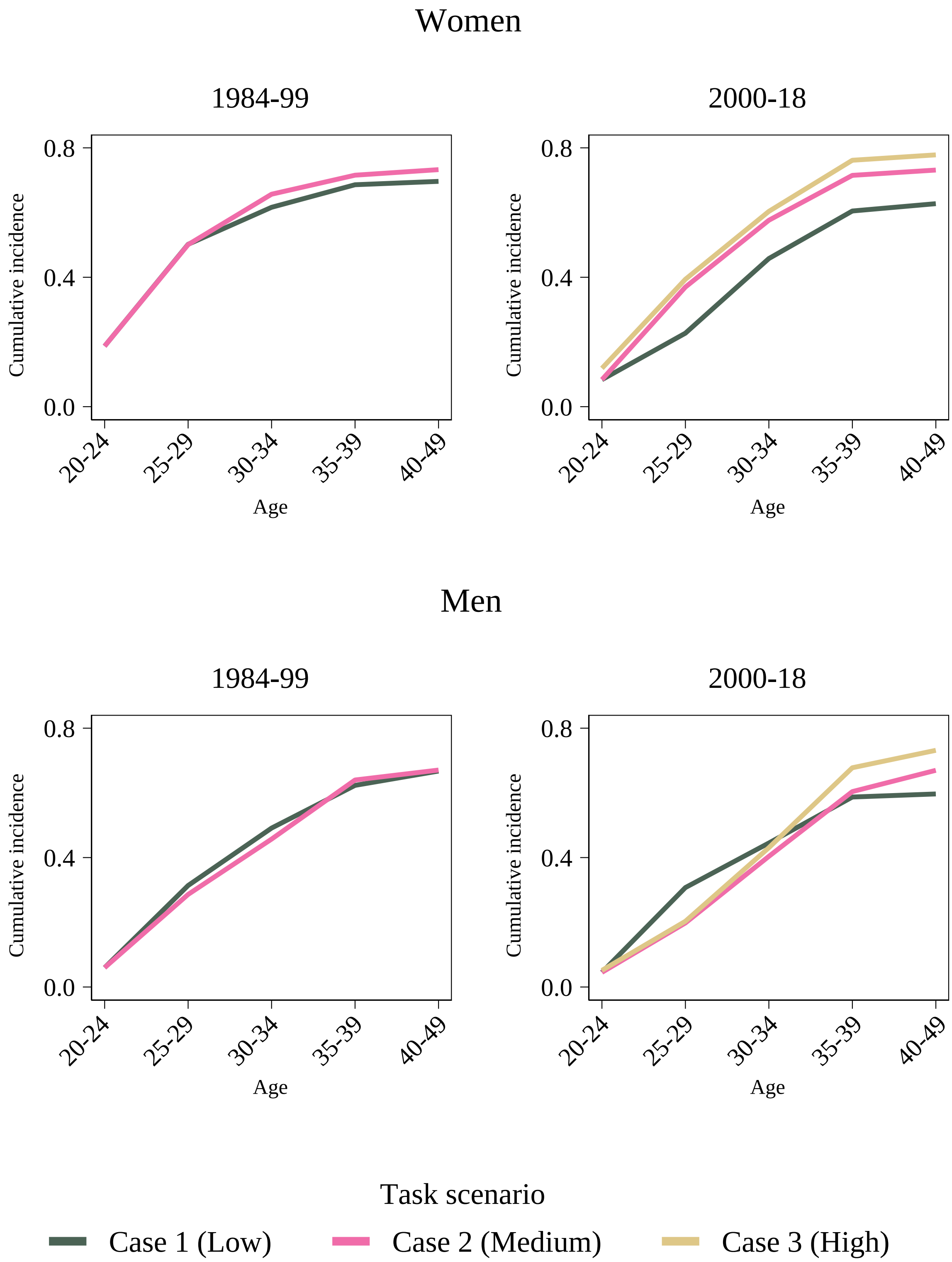

Figure 6 Cumulative incidence of first birth calculated from models with an interaction of *interactive* task measure and respondent age, Germany

Notes: For model results, see Figure 4. Case 1: a person who enters the labour market before age 20 and then has a job with low interactive task intensity. Case 2: a person is in education until age 24 and then has a job with medium task interactive intensity. Case 3: a person is in education until age 29 and then has a job with high interactive task intensity. Other covariates are set to: residence = West Germany; number of siblings = one. We do not observe workers with high cognitive task intensity before 2000. For 1984–1999: person-years = 10,929 for women, 15,148 for men. For 2000–18: person-years = 25,273 for women, 30,044 for men.

Source: As for Figure 1.

pattern is slightly different. Women who end up in jobs with medium/high analytic task intensity (Cases 2 and 3; Figure 5) tend to postpone motherhood during their 20s to the same extent as women who end up in jobs with low analytic task intensity (Case 1). Nonetheless, the former still accelerate childbearing at older ages and are in the end less likely to remain childless. Women in occupations with medium/high social/interactive task intensity (Figure 6) are also less likely to remain childless than those in occupations with low social/interactive task intensity, but the relative advantage of the former emerges at younger ages and prevails throughout their life courses.

Patterns were rather different in the earlier period (1984–99). As already noted, occupations that require a high task intensity barely existed in practice at that time. Furthermore, the fertility schedules of people who eventually achieved jobs with low or medium cognitive task intensity were similar, in terms of both first-birth timing and the probability of remaining childless.

Robustness checks

We also conduct two robustness checks. In our main models, we excluded people with non-German citizenship, as foreigners and migrants in Germany typically exhibit different fertility schedules from the native born (Milewski 2010). As a first robustness check, we repeat the (main) first-birth model for individuals and include non-German citizens but control for citizenship. Second, we redefine the categorial task measures by imputing occupation linearly interpolated independently from labour force status (except for individuals in education). Thus, we account for the fact that joblessness might be a temporary status, which is not always indicative of an individual's labour market prospects. The findings from these two robustness checks are presented in Appendix Figures A2 and A3, respectively. The robustness checks do not yield significantly different findings from our (main) model presented in Figure 2. Thus, we conclude that our models are reasonably robust to the inclusion/exclusion of migrant populations or specific definitions of task measures.

Discussion

Globalization and technological change have led to tremendous changes in the labour market. These changes—reflected in increased demand for cognitive skills, expansion of flexible work schedules, and greater emphasis on workers' performance—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 our study, we sought to fill this research gap by focusing on the transition to parenthood. Drawing on the literature on the task content of occupations, we classified occupations into three groups, ranging from those that involve low cognitive intensity tasks to those that involve highly cognitive work. We conducted our study in Germany, which transitioned to a knowledge economy from the late 1960s and where demand for highly skilled labour is currently strong.

The results of our analysis support the findings from prior labour market research, which has indicated that young individuals in Germany currently work in completely different occupations from three decades ago (Baumgarten et al. 2020; Koomen and Backes-Gellner 2022). Based on a sample of nulliparous women and men, we showed that jobs currently considered high in cognitive task intensity barely existed in the 1980s. In fact, such jobs started to appear and gain importance among young childless individuals in the 1990s. We also demonstrated that these young adults, who had not yet become parents, were currently far more likely to work in occupations characterized by medium cognitive task intensity and less likely to be in occupations with low cognitive task intensity than in the past. In fact, occupations with low cognitive task intensity turned out to be marginal in our sample of women and men from 2000–04 onwards.

At the same time, we found that cognitive task intensity was tightly associated with entry to parenthood for both women and men. Specifically, we found that both women and men with highly cognitive jobs were on average more likely to become parents than those with non-cognitive jobs, supporting Hypothesis 1a. However, a more detailed analysis of these relationships revealed some changes over time as the structural changes in the labour market progressed, destroying employment opportunities for low-skilled workers. While first-birth probabilities for non-working women and workers in jobs with low cognitive intensity were fairly high in the late 1980s and 1990s, they later decreased below the levels observed for workers with medium and high task intensities. We also observed that women working in occupations which require high cognitive task intensity displayed an increase in first-birth probabilities during the most recent decade. Consistent with Hypothesis 1b, these developments have led to a divergence in first-birth intensities with respect to workers' cognitive task intensity.

In the next step of the analysis, we investigated whether these patterns had been driven by changes in fertility quantum or only by an acceleration of the transition to parenthood at high reproductive ages among workers who acquire jobs high in cognitive tasks only at more advanced ages. We indeed found that individuals who reached high cognitive task intensity were initially most likely to postpone entry to parenthood and then accelerate it afterwards. However, we also demonstrated that these workers were eventually most likely to become parents by age 50 and thus the least likely to remain childless. The only exception was women who worked in occupations high in social/interactive tasks: these women were also less likely to remain childless than those in occupations with low social/interactive task intensity but they built their advantage in childbearing earlier in the life course. All in all, however, these findings imply that the structural labour market changes have benefited highly cognitive workers and are likely to result in higher (although delayed) fertility among highly skilled workers in comparison to the low skilled.

We also investigated whether the associations between cognitive task intensity and first-birth probabilities became more similar for women and men over time (Hypothesis 2a) and whether they varied by the type of cognitive task (analytic vs social/interactive; Hypothesis 2b). Our findings indeed lend support to Hypothesis 2a, as we observed a clear decline in first-birth intensities among women with low cognitive task intensities and among non-working women. As a result of these changes, the patterns in cognitive work and transition to parenthood became more similar among women and men. These findings signify an important change in gender roles, with women's economic position becoming an increasingly important factor in family formation. At the same time, some slight differences between women and men emerged when it came to the type of cognitive tasks they performed (Hypothesis 2b). Women and men with high analytic task intensity were both more likely to have a child by age 50 than those with low analytic task intensity. However, high social/interactive task intensity was far more positively related to childbearing among women than men. This latter finding was contrary to our expectations, as we had presupposed that social/interactive task intensity would be more positively related to first-birth probabilities among men as they tend to work on social/interactive tasks that are better paid compared with women (i.e. managerial tasks) (Matysiak et al. 2024). This is likely caused by the fact that jobs rich in managerial tasks are associated with higher time pressure and uncertainty than jobs in the care sector or education.

All in all, these findings suggest that the structural changes in labour demand brought about by technology and globalization 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. At the same time, the conditions for earning income and combining paid work with family life have worsened for all other workers, who are being increasingly left behind, in terms of their options not only for engaging in economic activity and earning income but also for having a family. Consistent with our expectations, we observed that as the structural labour market changes progressed, workers with highly cognitive jobs became more likely to enter parenthood (and less likely to remain childless) than workers with non-cognitive occupations and the non-employed. As these labour market changes will likely continue, with technologies further increasing the demand for the most skilled labour and destroying jobs for the less skilled, we may observe further increases in first-birth disparities between these two groups of workers in future.

Despite being novel, our study had 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 non-routine manual tasks—we were not able to quantify them consistently in a longitudinal setting (Rohrbach-Schmidt and Tiemann 2013). Thus, while we could draw conclusions about the fertility behaviours of individuals in 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 performing routine tasks) were most likely to postpone parenthood. Furthermore, we were not able to measure the task content of work at the individual level because information about job tasks is not usually available in longitudinal surveys. For this reason, we had to rely on occupational task measures. Although 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, and this may even have affected the first occupation they chose post education. Another important limitation was that our data did not allow us to control for partner's occupational status in our models. This was due to the relatively low fraction of couple households in which both partners were present at the interview and could participate in the GSOEP. Taking a couple approach would thus have substantially reduced our sample and limited the opportunities for conducting a reliable study.

Despite these limitations, our study is one of the first to investigate the impact of structural labour market changes on entry to parenthood. Only a few previous studies have addressed this problem, namely Seltzer (2019), Matysiak et al. (2023), and Anelli et al (2024), but they all adopted a macro-level approach. In our study, we took a first step towards providing a theoretical conceptualization and empirical assessment of labour market prospects and their role in fertility at the individual level. Further research on this topic needs to apply more refined measures and a cross-national comparative framework. 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, including fathers, to better organize their professional activities around their family obligations. It is obviously vital to tease these two explanations apart because they will lead us to completely different conclusions about the gendered effects of the digital transformation of the labour market.

Notes and acknowledgements

1 Honorata Bogusz and Anna Matysiak are based in the Interdisciplinary Centre for Labour Market and Family Dynamics (LabFam), Faculty of Economic Sciences, University of Warsaw, Poland. Michaela Kreyenfeld is based at Hertie School, Berlin, Germany.
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4 Funding: This research was supported by the Polish National Agency for Academic Exchange (Polish Returns Programme 2019) and the European Research Council under the ERC Consolidator Grant 'Globalization- and Technology-Driven Labour Market Change and Fertility' (LABFER, grant agreement number 866207).
5 The authors acknowledge useful comments from John Ermisch, Wojciech Hardy, Beata Osiewalska, Christine Percheski, Daniela Rohrbach-Schmidt, and the three anonymous reviewers, as well as participants at the following conferences: PAA 2022, RC28 spring meeting 2022, EPC 2022, BSPS 2022, and 'Gender and social inequality in fertility' in Oslo, 2024.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1 Beta coefficients from pooled OLS regression: Outcome variable = task measure (analytic or interactive)

	Women			Men	
Covariate	Analytic	Interactive		Analytic	Interactive
Working overtime: No			(Ref.)		
Working overtime: Yes	5.127***	5.530***		3.228***	5.278***
	(0.413)	(0.528)		(0.511)	(0.570)
Working under pressure: Never			(Ref.)		
Working under pressure: Seldom	10.100***	8.824***		12.010***	6.323***
	(0.995)	(1.273)		(1.376)	(1.533)
Working under pressure: Sometimes	14.28***	13.82***		17.32***	12.52***
	(0.889)	(1.138)		(1.272)	(1.417)
Working under pressure: Frequently	16.64***	15.63***		18.54***	15.73***
	(0.879)	(1.125)		(1.255)	(1.399)
Monthly wage	0.010*	−0.010		0.018***	0.015**
	(0.005)	(0.007)		(0.006)	(0.007)
Education: Low			(Ref.)		
Education: Middle	10.17***	11.56***		6.504***	8.364***
	(0.691)	(0.884)		(0.723)	(0.807)
Education: High	19.02***	15.89***		17.23***	15.63***
	(0.759)	(0.970)		(0.771)	(0.860)
Work from home: Yes	11.29***	13.66***		14.16***	15.70***
	(0.429)	(0.549)		(0.477)	(0.532)
N	13,489	13,497		13,320	13,317

Notes: *** 1 per cent, ** 5 per cent, * 10 per cent. Further controls include age and calendar year. Standard errors in parentheses. (Ref.) is the reference category.
Source: Regressions were conducted on pooled BIBB Employment Survey waves for 2006 and 2018.

Table A2 Full results from first-birth models without interactions

Covariate	Women			Men	
	Analytic	Interactive		Analytic	Interactive
Task measure: Residual	0.675***	0.614***		0.722***	0.581***
	(0.048)	(0.089)		(0.055)	(0.083)
Task measure: In education	0.290***	0.379***		0.309***	0.362***
	(0.018)	(0.020)		(0.022)	(0.019)
Task measure: Low			(Ref.)		
Task measure: Medium	1.094	1.062		1.138*	0.978
	(0.077)	(0.080)		(0.083)	(0.073)
Task measure: High	1.271*	1.480***		1.322***	1.229**
	(0.163)	(0.179)		(0.142)	(0.116)
Period: 1984–99			(Ref.)		
Period: 2000–07	0.743***	0.779***		0.718***	0.818**
	(0.056)	(0.063)		(0.054)	(0.066)
Period: 2008–18	0.729***	0.734***		0.690***	0.767***
	(0.070)	(0.053)		(0.066)	(0.058)
Age: 20–24			(Ref.)		
Age: 25–29	2.635***	5.069***		2.641***	5.095***
	(0.160)	(0.495)		(0.159)	(0.497)
Age: 30–34	2.959***	7.381***		2.966***	7.514***
	(0.270)	(0.783)		(0.269)	(0.797)
Age: 35–39	1.985***	6.770***		1.982***	6.902***
	(0.199)	(0.729)		(0.195)	(0.755)
Age: 40–49	0.191***	1.515***		0.191***	1.531***
	(0.0350)	(0.218)		(0.035)	(0.224)

(*Continued*)

Table A2 Continued.

Covariate	Women		Men	
	Analytic	Interactive	Analytic	Interactive
Number of siblings: Zero		(Ref.)		
Number of siblings: One	1.074	1.099	1.075	1.108
	(0.071)	(0.076)	(0.069)	(0.076)
Number of siblings: Two or more	1.192***	1.213***	1.190***	1.208***
	(0.071)	(0.084)	(0.071)	(0.084)
West Germany		(Ref.)		
East Germany	1.292***	0.955	1.293***	0.958
	(0.104)	(0.067)	(0.104)	(0.068)
N	36,076	45,100	36,076	45,100
AIC	13,322.9	12,771.4	13,320.4	12,781.8
Log-likelihood	−6,646.5	−6,371.7	−6,644.2	−6,375.9

Notes: *** 1 per cent, ** 5 per cent, * 10 per cent. Exponentiated coefficients. Standard errors in parentheses. Task measures and residence (West vs East Germany) are time-varying and are lagged by two years. Other covariates are time-constant. (Ref.) is the reference category.
Source: Authors' analysis of data from BIBB Employment Survey and GSOEP.

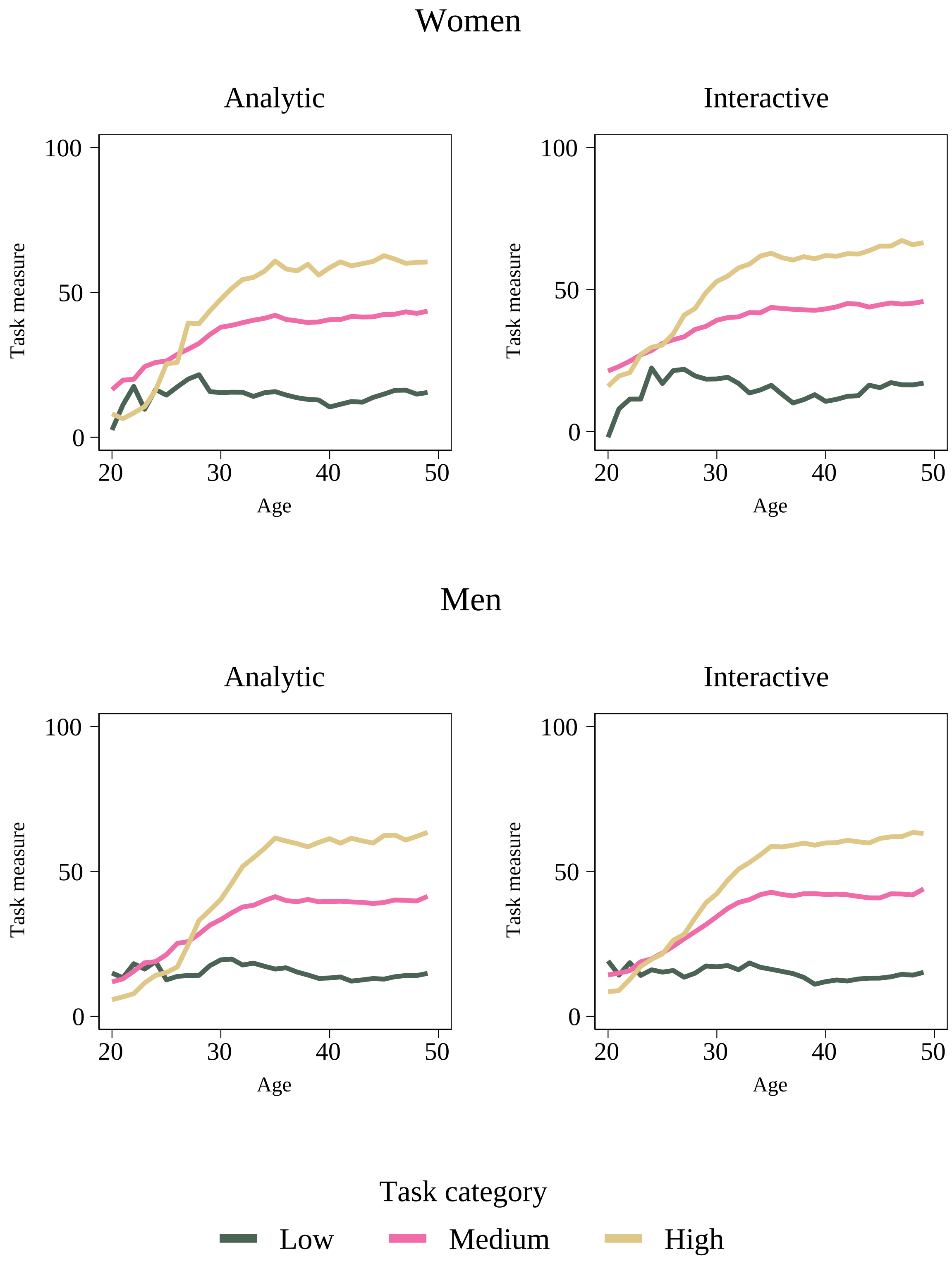

Figure A1 Mean analytic task measure by highest task measure achieved at age 35+: Patterns by sex and age
Notes: Unweighted estimates from employed respondents in analytical sample. Person-years at age 35+ = 16,353 for women, 24,695 for men.
Source: Authors' analysis of data from BIBB Employment Survey and GSOEP.

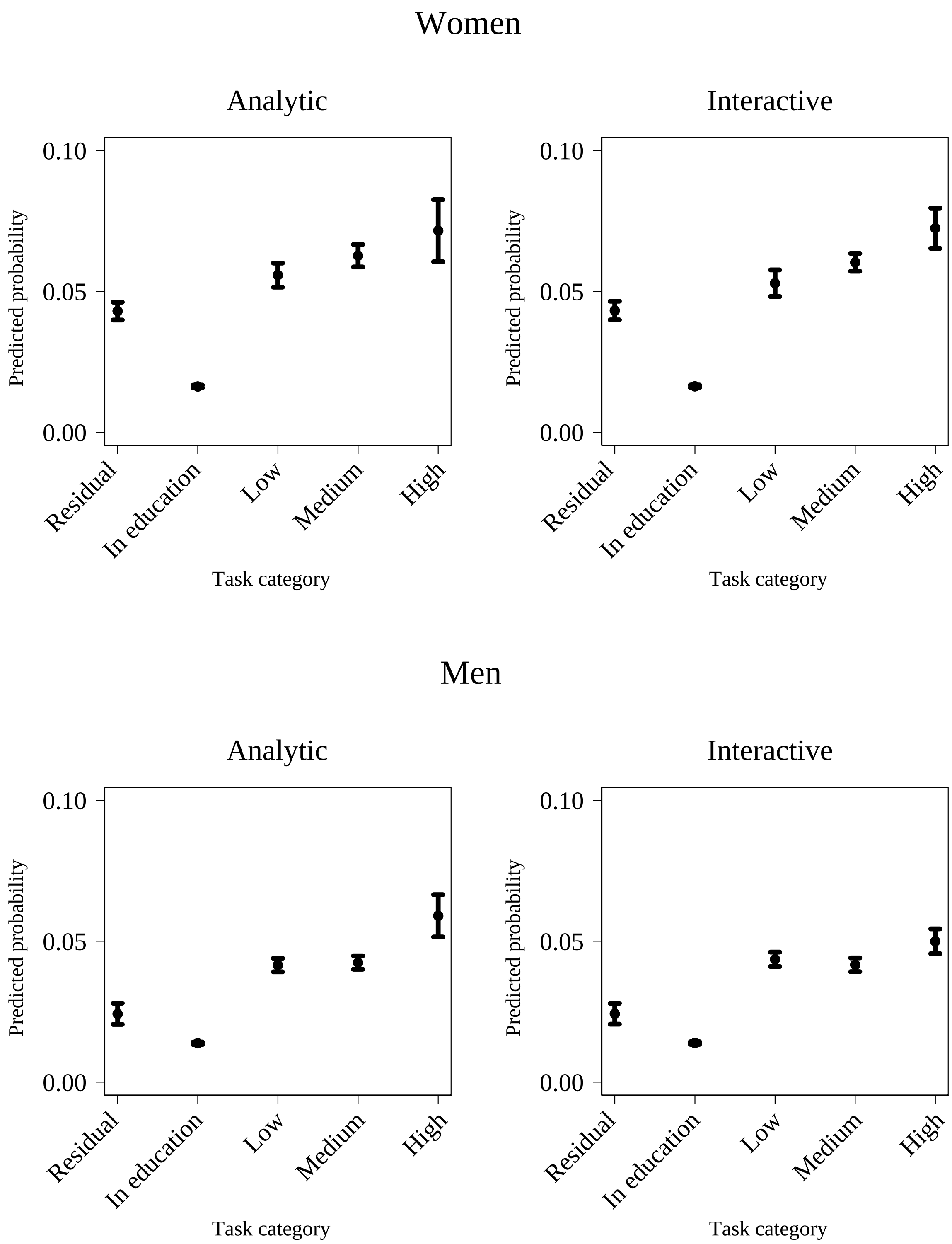

Figure A2 Average predicted probabilities from first-birth models (with 83 per cent confidence intervals): Robustness check including migrants and controlling for German citizenship status

Notes: Further controls in the model are age (time-varying), period, residence (West vs East Germany), and number of siblings. Reference category = low task measure [0, 33). Person-years = 40,313 for women, 50,816 for men.

Source: As for Figure A1.

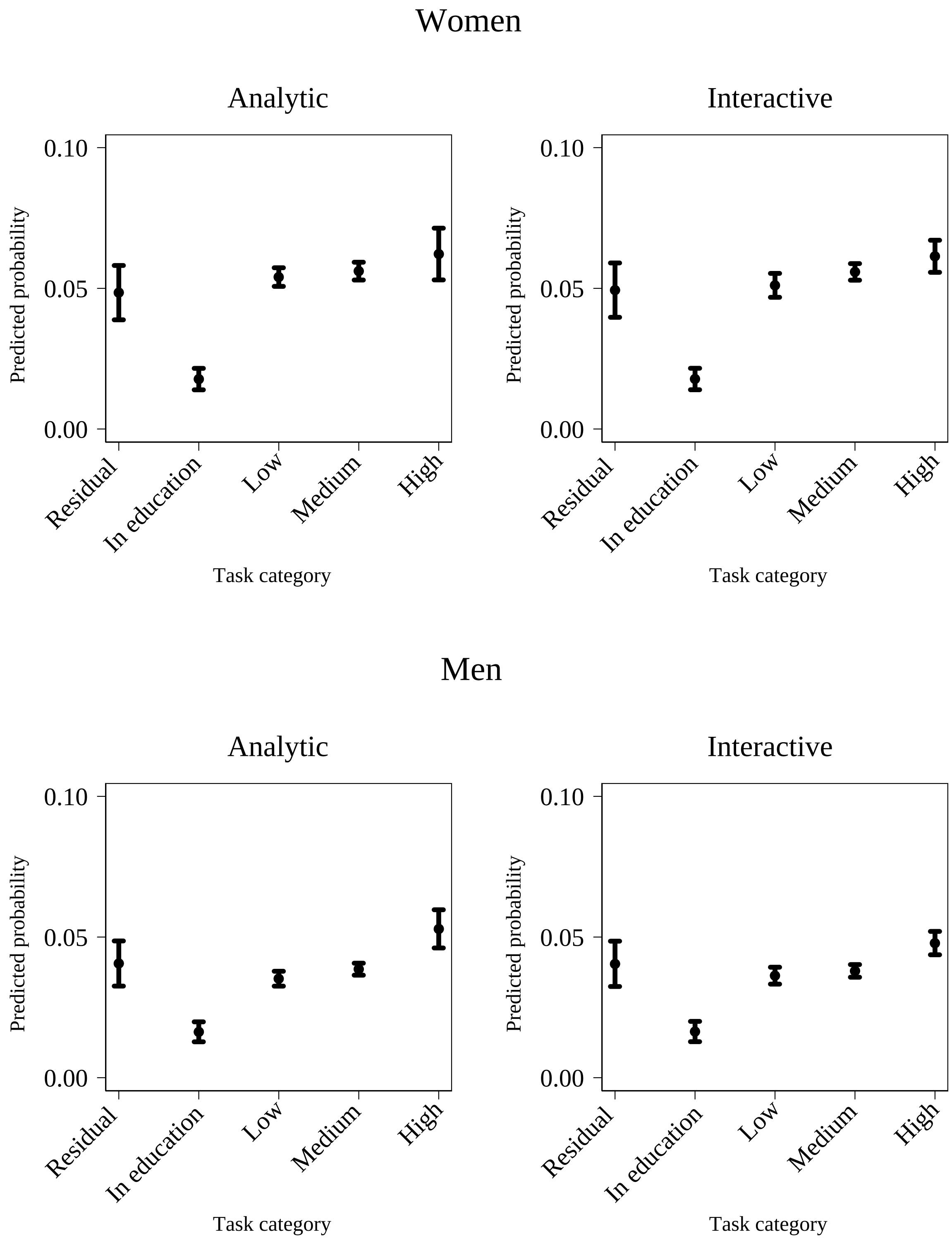

Figure A3 Average predicted probabilities from first-birth models (with 83 per cent confidence intervals): Robustness check with task measures redefined in a way where occupation is linearly interpolated independent of labour market status

Notes: Further controls in the model are age (time-varying), period, residence (West vs East Germany), and number of siblings. Reference category = low task measure [0, 33). Person-years = 34,387 for women, 43,150 for men.

Source: As for Figure A1.

2.3 Paper III: *Task content of jobs and mothers' employment transitions in Germany*

PAPER III

"*Task content of jobs and mothers' employment transitions in Germany*"

H. Bogusz

COMMENTARY

Becoming a mother can be considered a pivotal event in women's careers, marking a moment of notable gender divergence in labor market outcomes in developed countries (Goldin, 2021). Children clearly impose a career cost, one borne predominantly by women (Adda et al., 2017). In fact, many women reduce their working hours or exit the labor market altogether after becoming mothers (Arntz et al., 2017a; Waldfogel et al., 1999), particularly in conservative welfare states (Gustafsson et al., 1996; Gutiérrez-Domènech, 2005). Prior research has shown a substantial class gradient in women's likelihood of returning to the labor market, with higher socio-economic status women being more likely to re-enter the workforce and work full-time (Arntz et al., 2017a). Thus, maternity can be considered a factor that reinforces inequalities and hinders social mobility.

This study advances the existing literature by exploring how the task content of jobs affects mothers' return to the labor market. Specifically, it investigates the diverse career costs of parenthood, which may be further intensified by modern labor market shifts driven by technology and globalization. To analyze the relationship between job task content and mothers' employment transitions after the first birth in Germany, I develop job task measures based on data from the Employment Survey conducted by the German Federal Institute for Vocational Education and Training[5]. These measures are then linked to detailed individual register data from the German Pension Fund, covering the period from 2012 to 2020[6]. Using competing risks models, I assess the probability of four possible post-birth outcomes: returning to employment, becoming unemployed, having a second child, or remaining inactive.

The findings reveal that women employed in occupations with high analytic and interactive task content—jobs that are in high demand but less compatible with maternity-related employment breaks—are the most likely to return to work after their first birth. In contrast, women in occupations intense in routine tasks, which are more vulnerable to automation or trade competition, are more likely to experience unemployment. However, women in highly cognitive jobs are also the most likely to transition directly to the second birth.

This paper was carried out entirely by me. I presented this study at several conferences, e.g. British Society for Population Studies Annual Conference (2023) or International Association for Feminist Economics Annual Conference (2024), as well as at the German Pension Fund (Deutsche Rentenversicherung). The codes employed for the analysis are publicly available on Github.

[5]Hall and Tiemann, 2020.

[6]Forschungsdatenzentrum der Rentenversicherung (FDZ-RV), 2024a, 2024b.

Bogusz *J Labour Market Res* (2024) 58:25
https://doi.org/10.1186/s12651-024-00384-9

Journal for Labour Market Research

ORIGINAL ARTICLE **Open Access**

Task content of jobs and mothers' employment transitions in Germany

Honorata Bogusz[1*]

Abstract

I study the association between task content of jobs and mothers' employment transitions after the first birth in Germany. I construct measures of task content of jobs using data from the Employment Survey conducted by the German Federal Institute for Vocational Education and Training (BiBB). These indicators illustrate the career cost of children and how it is impacted by the technology- and globalization-driven labour market change. The measures are then linked to high-quality individual register data from the German Pension Fund (FDZ-RV) covering the years 2012–2020. Utilizing competing risk models, I show that women engaged in occupations with analytic and interactive task content, which are in high demand and incompatible with maternity-related employment breaks, are the most likely to transition to employment after their first birth. Conversely, women with occupations intense in routine tasks, which are more susceptible to automation or trade competition, are more likely to experience unemployment.

Keywords Task content of jobs, Employment transitions, Competing risk, Germany

JEL Classification J13, J16

1 Introduction

Becoming a mother can considered a pivotal event in women's careers. Indeed, numerous studies have identified maternity as a key contributor to gender inequality in Western societies (Kleven et al. 2019; Goldin 2021; Kleven et al. 2023). Women experience diverse employment trajectories following motherhood, with many opting for part-time work or choosing not to re-enter the workforce at all (Waldfogel et al. 1999; Arntz et al. 2017), particularly in conservative welfare regimes such as Germany (Gustafsson et al. 1996; Gutiérrez-Doménech 2005). Prior research has demonstrated that women with higher wages (Barrow 1999; Arntz et al. 2017), more secure job positions (Saurel-Cubizolles et al. 1999; Arntz et al. 2017), better education (Arntz et al. 2017), those from higher social strata (Saurel-Cubizolles et al. 1999), and those in professional jobs (Smeaton 2006) are more likely to re-enter employment after giving birth. Conversely, women from lower social strata, with lower educational attainment, and engaged in low-skilled occupations face the greatest risk of transitioning to unemployment post-maternity (Arntz et al. 2017). Existing research suggests, therefore, that maternity significantly exacerbates employment disparities among workers and impedes social mobility. This study contributes to the literature by examining the relationship between the task content of jobs and mothers' return to the labour market-an exploration of the heterogeneous career costs associated with parenthood, which I argue may be exacerbated by the contemporary labour market shifts driven by technology and globalization.

Previous research on the career implications of parenthood has primarily focused on child penalties, referring to the sustained decrease in earnings or employment experienced by new mothers, a phenomenon not observed in men (instead, men often experience child premiums; see Baranowska-Rataj and Matysiak (2022)) or women without children. Across Western institutional contexts, child penalties are largely attributed to the

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reduction in hours worked by women following the birth of their first child (e.g., Kleven et al. 2019; Huber et al. 2023; Waszkiewicz and Bogusz 2023; Kleven et al. 2024). Some recent studies have suggested that cultural and gender norms underpin this gender disparity in labour market outcomes. Kleven et al. (2023) examined child penalties in employment across 134 countries worldwide and demonstrated that they constituted the largest component of gender inequality, with an increase in a country's level of development and wealth. Andresen and Nix (2022) compared child penalties among different-gender couples with biological and adoptive children and among female same-gender couples (who generally exhibit less specialization than different-gender couples; see Ciscato et al. (2020)) in Norway. They found no disparity in penalties between different-gender biological and adoptive parents but identified considerably smaller and more evenly distributed penalties among female same-gender parents. The significance of norms concerning gender and parenthood was reinforced by Kleven et al. (2024), who demonstrated that family policies (such as the expansion of parental leave or childcare subsidies) had no significant impact on child penalties in Austria. Other studies conducted in German-speaking countries identified a positive effect of increased childcare availability on maternal part-time employment but observed no effect on women's careers (Krapf et al. 2020; Huber et al. 2023).

While predominantly influenced by gender norms, the magnitude of child penalties in women's earnings or employment is contingent upon their position on the career-family continuum and associated occupational choices, as demonstrated for Germany from 1972 to 2001 by Adda et al. (2017). Career-focused women in vocational training sorted themselves into occupations characterised by abstract (cognitive) tasks from an early age, while their family-oriented counterparts opted for occupations involving routine or manual work. Qualifications in jobs with abstract tasks are prone to evolve more rapidly than those in routine and manual jobs, necessitating constant skill updating-a demand that clashes with employment breaks associated with motherhood. Thus, a job intensive in abstract tasks might be less compatible with maternity than a job with routine or manual tasks. From this perspective, the task content of jobs can be viewed as reflecting the career costs of parenthood. Consistent with this argument, Adda et al. (2017) found that women in jobs involving abstract tasks were more inclined to remain childless or have only one child compared to their peers in routine and manual jobs. Furthermore, women in abstract jobs potentially face much higher opportunity costs of parenting due to steep earning profiles, a changing environment, and rapidly depreciating human capital, than women in routine or manual jobs. Consequently, women may be inclined to return to abstract jobs more quickly (in addition to being more career-oriented). However, the link between the task content of work and a woman's return to the labour market after the first birth has not yet been addressed. Investigating this link is further motivated by the labour market transformations propelled by technology and globalisation, which took off in developed nations in the mid-20th century but gained momentum in the past three decades, thereby reshaping task demands (Acemoglu et al. 2011; Autor 2013; Lewandowski et al. 2022). As routine jobs increasingly become low-paid and unattractive, or disappear altogether, these shifts may have modified the extent to which tasks represent the career cost of children. They underscore the need for ongoing research into the task content of jobs and women's labour market outcomes in more recent periods, as presented in this study.

Technological advancements and globalization have profound ramifications for the workforce (OECD 2019; World Bank 2019). Empirical economic literature suggests that automation and globalization contribute to significant polarization of job opportunities in Western labour markets, primarily through the deroutinization of work (Goos et al. 2009; Autor and Dorn 2013). Technology, skill supply, and globalization (in terms of trade liberalization) account for the majority of the contemporary shift from routine to non-routine cognitive work globally (Lewandowski et al. 2022). While the supply of skills (alongside technology) drives the transformation of work tasks for highly skilled professionals, globalization plays a more prominent role for workers in low-skilled occupations (Ibid.). Research indicates that automation and trade liberalization lead to decreased employment (Acemoglu and Restrepo 2020; Dauth et al. 2021; Keller and Utar 2023) and wages (Baumgarten et al. 2013; Acemoglu and Restrepo 2020), particularly affecting low- and middle-skilled workers, as well as those in the manufacturing sector, and exacerbating economic inequality across Western contexts (Huber and Winkler 2019; Doorley et al. 2023; Acemoglu and Johnson 2023). On one hand, lower-skilled workers face setbacks as their occupations (or specific tasks within occupations) are displaced by technologies such as industrial robots (Acemoglu and Restrepo 2020; Dauth et al. 2021) and Chat GPT (Eloundou et al. 2023; Felten et al. 2023; Gmyrek et al. 2023), or vanish due to increased import competition (Autor et al. 2013). Conversely, highly skilled professionals benefit, possessing analytical skills necessary for working with these technologies or skills integral to jobs involving human interactions, which are challenging for machines to replicate and cannot be outsourced (Deming 2017; Deming and Kahn 2018). Moreover, studies conducted in Europe have found that women are disproportionately represented in routine occupations, which are most susceptible to displacement and are increasingly of low quality (Piasna and Drahokoupil 2017; Brussevich et al. 2019).

This study is situated in Germany, arguably the most technologically advanced European country, where structural changes in the labour market are particularly pronounced, evidenced by the widespread adoption of industrial robots (Dauth et al. 2021; Deng et al. 2023) and increasing demand for cognitive labour (Spitz-Oener 2006; Rohrbach-Schmidt and Tiemann 2013; Bogusz et al. 2024). Germany is also one of the few European countries that maintain modernized manufacturing and compete in production processes (Dauth et al. 2017; Thelen 2019), rendering it potentially susceptible to import competition. Additionally, Germany is characterized by a conservative welfare regime, where many women transition to part-time employment upon becoming parents, and it is not uncommon for mothers, particularly in Western Germany, to exit the labour market for a longer period of time (Boll and Lagemann 2019; Mueller et al. 2020).

I measure the task content of jobs using the 2006 Employment Survey conducted by the German Federal Institute for Vocational Education and Training (BiBB) (Hall et al. 2006). These data enable me to construct five measures of task intensity commonly employed in economic literature (Autor et al. 2003; Spitz-Oener 2006; Hardy et al. 2018): analytic, interactive, non-routine manual, routine cognitive, and routine manual (with the latter two measures aggregated into a routine measure, as detailed in Sect. 2.2) at the three-digit occupation level. I link these occupation-specific measures to individual-level administrative data from the German Pension Fund for the years 2012 to 2020 (FDZ-RV 2024a, b). Employing the competing risk model (Fine et al. 1999), I explore women's employment transitions following their first childbirth, with the task content of jobs serving as the primary covariate of interest. This model offers an advantage over standard duration models as it takes into account the possibility of individuals experiencing multiple events during the follow-up period. I distinguish between the following states that young mothers transition into after their maternity leave: employment, unemployment, and second birth. I focus on mothers' return to the labour market and present supplementary findings for second birth in the appendix, complementing the main results for employment and unemployment. Transitions to other states, such as inactivity, present identification challenges (see Sect. 2.1). I do not explicitly examine them as outcomes, but treat them as censored cases. As women sort themselves selectively into specific occupations following their family-career orientation as early as in puberty (Adda et al. 2017), the results of the competing risk models presented here should be interpreted only as correlations.

The findings are consistent with previous labour market research in Germany, indicating that the likelihood of women returning to employment after their first childbirth is significantly associated with their socioeconomic status (Arntz et al. 2017) and the expected career cost of children as indicated by the type of tasks done (Adda et al. 2017). Women employed in jobs primarily involving non-routine cognitive tasks (analytical and interactive) have the highest probability of transitioning to employment after their first childbirth. Conversely, women in occupations characterised by intensive routine tasks, which increasingly become less attractive, exhibit a higher incidence of transitioning to unemployment. In summary, these results suggest that structural changes in the labour market driven by technology and globalization exacerbate employment disparities by placing mothers who do not hold jobs in high demand and are less career-oriented at a disadvantage regarding their employment status.

The remainder of the paper is organized as follows. Section 2 provides details on the data, the task content

Table 1 Availability of activities performed at work and their classification to task categories

	Activity	Task category
1	Organizing	Analytic
2	Researching	Analytic
3	Investigating	Analytic
4	Programming	Analytic
5	Teaching	Interactive
6	Consulting	Interactive
7	Buying	Interactive
8	Promoting	Interactive
9	Repairing	Non-routine manual
10	Caring	Non-routine manual
11	Accommodating	Non-routine manual
12	Protecting	Non-routine manual
13	Measuring	Routine (cognitive)
14	Operating	Routine (manual)
15	Manufacturing	Routine (manual)
16	Storing	Routine (manual)

of work framework, and the empirical strategy. Section 3 presents the model results. Finally, Sect. 4 concludes.

2 Data and methods

2.1 Analytical sample

The primary data source for this analysis is the individual-level administrative data obtained from the German Pension Fund. The Pension Fund offers process-induced labour market data, encompassing approximately 90% of the population, with exceptions for certain professional groups such as farmers, lawyers, doctors, and civil servants (AKVS, FDZ-RV (2024)). While administrative data typically offer less detailed information compared to survey data, they compensate with larger sample sizes, particularly advantageous when studying specific sub-populations, as in the case of mothers in this study. Hence, the dataset from the German Pension Fund is more suitable for the analysis presented here than the German Socioeconomic Panel (SOEP), which records only about 4,000 first births-a figure too small for modelling occupational diversity. Although the Sample of Integrated Labour Market Biographies (SIAB) from the Institute of Employment Research (IAB) provides a sufficiently large 2% random sample of the German workforce, the identification of births in that data relies on information about employment interruptions due to entitlement to other compensation by the statutory health insurance provider, conflating maternity leave with long-term sickness and failing to identify birth parity (Mueller et al. 2017). In contrast, data from the German Pension Fund offers precise dates of subsequent births, as well as parental leave periods with monthly precision. Exact identification of births is pivotal for the analysis presented here for two reasons. First, the first birth holds special significance compared to higher-order parities, defining the exact moment of gender divergence in labour market outcomes (Goldin 2021). Second, the second birth is treated as an explicit competing event in the methodology employed (see details in Sect. 2.3). In summary, administrative data from the German Pension Fund represent the only dataset enabling the analysis undertaken in this study (for Germany).

These data encompass labour market information for over 20 million women in Germany since 2011, with data containing occupational codes (AKVS, FDZ-RV (2024)). However, information on childbirth is available only for a 2% random sample (VSKT, FDZ-RV (2024)), significantly reducing the counts. Further restrictions are applied to the analytical sample: only women with German citizenship are included, as migrant women in Germany typically follow different fertility patterns (Milewski et al. 2010) and fertility histories of women with foreign citizenship are incomplete in the data (Kreyenfeld and Mika 2008). Women who died within the observation period are excluded, thereby disregarding death as a source of right censoring. Moreover, only women who experienced their first birth between the beginning of 2012 and the end of 2018 are retained. This time frame allows for a sufficiently extended period to observe women's potential return to the labour market before the onset of the Covid-19 pandemic. Lastly, only women aged 20 to 45 at their first childbirth are included, and those who gave birth as a result of a multiple fetus pregnancy are excluded. The final sample comprises 63,929 women.

The data are structured for a competing risk analysis (Fine et al. 1999). Observation of women starts one month after they give birth, and the observation period ends either upon the occurrence of the first considered event or when they are right-censored. The three primary events that new mothers transition to are employment, unemployment, and a second birth. Transitions to employment or unemployment can be directly identified from information on the month when a mother concludes maternity leave (lasting 14 weeks in total, with at least 8 weeks taken after the birth) or parental leave and begins paying social contributions or receives unemployment benefits. However, the monthly data available do not allow for distinguishing transitions to full-time versus part-time employment, representing a limitation in understanding women's labour market mobility in Germany. Information on the month and year when a woman has a second birth is provided in the data. Transitions to inactivity are not analysed as an event due to the challenge in precisely defining the moment when it occurs. Although transitions to self-employment could theoretically be defined based on the type of social contributions self-employed individuals pay to the Pension Fund, such contributions are voluntary, resulting in the identification of only a subset of self-employed individuals with an unknown share. Given that self-employment is relatively uncommon in Germany, particularly among women (OECD 2023), this poses a minor concern. Transitions to inactivity, self-employment, or other infrequent states (e.g., permanent disability) are treated as censored. The histories are documented with monthly precision, and observation of women begins one month after they give birth.

There are no overlapping events. Additionally, it is assumed that the second birth can occur at the earliest after eight full months from the first birth.

Table 2 presents the proportions of women who experienced various events following their first childbirth, with the first event assigned to each of them. Approximately 63% of mothers transitioned to employment as the first event after giving birth. Around 19% transitioned to unemployment, 14% transitioned to a second birth, and 4% were censored. Additionally, Fig. 3 illustrates the percentages of experienced events by the birth year of the first child. While the shares remain relatively stable over time, the proportion of mothers returning to employment decreased between 2017 and 2018. Simultaneously, the proportion of censored women increased during that period. This is attributed to the fact that the sample is censored on February 28, 2020 (i.e., before the Covid-19 pandemic), and mothers who gave birth in 2017 or 2018 had "less time" to transition to employment, unemployment, or a second birth compared to mothers in the sample who gave birth between 2012 and 2016. Consequently, their transitions had not yet been observed. Supplementary Fig. 4 presents the duration in months by event. Most women are censored after approximately 20 months, likely those who had their first child around 2017 and had not re-entered the labor market or had a second child yet. Censored women with longer durations may have permanently transitioned to inactivity. On the other hand, the majority of women returning to employment do so after approximately 12 months. After 40 months of inactivity, mothers rarely return to employment. The pattern is more varied for mothers transitioning to unemployment-it occurs either after the first two months of being a mother or after a year. For women having a second child without returning to the labor market between births, the majority give birth to their second child after approximately 24 months from the first birth.

2.2 Task measures

Next, I construct aggregate measures of task content of work using the 2006 Employment Survey of the German Federal Institute for Vocational Education and Training (BiBB) (Hall et al. 2006) and merge them with the individual data from the German Pension Fund by occupational codes.

To describe and quantify changes in labor demand caused by technology and globalization, economists have proposed using a task-based approach (Autor et al. 2003; Acemoglu et al. 2011). This approach posits that occupations consist of various tasks, and the composition of these tasks is altered with changes in labor demand. Tasks differ in complexity, as well as in the level of skills and education needed to perform them. Technology and globalization have reshaped the structure of tasks demanded in the labor market, automating or offshoring some tasks and creating new ones. As a result, they have altered the demand for skills, impacting workers' labor market opportunities. The literature has proposed five task domains: analytic, involving activities requiring complex analysis of data or concepts, such as programming or conducting statistical analyses; interactive/interpersonal, covering tasks relying on human interactions, such as counseling or negotiating; non-routine

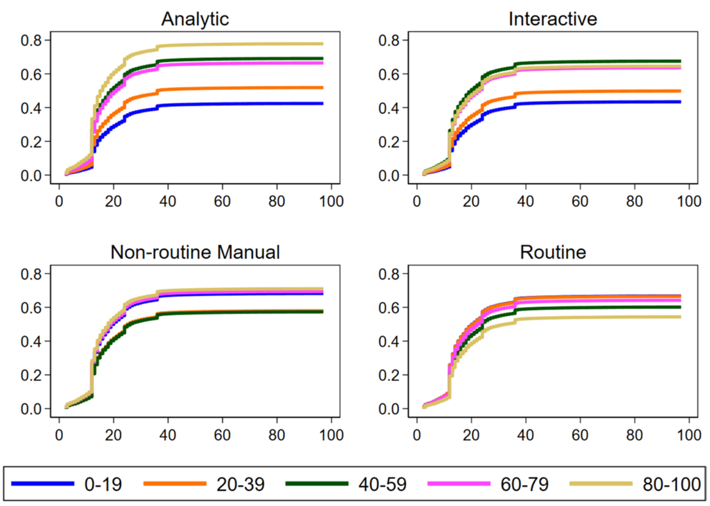

Fig. 1 Cumulative Incidence Functions from models with employment set as the main event. Controls include: year of event, age at first childbirth, residence (Bundesland) at first childbirth, education at first childbirth. N = 63,929

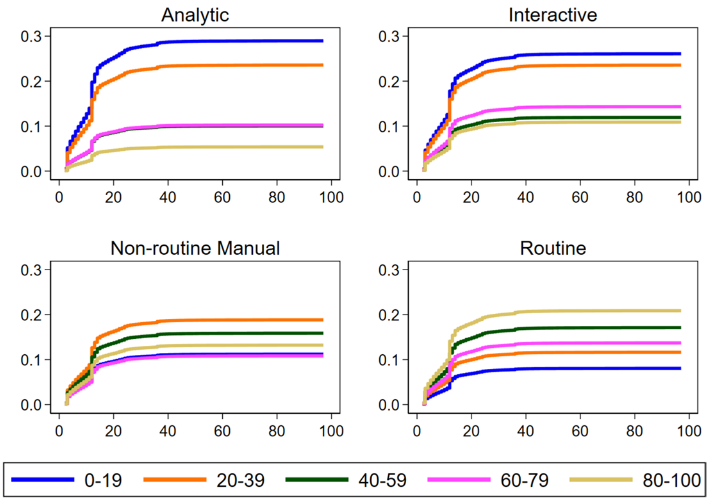

Fig. 2 Cumulative Incidence Functions from models with unemployment set as the main event. Controls include: year of event, age at first childbirth, residence (Bundesland) at first childbirth, education at first childbirth. N = 63,929

manual, encompassing tasks performed in a non-repetitive manner but using one's hands, such as massaging or hair styling; routine manual, representing tasks done with one's hands in a constant way, such as cleaning or sorting goods on a factory production line; and routine cognitive, involving activities of a cognitive nature performed in a routine fashion, such as measuring or bookkeeping (Autor et al. 2003; Spitz-Oener 2006; Hardy et al. 2018). These task categories provide a framework for understanding how technological change and globalization impact the demand for different skills in the labor market.

To assess the content of occupations, I employ five measures based on the work of Autor et al. (2003), adapted to the German context by Spitz-Oener (2006) and Rohrbach-Schmidt and Tiemann (2013). These measures are derived using data from the 2006 Employment Survey of the German Federal Institute for Vocational Education and Training (BiBB) (Hall et al. 2006). The BiBB Employment Survey is a cross-sectional survey conducted every 6-7 years since 1979. The choice of the 2006 survey, rather than a later one, ensures an exogenous measurement of task content of work. The survey comprises over 20,000 participants and includes a comprehensive set of questions about the activities performed at work. Respondents indicate whether they frequently, occasionally, or never perform specific activities. I categorize these activities into the five domains using the criterion validation method proposed by Rohrbach-Schmidt and Tiemann (2013). Table 1 presents these activities along with the categories to which they were classified. It's important to note that the routine cognitive measure is defined by just one task item, *measuring* (see Table 1), making it potentially unreliable. For this reason, I combine the routine cognitive and routine manual measures together into a *routine* measure.

The *j* task measure can be expressed as:

$$j \text{ task measure}_o = \frac{\sum_{i=1}^{N} j \text{ task measure}_{o,i}}{N} \tag{1}$$

where

$$j \text{ task measure}_{o,i} = \frac{\text{number of items in category } j \text{ performed by } i}{\text{total number of items in category } j} \tag{2}$$

and $j \in \{\text{analytic, interactive, non} - \text{routine manual, routine}\}$. Suppose a worker performs organizing and researching. Their analytic task measure would then be 50, as they engage in two activities out of the four classified under the analytic category (see Table 1). Since task measures quantify proportions, they range from 0 to 100. Equation 1, expressed at an occupation level, is a simple average of individual measures (Eq. 2). Occupation-level aggregated task measures are merged with the individual-level dataset constructed from the German Pension Fund Data using 3 digit occupational codes of the German occupational classification (Klassifikation der Berufe 2010). To avoid simultaneity issues, women's occupations are assigned to one year before their first childbirth. About 25% of women in the analytical sample change occupation in the year of childbirth - this includes also a shift between having an occupation at all and exiting the labour market or vice versa.

The total number of 3 digit occupational codes used to compute the aggregate task measures is equal to 144, 28 of which rely on fewer than 10 individual observations. This can raise a question of whether the scores calculated using such a low number of observations are reliable. An alternative approach would be to use task indices quantified on a 2 digit level, which would include 37 occupations, all relying on at least 32 individual observations. Figure 7 compares the distributions of the number of individual observations used to calculate task measures on a 3 digit and 2 digit level. The number of cases used for the indices on a 3 digit level is clearly skewed towards zero. However, the distributions of 3 digit and 2 digit task measures for mothers in the sample are very similar (Fig. 8) and highly correlated (Table 8). Hence, I use the more detailed 3 digit task measures in the main analysis presented here and conduct a robustness check with 2 digit task measures, which yields very similar findings.

Figure 5 displays unweighted means of task measures by the birth year of the first child. Since the task measures are fixed in time in my setup, any variation over time would result from substantial changes in the composition of occupations where women are employed a year before the first birth. However, no such variations are visible in Fig. 5. The plot also reveals that the analyzed sample exhibits the highest task intensities for the interactive category. This implies that German women were most frequently employed in occupations intense in such tasks within the considered time period, partially aligning with the recent findings of Matysiak et al. (2024), who identified that women in Europe are overrepresented in outward-oriented social tasks.

2.3 Competing risk

I analyze transitions to events as a competing risk problem. This approach was previously used by Arntz et al. (2017) to study post-birth employment transitions of women in Germany in an earlier period than presented here. It considers the possibility that an individual may experience more than one type of event during the follow-up period (e.g., return to employment or transition to second birth) and enables the estimation of the cumulative incidence of each event type while accounting for the occurrence of competing events. The Cumulative Incidence Function (CIF) represents the marginal probability for each competing event. Marginal probability is defined as the probability of subjects who actually developed the event of interest, regardless of whether they were censored or failed from other competing events. By definition, the marginal probability does not assume the independence of competing events, and it is the most popular approach to analyzing competing events data, due to its appealing interpretation.

Fine et al. (1999) proposed a parametric hazards model that allows modelling the CIF with covariates by treating the CIF as a subdistribution function. The subdistribution function is analogous to the Cox proportional hazard model, except it models a hazard function derived from a CIF. The Fine and Gray subdistribution hazard function for event e can be expressed as

$$\bar{h}_e(t) = \lim_{\Delta \to 0} \frac{P(t < T < t + \Delta t \text{ and } e) \mid T > t \text{ or } (T \leq t \text{ and not } e)}{\Delta t}. \tag{3}$$

The above function estimates the hazard rate for event type e at time t based on the risk set that remains at time t after accounting for all previously occurring event types, which includes competing events. The CIF can be computed from the subdistribution hazard as

$$\mathrm{CIF}_e(t) = 1 - \exp\{-\overline{H}_e(t)\} \tag{4}$$

where $\overline{H}_e(t) = \int_0^t \bar{h}_e(t)\, dt$ is the cumulative subhazard.

The CIF-based proportional hazard model is then defined as

$$\bar{h}_e(t|x) = \bar{h}_{e,0}(t) \exp(x\beta). \tag{5}$$

This model satisfies the proportional hazard assumption for the subpopulation hazard being modeled. I estimate the competing risk models using the Stata-core *stcrreg* command.

2.4 Analytical strategy

The task measures are categorised into five equal groups to accommodate cases where the occupation is unknown-missing values constitute the sixth group and are recorded for women who did not work a year before the first birth or if their occupation was not observed in the data. The task measures are included separately in the models. Thus, I run four models, one for each task measure, for each of the three outcomes (employment, unemployment, second birth). The control variables are consistent across all models and include calendar year, the mother's age, her residence (Bundesland), and education level (low/unknown, middle, high). Since information on occupation, education, and residence is available in the original data with yearly accuracy, all variables are set to one year before the first childbirth (i.e., lagged by one year with respect to the start of the observation period), except for the calendar period, which corresponds to the year of the event. Age is categorised into four groups.

The results of the models presented here should be interpreted solely as correlations for several reasons. First, the administrative data from the German Pension Fund, which relies on information about social contributions and collects limited personal details, lacks the capability to identify marriages or partnerships. Additionally, it provides no additional job characteristics beyond earning points (total gross income centred around the mean and adjusted for inflation). While I can control for some potential confounders such as region (as women might selectively move to regions with better childcare, see Bauernschuster et al. (2015); Mueller et al. (2020)), I cannot include others like partner's characteristics or women's labour market history. Second, the issue of selection into occupations following fertility intentions and labour market abilities is an omnipresent problem. Adda et al. (2017) studied women in the vocational track in Germany and demonstrated that this selection occurs as early as the end of primary school, making it practically impossible to circumvent. Third, constraints in data and methodology limit my ability to assess specific mechanisms (such as the income effect) that sort women into different situations post-birth. Although I have information about earning points at my disposal, income can be considered a bad control (Cinelli et al. 2022) because women with higher incomes might face opportunity costs of childbearing and thus selectively transition to employment rather than experiencing a second birth or inactivity. Additionally, there is currently no statistical method available to conduct mediation analysis in a competing risk setting. However, to explore income as a potential mechanism that channels women into various employment transitions after the first birth, I compute Spearman correlations between the task measures and earning points. Finally, global phenomena may simultaneously impact the content of work and the outcomes. Although setting task measures to 2006 partially addresses this, employing instruments in a competing risk setting presents an unsolved methodological challenge. In all regressions, standard errors are clustered at the occupation level. This clustering approach is employed to mitigate the potential impact of measurement error arising from the hierarchical data structure, where task measures are expressed at the occupation level.

3 Results

Figures 1, 2, and 6 present cumulative incidences of employment, unemployment, and second birth by task measure, with full model results available in Tables 4, 5, 6, and 7. Notably, women with the highest analytic task measure (between 80 and 100) are the most likely to transition to employment after the first birth. Similarly, women with jobs intensive in interactive and non-routine manual tasks also exhibit high cumulative incidences of transitioning to employment, albeit slightly smaller than those with highly analytic jobs. In contrast, women with jobs intense in routine tasks are less likely to transition to employment.

Figure 2 illustrates cumulative incidences of unemployment and shows that women with routine jobs are disproportionately likely to be unemployed after becoming mothers. Correspondingly, women with low analytic and interactive task intensities are also the most likely to transition to unemployment. This transition happens either right after the maternity leave (after 2–3 months) or after the parental leave (after 12 months). These patterns align with economic literature highlighting the labour-replacing consequences of automation and globalization, particularly in routine tasks (e.g., Autor et al. 2003; Hardy et al. 2018). Even if women are guaranteed to return to their job after the maternity/parental leave, they might voluntarily enter inactivity or unemployment, as routine jobs become less attractive. It is also in line with the work of Adda et al. (2017), who showed that family-oriented women, who are overall the most likely to withdraw from the labour market after they become mothers, sorted themselves into routine occupations in Germany.

Additionally, Fig. 6 demonstrates that women with the highest cumulative incidence of a second birth are those with high analytic and low routine measures. Notably, women in the top analytic category record the lowest cumulative incidence of a second birth among all mothers in the sample.

Furthermore, Table 3 presents correlations of continuous task measures with earning points for mothers in the sample. These correlations, given the difference in measurement levels (individual level for earning points and occupation level for task measures), are naturally lower. However, distinct differences between task measures emerge, with the analytic measure showing the highest positive correlation with earnings. On the other hand, the interactive measure exhibits a small positive correlation with earnings, while the two other measures are negatively correlated. This aligns with previous economic research indicating a steady decline in demand for certain types of tasks (Autor et al. 2003; Spitz-Oener 2006; Hardy et al. 2018), as well as wage differentials between task types (Matysiak et al. 2024). These correlations may help explain why women with highly analytic jobs, facing high opportunity costs, are most likely to transition to employment after their first child.

Finally, Tables 9, 10, 11, and 12 show the results of the robustness check in which the task measures are calculated and merged on a 2 digit occupational level. These findings do not differ substantially from the main 3 digit specification presented here.

4 Discussion

Technology and globalization have brought about unprecedented changes in the world of work. These transformations have led to a significant polarization of opportunities, particularly between workers with cognitive skills and those with routine/manual skills and occupations. Simultaneously, extensive research on the career impact of childbearing has highlighted socioeconomic disparities in women's labour market outcomes following the birth of their first child. This study aims to integrate these two strands of literature by investigating how the task content of women's work, indicative of their long-term labour market situation and their positioning on the career-family continuum, influences their employment transitions after their first childbirth. The study is situated in Germany, a conservative welfare state experiencing the labour-replacing effects of automation and import competition in certain sectors, along with a high demand for cognitive labour in others.

The results of my analysis align with prior research on the European labour market, indicating that women are predominantly employed in jobs characterized by high levels of interactive tasks (Matysiak et al. 2024). This trend persists when focusing specifically on mothers. Additionally, I identified task disparities in the employment transitions of new mothers. Women in jobs involving analytic and interactive tasks were more likely to transition to employment, while those in routine jobs were more prone to moving into unemployment. However, it remains unclear whether this pattern arises from shifting task demands (and voluntary unemployment as a results of diminishing quality and attractiveness of routine jobs), differences in women's career-family orientations, changing gender norms, or depreciating human capital. Several limitations affect this research. First, due to data constraints, I could not control for potentially relevant confounders such as partnership status. Second, the issue of selection into occupations based on family orientation was pervasive. Third, I was unable to differentiate between full-time and part-time employment or explore specific underlying mechanisms.

Despite these limitations, this study represents the first attempt to investigate the connection between structural labour market changes, the career impact of children, and mothers' employment transitions in a contemporary context. While a few studies have examined the influence of labour market changes driven by technology and globalization on female employment and careers (Black and Spitz-Oener 2010; Adda et al. 2017; Brussevich et al. 2019; Matysiak et al. 2024), the aspect of maternity has received relatively little attention in this regard. Given the significant automation witnessed through the adoption of industrial robots and AI, along with increasing trade competition and growing economic inequalities in Europe (Piketty and Goldhammer 2014), understanding the intersection of these phenomena is crucial for comprehending their implications for social inequality.

Appendix

Appendix A

See Tables 2, 3, 4, 5, 6, 7 and Figs. 3, 4, 5, 6.

Table 2 Share of event occurrence for mothers in the sample

	Event	Count	Share (%)
1	Employment	40,371	63.15
2	Unemployment	12,053	18.85
3	Second birth	9,265	14,49
4	Censored	2.240	3,50
	Total	63,929	100

Table 3 Correlation of task measures with earning points for mothers in the sample

Task Measure	Correlation with earning points
Analytic	0.3508
Interactive	0.0731
Non-routine manual	− 0.1720
Routine	−0.1974

Earning points are calculated by centering the total gross income around the mean and they are adjusted for inflation (https://www.gesetze-im-internet.de/sgb_6/anlage_1.html)

Table 4 Full model results: analytic task measure, 3 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	1.124 *** (0.018)	0.699 *** (0.010)	1.332 *** (0.023)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	1.323 *** (0.035)	0.786 *** (0.027)	0.954 (0.039)
Task measure: 40–60	2.127 *** (0.068)	0.310 *** (0.023)	0.914 (0.051)
Task measure: 60–80	1.976 *** (0.212)	0.316 *** (0.042)	1.229 (0.263)
Task measure: 80–100	2.726 *** (0.102)	0.162 *** (0.052)	0.648 *** (0.070)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.855 *** (0.110)	0.397 *** (0.013)	1.217 ** (0.120)
Age: 30–34	2.140 *** (0.121)	0.289 *** (0.014)	1.003 (0.152)
Age: 35+	2.305 *** (0.148)	0.316 *** (0.015)	0.540 *** (0.069)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.770 *** (0.026)	0.739 *** (0.016)	4.685 *** (0.451)
2016–2017	0.742 *** (0.041)	0.584 *** (0.018)	6.157 *** (0.586)
2018–2029	0.764 *** (0.051)	0.450 *** (0.014)	6.606 *** (0.686)
2020	0.301 *** (0.020)	0.150 *** (0.028)	9.737 *** (0.935)
Schleswig-Holstein	1.139 *** (0.040)	0.919 * (0.047)	0.781 *** (0.067)
Hamburg	1.162 *** (0.033)	0.995 (0.050)	0.673 *** (0.048)
Niedersachsen	1.088 *** (0.022)	0.908 ** (0.034)	0.879 *** (0.038)
Bremen	0.957 (0.062)	1.431 *** (0.096)	0.738 ** (0.098)
Nordrhein-Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.127 *** (0.033)	0.823 *** (0.046)	0.837 *** (0.050)
Rheinland-Pfalz	1.054 ** (0.026)	0.744 *** (0.032)	1.002 (0.051)
Baden-Wuerttemberg	0.973 (0.022)	0.663 *** (0.024)	1.361 *** (0.044)
Bayern	1.060 * (0.033)	0.571 *** (0.024)	1.184 *** (0.045)
Saarland	1.177 *** (0.045)	0.980 (0.065)	0.730 *** (0.078)
Berlin	1.266 *** (0.052)	1.364 *** (0.064)	0.342 *** (0.042)
Brandenburg	1.792 *** (0.063)	0.883 ** (0.054)	0.126 *** (0.037)
Mecklenburg-Vorpommern	1.572 *** (0.087)	1.112 (0.096)	0.203 *** (0.043)
Sachsen	1.421 *** (0.049)	0.992 (0.058)	0.260 *** (0.024)
Sachsen-Anhalt	1.531 *** (0.075)	1.098 (0.070)	0.187 *** (0.039)
Thueringen	1.555 *** (0.057)	1.127 * (0.071)	0.153 *** (0.025)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.182 *** (0.035)	0.700 *** (0.026)	1.021 (0.038)
Education: high	1.336 *** (0.053)	0.538 *** (0.043)	1.023 (0.093)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Full model results: interactive task measure, 3 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	1.164 *** (0.028)	0.669 *** (0.016)	1.329 *** (0.024)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	1.211 *** (0.066)	0.889 *** (0.024)	0.882 *** (0.034)
Task measure: 40–60	1.974 *** (0.083)	0.420 *** (0.051)	0.866 ** (0.053)
Task measure: 60–80	1.774 *** (0.122)	0.512 *** (0.067)	0.969 (0.050)
Task measure: 80–100	1.819 *** (0.145)	0.381 *** (0.017)	1.051 (0.181)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.962 *** (0.105)	0.365 *** (0.014)	1.211 ** (0.117)
Age: 30–34	2.318 *** (0.131)	0.251 *** (0.018)	1.000 (0.148)
Age: 35+	2.517 *** (0.166)	0.268 *** (0.021)	0.539 *** (0.067)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.775 *** (0.026)	0.749 *** (0.017)	4.674 *** (0.451)
2016–2017	0.747 *** (0.040)	0.604 *** (0.019)	6.138 *** (0.581)
2018–2029	0.772 *** (0.050)	0.464 *** (0.016)	6.573 *** (0.679)
2020	0.300 *** (0.019)	0.162 *** (0.033)	9.713 *** (0.916)
Schleswig–Holstein	1.127 *** (0.039)	0.945 (0.049)	0.783 *** (0.068)
Hamburg	1.154 *** (0.033)	0.995 (0.053)	0.674 *** (0.048)
Niedersachsen	1.075 *** (0.023)	0.927 ** (0.035)	0.881 *** (0.038)
Bremen	0.931 (0.062)	1.466 *** (0.094)	0.742 ** (0.098)
Nordrhein-Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.125 *** (0.033)	0.820 *** (0.046)	0.840 *** (0.050)
Rheinland-Pfalz	1.045 * (0.026)	0.766 *** (0.034)	1.006 (0.050)
Baden-Wuerttemberg	0.972 (0.022)	0.672 *** (0.023)	1.373 *** (0.042)
Bayern	1.061 * (0.033)	0.578 *** (0.025)	1.192 *** (0.043)
Saarland	1.151 *** (0.048)	1.000 (0.060)	0.730 *** (0.078)
Berlin	1.249 *** (0.052)	1.373 *** (0.067)	0.344 *** (0.043)
Brandenburg	1.758 *** (0.062)	0.891 * (0.055)	0.126 *** (0.037)
Mecklenburg–Vorpommern	1.517 *** (0.086)	1.123 (0.102)	0.204 *** (0.044)
Sachsen	1.401 *** (0.047)	1.001 (0.057)	0.263 *** (0.024)
Sachsen–Anhalt	1.490 *** (0.069)	1.123 * (0.069)	0.188 *** (0.039)
Thueringen	1.537 *** (0.053)	1.131 ** (0.068)	0.154 *** (0.025)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.268 *** (0.056)	0.611 *** (0.041)	1.006 (0.038)
Education: high	1.525 *** (0.095)	0.386 *** (0.041)	1.047 (0.122)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Full model results: non-routine manual task measure, 3 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	0.580 *** (0.046)	1.660 *** (0.290)	1.607 *** (0.080)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	0.756 *** (0.051)	1.756 *** (0.285)	1.128 ** (0.068)
Task measure: 40–60	0.743 *** (0.055)	1.454 (0.331)	1.427 *** (0.149)
Task measure: 60–80	1.033 (0.077)	0.963 (0.203)	0.897 (0.080)
Task measure: 80–100	1.080 (0.079)	1.192 (0.374)	0.562 *** (0.125)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.941 *** (0.109)	0.369 *** (0.014)	1.230 ** (0.116)
Age: 30–34	2.269 *** (0.134)	0.258 *** (0.017)	1.023 (0.148)
Age: 35+	2.435 *** (0.164)	0.280 *** (0.019)	0.554 *** (0.066)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.772 *** (0.026)	0.751 *** (0.018)	4.685 *** (0.451)
2016–2017	0.747 *** (0.040)	0.598 *** (0.019)	6.127 *** (0.579)
2018–2029	0.772 *** (0.050)	0.457 *** (0.016)	6.565 *** (0.673)
2020	0.304 *** (0.019)	0.158 *** (0.031)	9.572 *** (0.883)
Schleswig–Holstein	1.133 *** (0.040)	0.933 (0.049)	0.776 *** (0.067)
Hamburg	1.161 *** (0.035)	0.992 (0.057)	0.672 *** (0.048)
Niedersachsen	1.091 *** (0.023)	0.915 ** (0.034)	0.875 *** (0.038)
Bremen	0.935 (0.060)	1.472 *** (0.092)	0.750 ** (0.102)
Nordrhein-Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.127 *** (0.033)	0.823 *** (0.046)	0.839 *** (0.052)
Rheinland–Pfalz	1.053 ** (0.026)	0.749 *** (0.032)	1.003 (0.051)
Baden–Wuerttemberg	0.975 (0.022)	0.666 *** (0.022)	1.363 *** (0.044)
Bayern	1.067 ** (0.034)	0.568 *** (0.022)	1.185 *** (0.045)
Saarland	1.167 *** (0.046)	0.977 (0.064)	0.724 *** (0.077)
Berlin	1.272 *** (0.051)	1.322 *** (0.058)	0.340 *** (0.042)
Brandenburg	1.769 *** (0.063)	0.880 ** (0.051)	0.126 *** (0.037)
Mecklenburg–Vorpommern	1.573 *** (0.088)	1.076 (0.099)	0.199 *** (0.042)
Sachsen	1.427 *** (0.045)	0.975 (0.047)	0.258 *** (0.024)
Sachsen–Anhalt	1.513 *** (0.075)	1.092 (0.070)	0.186 *** (0.039)
Thueringen	1.550 *** (0.055)	1.123 * (0.072)	0.153 *** (0.025)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.279 *** (0.057)	0.585 *** (0.037)	1.056 (0.035)
Education: high	1.522 *** (0.097)	0.370 *** (0.046)	1.132 (0.137)
Observations	62,307	62,307	62,307

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Full model results: routine task measure, 3 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	0.614 *** (0.057)	2.338 *** (0.692)	1.135 *** (0.055)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	0.995 (0.081)	1.473 (0.449)	0.802 *** (0.042)
Task measure: 40–60	0.837 (0.093)	2.236 ** (0.713)	0.800 *** (0.061)
Task measure: 60–80	0.933 (0.092)	1.758 (0.606)	0.833 ** (0.072)
Task measure: 80–100	0.713 *** (0.080)	2.791 *** (0.882)	0.856 ** (0.058)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.944 *** (0.106)	0.372 *** (0.016)	1.213 ** (0.119)
Age: 30–34	2.282 *** (0.128)	0.261 *** (0.018)	0.996 (0.150)
Age: 35+	2.468 *** (0.156)	0.282 *** (0.018)	0.535 *** (0.069)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.772 *** (0.026)	0.751 *** (0.018)	4.681 *** (0.451)
2016–2017	0.745 *** (0.040)	0.602 *** (0.019)	6.159 *** (0.587)
2018–2029	0.769 *** (0.050)	0.462 *** (0.016)	6.601 *** (0.686)
2020	0.299 *** (0.020)	0.162 *** (0.033)	9.775 *** (0.944)
Schleswig-Holstein	1.130 *** (0.039)	0.938 (0.050)	0.783 *** (0.067)
Hamburg	1.162 *** (0.036)	0.995 (0.056)	0.671 *** (0.049)
Niedersachsen	1.082 *** (0.023)	0.922 ** (0.036)	0.880 *** (0.038)
Bremen	0.932 (0.061)	1.462 *** (0.088)	0.741 ** (0.097)
Nordrhein–Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.128 *** (0.033)	0.826 *** (0.047)	0.837 *** (0.051)
Rheinland–Pfalz	1.047 * (0.026)	0.759 *** (0.033)	1.008 (0.049)
Baden–Wuerttemberg	0.973 (0.023)	0.672 *** (0.023)	1.367 *** (0.043)
Bayern	1.063 * (0.034)	0.576 *** (0.024)	1.189 *** (0.043)
Saarland	1.163 *** (0.047)	0.973 (0.062)	0.730 *** (0.078)
Berlin	1.260 *** (0.053)	1.347 *** (0.063)	0.345 *** (0.043)
Brandenburg	1.763 *** (0.063)	0.883 ** (0.051)	0.126 *** (0.037)
Mecklenburg–Vorpommern	1.547 *** (0.088)	1.080 (0.104)	0.203 *** (0.043)
Sachsen	1.413 *** (0.044)	0.987 (0.050)	0.262 *** (0.024)
Sachsen–Anhalt	1.498 *** (0.070)	1.095 (0.070)	0.188 *** (0.039)
Thueringen	1.539 *** (0.052)	1.127 * (0.069)	0.154 *** (0.025)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.312 *** (0.066)	0.568 *** (0.046)	1.004 (0.041)
Education: high	1.534 *** (0.103)	0.383 *** (0.046)	1.058 (0.137)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parenthesess

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

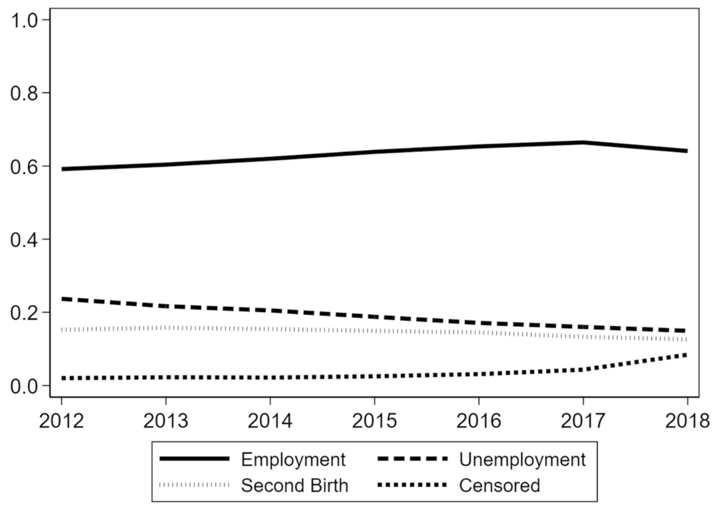

Fig. 3 Share of event occurrence by birth year of the first child. N = 63,929

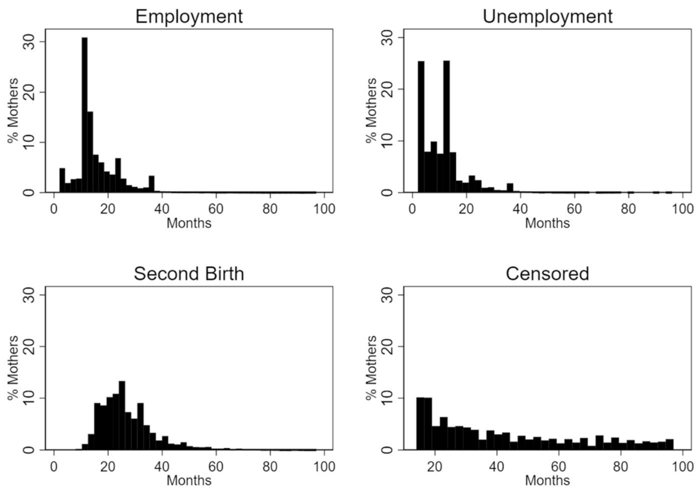

Fig. 4 Duration by event in months. N = 63,929

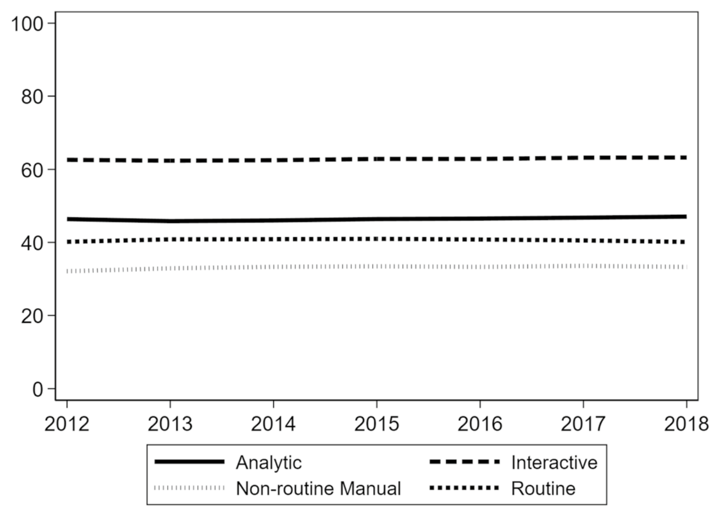

Fig. 5 Mean of task measures by birth year of the first child. N = 53,922, i.e. mothers for whom I observe an occupation a year before the first childbirth

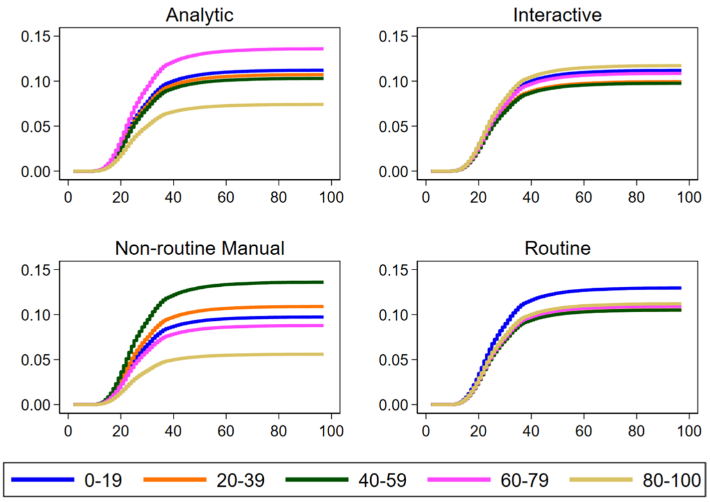

Fig. 6 Cumulative Incidence Functions from models with the second birth set as the main event. Controls include: year of event, age at first childbirth, residence (Bundesland) at first childbirth, education at first childbirth. N = 63,929

Appendix B: Sensitivity analysis

See Tables 8, 9, 10, 11, 12 and Figs. 7, 8.

Table 8 Correlation of continuous task measures calculated on a 3 digit level and 2 digit level for mothers in the sample

Task measure	Correlation 3 digits with 2 digits
Analytic	0.8924
Interactive	0.8692
Non-routine manual	0.9041
Routine	0.8750

N = 53,922, i.e. mothers for whom I observe an occupation a year before the first childbirth

Table 9 Full model results: analytic task measure, 2 digits

	(1) **Employment**	(2) **Unemployment**	(3) **Second birth**
Task measure: unknown	1.137 *** (0.024)	0.691 *** (0.010)	1.327 *** (0.024)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	1.368 *** (0.022)	0.771 *** (0.019)	0.927 *** (0.024)
Task measure: 40–60	2.034 *** (0.082)	0.352 *** (0.034)	0.937 (0.049)
Task measure: 60–80	1.942 *** (0.258)	0.328 *** (0.053)	1.230 (0.288)
Task measure: 80–100	2.613 *** (0.120)	0.184 *** (0.008)	0.616 *** (0.032)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.888 *** (0.124)	0.388 *** (0.017)	1.209 * (0.126)
Age: 30–34	2.200 *** (0.147)	0.276 *** (0.018)	0.994 (0.158)
Age: 35+	2.377 *** (0.168)	0.299 *** (0.019)	0.536 *** (0.071)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.770 *** (0.032)	0.744 *** (0.015)	4.683 *** (0.582)
2016–2017	0.743 *** (0.049)	0.593 *** (0.021)	6.157 *** (0.682)
2018–2029	0.765 *** (0.061)	0.457 *** (0.019)	6.602 *** (0.823)
2020	0.299 *** (0.025)	0.155 *** (0.032)	9.765 *** (1.101)
Schleswig–Holstein	1.142 *** (0.047)	0.922 (0.048)	0.782 *** (0.069)
Hamburg	1.163 *** (0.026)	0.981 (0.049)	0.673 *** (0.061)
Niedersachsen	1.084 *** (0.026)	0.916 ** (0.034)	0.880 *** (0.042)
Bremen	0.951 (0.062)	1.449 *** (0.098)	0.738 *** (0.080)
Nordrhein–Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.126 *** (0.031)	0.820 *** (0.046)	0.837 *** (0.050)
Rheinland–Pfalz	1.052 ** (0.021)	0.742 *** (0.028)	1.004 (0.043)
Baden–Wuerttemberg	0.972 (0.024)	0.667 *** (0.018)	1.364 *** (0.048)
Bayern	1.060 * (0.036)	0.573 *** (0.020)	1.186 *** (0.046)
Saarland	1.168 *** (0.050)	0.981 (0.078)	0.729 ** (0.093)
Berlin	1.268 *** (0.048)	1.347 *** (0.059)	0.343 *** (0.035)
Brandenburg	1.786 *** (0.062)	0.878 ** (0.051)	0.126 *** (0.037)
Mecklenburg-Vorpommern	1.566 *** (0.109)	1.097 (0.106)	0.203 *** (0.051)
Sachsen	1.415 *** (0.046)	0.994 (0.049)	0.260 *** (0.027)
Sachsen-Anhalt	1.512 *** (0.072)	1.105 (0.068)	0.188 *** (0.036)
Thueringen	1.546 *** (0.050)	1.118 * (0.072)	0.154 *** (0.029)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.208 *** (0.047)	0.673 *** (0.026)	1.010 (0.040)
Education: high	1.389 *** (0.069)	0.490 *** (0.041)	1.016 (0.089)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 Full model results: interactive task measure, 2 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	1.175 *** (0.034)	0.660 *** (0.016)	1.329 *** (0.023)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	1.388 *** (0.093)	0.859 *** (0.050)	0.918 *** (0.029)
Task measure: 40–60	1.952 *** (0.158)	0.452 *** (0.107)	0.840 *** (0.046)
Task measure: 60–80	1.773 *** (0.148)	0.508 *** (0.080)	0.965 (0.041)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.976 *** (0.122)	0.358 *** (0.015)	1.216 * (0.122)
Age: 30–34	2.338 *** (0.168)	0.246 *** (0.020)	1.004 (0.156)
Age: 35+	2.540 *** (0.198)	0.263 *** (0.024)	0.540 *** (0.068)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.775 *** (0.032)	0.752 *** (0.017)	4.679 *** (0.584)
2016–2017	0.747 *** (0.048)	0.605 *** (0.023)	6.143 *** (0.678)
2018–2029	0.773 *** (0.061)	0.463 *** (0.020)	6.585 *** (0.822)
2020	0.300 *** (0.025)	0.162 *** (0.035)	9.721 *** (1.079)
Schleswig–Holstein	1.126 *** (0.046)	0.940 (0.053)	0.784 *** (0.069)
Hamburg	1.154 *** (0.028)	0.998 (0.053)	0.673 *** (0.060)
Niedersachsen	1.075 *** (0.027)	0.931 * (0.036)	0.882 *** (0.042)
Bremen	0.929 (0.065)	1.478 *** (0.102)	0.744 *** (0.078)
Nordrhein-Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.122 *** (0.031)	0.820 *** (0.046)	0.840 *** (0.050)
Rheinland–Pfalz	1.042 ** (0.021)	0.763 *** (0.031)	1.011 (0.042)
Baden–Wuerttemberg	0.969 (0.023)	0.674 *** (0.016)	1.374 *** (0.047)
Bayern	1.059 * (0.037)	0.580 *** (0.021)	1.193 *** (0.045)
Saarland	1.158 *** (0.052)	0.987 (0.073)	0.728 ** (0.093)
Berlin	1.256 *** (0.052)	1.355 *** (0.072)	0.344 *** (0.035)
Brandenburg	1.757 *** (0.060)	0.886 ** (0.054)	0.126 *** (0.037)
Mecklenburg-Vorpommern	1.526 *** (0.113)	1.108 (0.118)	0.203 *** (0.051)
Sachsen	1.401 *** (0.049)	1.000 (0.053)	0.262 *** (0.027)
Sachsen-Anhalt	1.477 *** (0.069)	1.130 ** (0.069)	0.188 *** (0.037)
Thueringen	1.538 *** (0.048)	1.123 * (0.073)	0.154 *** (0.029)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.289 *** (0.068)	0.582 *** (0.037)	1.012 (0.038)
Education: high	1.555 *** (0.121)	0.359 *** (0.046)	1.071 (0.119)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11 Full model results: non-routine manual task measure, 2 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	0.578 *** (0.048)	1.852 *** (0.343)	1.540 *** (0.058)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	0.764 *** (0.062)	1.948 *** (0.353)	1.096 (0.081)
Task measure: 40–60	0.832 ** (0.059)	1.447 (0.407)	1.196 ** (0.085)
Task measure: 60–80	0.925 *** (0.027)	1.179 (0.177)	1.019 (0.024)
Age: 20–24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.939 *** (0.120)	0.372 *** (0.017)	1.227 ** (0.122)
Age: 30–34	2.267 *** (0.150)	0.262 *** (0.018)	1.020 (0.154)
Age: 35+	2.434 *** (0.176)	0.285 *** (0.020)	0.552 *** (0.067)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.772 *** (0.032)	0.750 *** (0.016)	4.682 *** (0.586)
2016–2017	0.747 *** (0.048)	0.599 *** (0.022)	6.140 *** (0.680)
2018–2029	0.771 *** (0.060)	0.459 *** (0.019)	6.586 *** (0.820)
2020	0.300 *** (0.025)	0.160 *** (0.034)	9.713 *** (1.077)
Schleswig–Holstein	1.130 *** (0.044)	0.939 (0.048)	0.780 *** (0.070)
Hamburg	1.157 *** (0.030)	0.991 (0.055)	0.674 *** (0.061)
Niedersachsen	1.084 *** (0.027)	0.917 ** (0.037)	0.878 *** (0.042)
Bremen	0.944 (0.063)	1.438 *** (0.098)	0.741 *** (0.080)
Nordrhein–Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.125 *** (0.031)	0.826 *** (0.047)	0.839 *** (0.050)
Rheinland–Pfalz	1.051 *** (0.020)	0.748 *** (0.031)	1.007 (0.042)
Baden–Wuerttemberg	0.975 (0.026)	0.667 *** (0.016)	1.371 *** (0.050)
Bayern	1.063 * (0.038)	0.572 *** (0.019)	1.192 *** (0.045)
Saarland	1.158 *** (0.051)	0.982 (0.077)	0.727 ** (0.092)
Berlin	1.269 *** (0.055)	1.325 *** (0.070)	0.344 *** (0.035)
Brandenburg	1.774 *** (0.064)	0.879 ** (0.048)	0.126 *** (0.037)
Mecklenburg–Vorpommern	1.557 *** (0.113)	1.084 (0.107)	0.201 *** (0.051)
Sachsen	1.426 *** (0.047)	0.971 (0.042)	0.260 *** (0.027)
Sachsen–Anhalt	1.512 *** (0.072)	1.087 (0.064)	0.186 *** (0.036)
Thueringen	1.549 *** (0.049)	1.116 * (0.074)	0.154 *** (0.029)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.303 *** (0.071)	0.582 *** (0.045)	1.011 (0.040)
Education: high	1.562 *** (0.111)	0.353 *** (0.042)	1.095 (0.129)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 Full model results: routine task measure, 2 digits

	(1) Employment	(2) Unemployment	(3) Second birth
Task measure: unknown	0.959 (0.048)	0.692 *** (0.035)	1.379 *** (0.043)
Task measure: 0–20	1.000 (.)	1.000 (.)	1.000 (.)
Task measure: 20–40	1.606 *** (0.070)	0.409 *** (0.054)	0.933 (0.042)
Task measure: 40–60	1.325 *** (0.107)	0.630 *** (0.113)	1.012 (0.058)
Task measure: 60–80	1.346 *** (0.114)	0.649 *** (0.093)	0.971 (0.073)
Task measure: 80–100	1.000 (.)	1.000 (.)	1.000 (.)
Age: 20–-24	1.000 (.)	1.000 (.)	1.000 (.)
Age: 25–29	1.941 *** (0.116)	0.370 *** (0.018)	1.225 ** (0.120)
Age: 30–34	2.277 *** (0.145)	0.259 *** (0.019)	1.012 (0.154)
Age: 35+	2.456 *** (0.172)	0.282 *** (0.020)	0.545 *** (0.068)
2012–2013	1.000 (.)	1.000 (.)	1.000 (.)
2014–2015	0.773 *** (0.032)	0.750 *** (0.016)	4.680 *** (0.583)
2016–2017	0.746 *** (0.048)	0.599 *** (0.022)	6.146 *** (0.679)
2018–2029	0.770 *** (0.060)	0.460 *** (0.019)	6.591 *** (0.819)
2020	0.299 *** (0.025)	0.161 *** (0.035)	9.742 *** (1.081)
Schleswig–Holstein	1.130 *** (0.045)	0.938 (0.048)	0.782 *** (0.069)
Hamburg	1.161 *** (0.030)	0.995 (0.055)	0.672 *** (0.061)
Niedersachsen	1.084 *** (0.028)	0.920 ** (0.038)	0.880 *** (0.041)
Bremen	0.935 (0.063)	1.458 *** (0.093)	0.741 *** (0.077)
Nordrhein–Westfalen	1.000 (.)	1.000 (.)	1.000 (.)
Hessen	1.127 *** (0.032)	0.825 *** (0.048)	0.838 *** (0.050)
Rheinland–Pfalz	1.047 ** (0.020)	0.755 *** (0.030)	1.008 (0.042)
Baden–Wuerttemberg	0.975 (0.026)	0.671 *** (0.015)	1.368 *** (0.047)
Bayern	1.064 * (0.038)	0.574 *** (0.020)	1.190 *** (0.045)
Saarland	1.157 *** (0.051)	0.984 (0.073)	0.729 ** (0.092)
Berlin	1.265 *** (0.051)	1.335 *** (0.066)	0.345 *** (0.035)
Brandenburg	1.768 *** (0.063)	0.877 ** (0.049)	0.126 *** (0.037)
Mecklenburg–Vorpommern	1.555 *** (0.114)	1.067 (0.114)	0.202 *** (0.052)
Sachsen	1.422 *** (0.045)	0.972 (0.042)	0.261 *** (0.028)
Sachsen–Anhalt	1.509 *** (0.072)	1.084 (0.065)	0.187 *** (0.037)
Thueringen	1.544 *** (0.049)	1.119 * (0.072)	0.154 *** (0.029)
Education: low/unknown	1.000 (.)	1.000 (.)	1.000 (.)
Education: middle	1.309 *** (0.072)	0.568 *** (0.045)	1.012 (0.038)
Education: high	1.512 *** (0.108)	0.389 *** (0.049)	1.089 (0.132)
Observations	62,325	62,325	62,325

Exponentiated coefficients; Standard eAPPENDIXrrors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

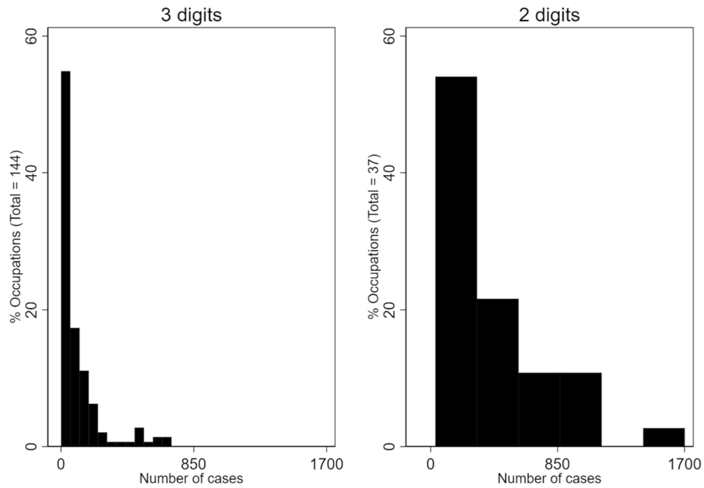

Fig. 7 Distirbution of the number of observations in the 2006 BiBB Employment survey used to compute task measures on a 3 digit and 2 digit occupation levels

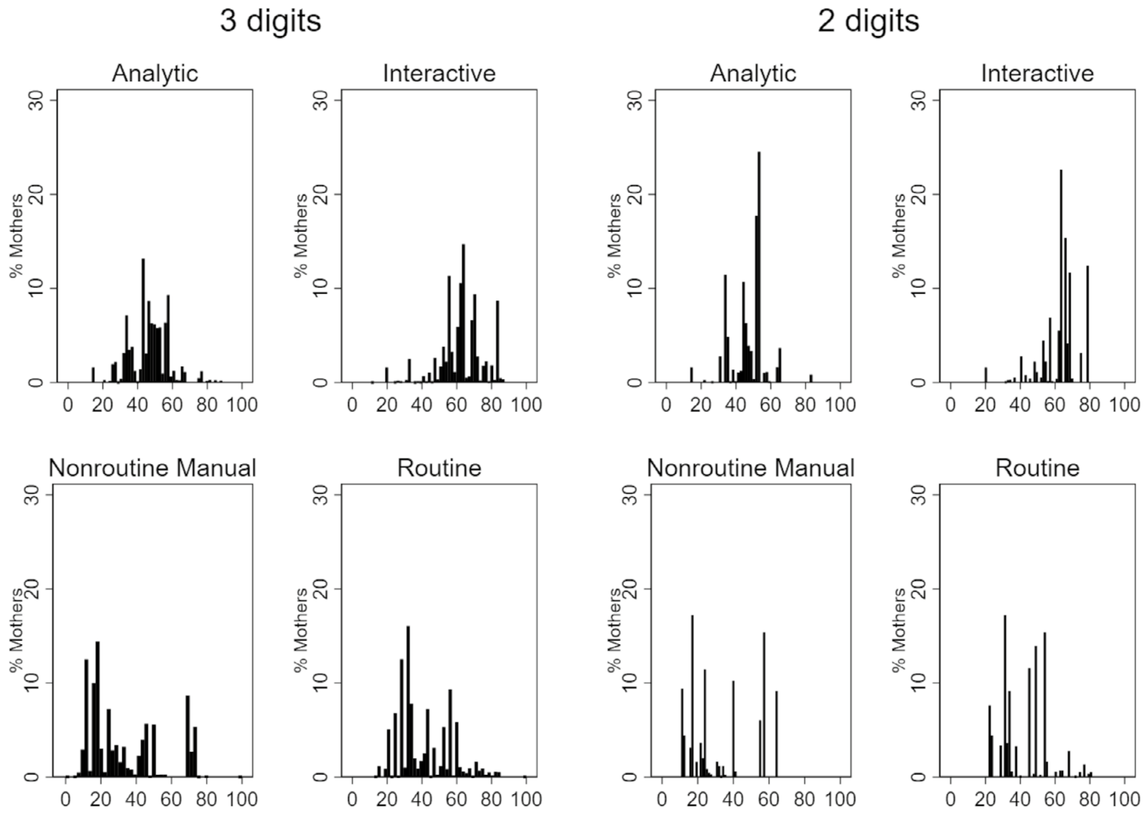

Fig. 8 Distribution of task measures for mothers in the sample, comparison of the measures calculated on 3 digit vs. 2 digit occupation level. N = 53,922, i.e. mothers for whom I observe an occupation a year before the first childbirth

Acknowledgements
I am grateful for the valuable feedback received from Michaela Kreyenfeld, Anna Matysiak, Beata Osiewalska, Lucas van der Velde, the two anonymous reviewers, members of RTG Dynamics in Berlin, and the participants of the British Society for Population Studies Annual Conference 2023. I also acknowledge the helpful advice on working with pension data provided by colleagues at the Forschung und Entwicklung Abteilung der Deutschen Rentenversicherung, especially Daniel Brueggmann.

Author contributions
HB did all of the work put into this manuscript, including data preparation and analysis, writing, and revising the text.

Funding
This research was supported by the European Research Council under the ERC Consolidator Grant *Globalization- and Technology-Driven Labour Market Change and Fertility* (LABFER, grant agreement no 866207, PI: Anna Matysiak).

Availability of data and materials
This paper utilized the AKVS and VSKT administrative datasets, accessible at the Research Data Centre of the German Pension Fund (FDZ-RV). The BiBB Employment Survey 2006 Scientific Use File is obtainable from the Federal Institute for Vocational Education and Training at https://doi.org/10.7803/501.06.1.1.30. Codes employed to generate the analyses presented in this paper can be accessed at https://github.com/LabFam/Bogusz_2024_JLMR.

Declarations

Competing interests
The author declares no Competing interests, financial or other.

Received: 4 December 2023 Accepted: 30 September 2024
Published online: 12 December 2024

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Publisher's Note

2.4 Paper IV: *Industrial robots and workers' well-being in Europe*

Paper IV

"*Industrial robots and workers' well-being in Europe*"

H. Bogusz and D. Bellani

Commentary

Subjective well-being is a crucial aspect of the human condition (Brockmann & Fernandez-Urbano, 2024). It is significantly influenced by labor market outcomes (Green et al., 2024; Morgan & O'Connor, 2022; Nikolova & Graham, 2020), while also affecting other life domains, such as fertility (Luppi & Mencarini, 2018; Vignoli et al., 2020b). At the same time, concerns that machines will displace jobs—and thereby negatively impact workers' well-being—have existed since at least the Industrial Revolution (Bellani & Bogusz, 2024; Mokyr et al., 2015). In the twenty-first century, a new wave of fear regarding job loss to technology has emerged, this time centered on advanced technologies such as artificial intelligence and industrial robots.

In this paper, we focus on the latter issue and contribute to the literature by empirically assessing the impact of industrial robot adoption on workers' subjective well-being in Europe. We construct a measure of robot density at the country-industry level using robot stock data from the International Federation of Robotics[7] and employment data from Eurostat[8]. This measure is then linked to individual-level data from the European Social Survey (2002–2018)[9], creating a pseudo-panel. We estimate linear models with instrumental variables, interacting robot density with education to account for differences in skill levels. Well-being is assessed through self-reported life satisfaction, job influence, happiness, and health, capturing its various dimensions. We also perform a heterogeneity analysis by gender, age, and welfare state type.

Consistent with the polarization hypothesis (Autor & Dorn, 2013; Goos et al., 2009), we find that robot adoption negatively impacts the well-being of medium-educated workers. In contrast, robots positively influence the well-being of both low- and highly-educated workers. These effects are less pronounced in countries with relatively stronger welfare states (e.g., Continental and Scandinavian countries) and are primarily driven by women. At the same time, the results are not stratified with respect to age.

I was responsible for leading this paper. I came up with the idea for the study, developed the analytical strategy, prepared the data, conducted the modeling, created all plots and tables presented in the paper. The conceptual framework was developed jointly by me and Daniela Bellani. I also participated in the literature review, wrote the first version of the manuscript, and edited all subsequent versions. I presented this study at the RC28 Spring Meeting (2024), and am the corresponding author. I will present this paper also at the Population Association America Annual Meeting (2025). The codes employed for the analysis will be published on Github upon the acceptance of the paper in the journal.

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[7]International Federation of Robotics (IFR), 2020a.

[8]Eurostat, 2023a.

[9]European Social Survey European Research Infrastructure (ESS ERIC), 2018a, 2018b, 2023a, 2023b, 2023c, 2023d, 2023e, 2023f, 2023g.

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WORKING PAPERS

No. 1/2025 (464)

INDUSTRIAL ROBOTS AND WORKERS' WELL-BEING IN EUROPE

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LabFam
INTERDISCIPLINARY CENTRE
FOR LABOUR MARKET AND FAMILY DYNAMICS

WARSAW 2025

ISSN 2957-0506

UNIVERSITY OF WARSAW
FACULTY OF ECONOMIC SCIENCES
WORKING PAPERS

Industrial robots and workers' well-being in Europe

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Abstract: In the 21st century, advancements in technologies such as industrial robots have raised concerns about their impact on employment and wages, prompting extensive research. However, their effects on workers' subjective well-being remain underexplored. This study addresses this gap ¬by examining whether workers experience a decline in well-being due to a loss of agency or maintain it by leveraging human skills to adapt to automation. Using data from the International Federation of Robotics, Eurostat, and the European Social Survey (2002–2018), we link robot density at the country-industry-year level to workers' life satisfaction, happiness, job influence, and health. Employing an instrumental variables approach, we find that robot adoption negatively affects medium-educated workers' well-being, particularly its eudaimonic dimension, supporting the decreasing agency thesis. In contrast, low- and highly educated workers experience positive effects. These impacts are more pronounced among women and weaker in countries with robust compensatory social policies.

Keywords: industrial robots, well-being, life satisfaction, Europe, education

JEL codes: I31, O33

Acknowledgements: We are grateful for the valuable feedback received from the participants of the RC28 Spring Meeting in Shanghai as well as the participants of the ECSR 2024 Meeting in Barcelona.

Honorata Bogusz acknowledges funding from the ERC Consolidator Grant "Globalization- and Technology-Driven Labour Market Change and Fertility" (LABFER, grant agreement no 866207, PI: Anna Matysiak).

1. Introduction

Concerns that automation will lead to widespread job losses date back at least two centuries to the onset of the Industrial Revolution (Mokyr et al., 2015). Although the Industrial Revolution initially had severe consequences for large segments of the population, it did not result in a long-term rise in aggregate unemployment (Frey, 2019). However, its benefits were unevenly distributed, primarily favouring those at the top of the wealth distribution (West, 2018; Iversen & Soskice, 2019; Acemoglu & Johnson, 2023).

In the twenty-first century, a new wave of anxiety over job displacement has emerged, driven by advancements in artificial intelligence and robotics (Brynjolfsson & McAfee, 2014). While several major international organisations (e.g. ILO, OECD, UNDP) have expressed concerns about the adoption of advanced industrial robots (Grimshaw, 2020), little is known about how technological change affects workers' well-being.

On the one hand, workers may recognise the disruptive potential of labour-displacing technologies and fear technological unemployment; on the other, they might also perceive new technologies as beneficial (Gallego et al., 2022). Against this backdrop, this study aims to enhance understanding of the effects of technological change on workers' well-being.

In line with this growing interest and the need to keep pace with real-world developments, this study focuses on a specific technology: industrial robots. More than other machines, robots embody technological innovation and serve as a key marker of contemporary technological change. Designed to perform versatile tasks without human intervention, industrial robots have been widely deployed in manufacturing and other industrial sectors. Their adoption has grown rapidly in Europe since the 1990s (see Figure 1) and remained resilient even during crises such as the Great Recession and the COVID-19 pandemic (Müller, 2024).

While the debate continues, considerable attention has been given to the economic winners and losers of robotization, particularly in terms of employment (Hötte & Theodorakopoulos, 2023). The displacement effect of robots—where tasks previously performed by human labour are substituted—has received empirical support in Europe (Graetz & Michaels, 2018), the United States (Acemoglu & Restrepo, 2020), and several Latin American countries (Carbonero et al., 2018; Brambilla et al., 2023). However, recent studies present more nuanced findings, reporting neutral effects (Dauth et al., 2021; Focacci, 2021) or even positive aggregate outcomes

(Acemoglu et al., 2020; Chung & Lee, 2023). Regarding employability, research suggests that robot exposure initially reduces employment but later fosters job creation.

Recently, scholars have adopted a more nuanced approach, examining the broader socioeconomic impacts of robots. Key areas of focus include their effects on the gender wage gap (Aksoy et al., 2021), fertility (Anelli et al., 2021b; Matysiak et al., 2023), mortality (O'Brien et al., 2022), support for the radical right (Anelli et al., 2021a), policy preferences (Gallego et al., 2022), and, more recently, workers' physical and mental health (Gihleb et al., 2022; Abeliansky et al., 2024) as well as substance abuse (Lu & Fan, 2024). Comparative studies highlight significant heterogeneities based on workers' education levels (e.g. Acemoglu & Restrepo, 2020), gender (e.g. Anelli et al., 2021), and institutional contexts (e.g. Matysiak et al., 2023).

Despite extensive research on the objective outcomes of robotization, its impact on workers' subjective well-being remains relatively underexplored (Martin & Hauret, 2020; Antón et al., 2023). This gap is somewhat surprising (Berg et al., 2023), given that workers increasingly interact with innovative technologies—particularly automation, industrial robots, and AI—experiencing significant non-monetary effects, including on subjective well-being. Understanding the subjective well-being of workers exposed to robotization, whether directly or indirectly, is crucial for both research and policy. These interactions shape individual and organizational outcomes, such as workplace performance and productivity, while also influencing broader social and political dynamics (Bliese et al., 2017). Indeed, these effects extend into the domestic sphere, affecting families, communities, and society at large (Chari et al., 2018).

This study seeks to address this gap by providing novel and complementary evidence on the implications of industrial robot adoption for workers' subjective well-being. A well-established relationship exists between the work environment and well-being (see Eurofound, 2019, for a review). Extensive evidence supports the spillover effect from work to overall life satisfaction, as work is not fully separate from other aspects of life (e.g. Sirgy et al., 2001; Green et al., 2024). Research indicates that workers' well-being extends beyond task performance and financial compensation. It also encompasses meaningful work, social connection, identity, workplace safety, health, and job security (e.g. Budd & Spencer, 2015).

Building on literature examining the well-being implications of technological change, we argue that robots affect various life domains that, in turn, influence workers' well-being, regardless of whether their adoption leads to aggregate job losses or employment growth. This argument is grounded in two competing perspectives on the impact of robotization on employed workers (i.e. those who are neither unemployed nor inactive, the focus of this study).

The first, which we term the *human leverage effect*, emphasises workers' superior capabilities over robots. Workers may experience—or anticipate—a comparative advantage due to their greater flexibility in performing new, more meaningful tasks, while robots take over physically demanding and hazardous work. Consequently, robotization is expected to enhance workers' well-being.

The second, which we call *decreasing workers' agency*, highlights the negative effects of robotization on job autonomy and the sense of purpose derived from work. Industrial robots may render certain jobs and skills obsolete, fostering anxiety about job security and diminishing workers' well-being (Dekker et al., 2017).

We expect that the relationship between robot adoption and workers' well-being depends on both individual characteristics and social context. In particular, and central to our contribution, we argue that the effects of robotization vary by workers' educational level. While significant attention has been given to the winners and losers of technological change in terms of education (Chiacchio et al., 2018; Dauth et al., 2021), less is known about the educational gradient of well-being outcomes. A key implication is that our analysis will be education-differentiated.

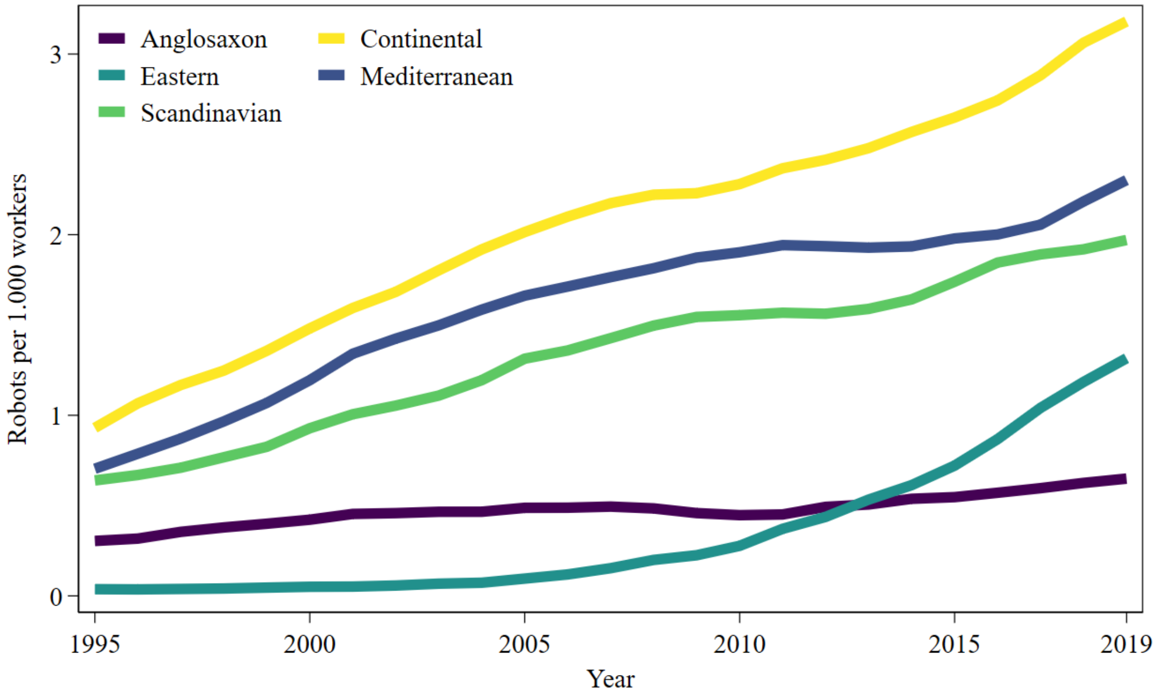
Beyond education, we contribute to the literature on the well-being effects of robotization by examining demographic disparities, specifically gender and age differences. Regarding gender, research indicates that women are overrepresented in medium-skilled jobs—those most vulnerable to technological change—at least in Europe (Brussevich et al., 2019; Piasna & Drahokoupil, 2017). Women also tend to perceive automation, including robotization, as less fair than men (Borwein et al., 2024) and have benefited less from robot-driven productivity gains (Aksoy et al., 2021).

Concerning age, studies suggest that younger workers may be more adversely affected by new technologies. In industries with a high incidence of robots, middle-educated youth face a longer adaptation period for acquiring new skills (Dauth et al., 2021; Lewandowski et al., 2020), bearing the cost of labour market adjustments. In contrast, older workers may be more engaged in task complementarity processes (Albinowski & Lewandowski, 2024).

Finally, we examine heterogeneity across countries. Few multi-country studies have investigated the effects of robots on sociodemographic dimensions, but those that have (e.g. Carbonero et al., 2020; Matysiak et al., 2023) reveal considerable variation, which is unsurprising given differences in institutional contexts. Figure 1 illustrates the distribution of robots across a selection of developed countries, with Germany (Continental) and Italy (Mediterranean) standing out due to their large automotive sectors. Although the automotive sector is a significant outlier in terms of robot adoption, similar upward trends are evident in other industries. This variation suggests that robotization rates are highly industry-specific, with national totals being heavily influenced by each country's industrial composition.

We find strong evidence supporting the *decreasing workers' agency* perspective among middle-skilled workers. Specifically, an increase in robot adoption adversely affects multiple dimensions of well-being among middle-educated workers, suggesting growing discontent within the middle class regarding technological innovation in the workplace. Moreover, our findings reveal that this educational gradient is accompanied by a gender disparity: the negative effects of robot adoption on well-being are significantly stronger for women, while for men they are smaller and largely statistically insignificant. In contrast, the impact of age is negligible. Finally, we highlight the crucial role of country-level institutional settings. The decline in life satisfaction among middle-educated workers is particularly pronounced in the UK and Eastern European countries, where weaker compensatory social policies, low union coverage, and decentralised labour unions may exacerbate these effects.

Figure 1. Robot density in Europe by country group and calendar year.



Notes: Calculated by dividing total robot stocks by employees in thousands in all industries. Country groups include countries listed in Table A1.
Sources: International Federation of Robotics (IFR) and Eurostat.

The remainder of the paper is structured as follows. Section 2 introduces the theoretical framework, while Section 3 outlines the moderating effects central to our analysis. Section 4 describes the data and provides descriptive evidence on the relationship between robotization and well-being across educational groups. Section 5 details our identification strategy and analytical methodology. In Section 6, we present our results, quantify the impact of robot adoption on the well-being of various demographic groups within different institutional contexts, and conduct robustness checks. Finally, Section 7 concludes.

2. The educational gradient in the link between robotization and well-being: theoretical framework

Subjective well-being has been conceptualised as comprising three distinct yet interrelated dimensions (Diener, 1984; Nikolova & Graham, 2020): evaluative well-being, which refers to an overall assessment of one's life and circumstances (life satisfaction); eudaimonic well-being, associated with a sense of purpose and autonomy; and hedonic well-being, which pertains to momentary feelings (happiness). Given that work constitutes a significant part of life, its influence necessarily spills over into these dimensions of subjective well-being (Green et al., 2024).

Life satisfaction, the first dimension of well-being, is closely associated with an individual's overall evaluation of their life. Among workers, studies have demonstrated that working conditions—such as job quality and job security—account for a significant proportion of the variation in life satisfaction (e.g. Drobnič et al., 2010; Williams et al., 2020). However, focusing exclusively on job satisfaction may not fully capture the broader relationship between employment and overall well-being (Rohenkohl & Clarke, 2023; Bellani & Bogusz, 2024).

The theoretical literature on the relationship between technological change (such as robotization) and life satisfaction has traditionally emphasised workers' skill levels and education as key factors. Proponents of the upskilling theory argue that automation increases the demand for highly skilled positions needed to manage the complexity of new technologies (Adler, 1992; Attewell, 1992). Similarly, the initial formulation of the skill-biased technological change (SBTC) framework posits that, in a simplified labour market model with three skill levels—low, medium, and high (Autor et al., 2003)—only low-educated workers suffer displacement effects, underemployment, and declining job quality, as technology tends to replace low-skilled labour (Katz & Murphy, 1992). More recently, proponents of routinization theory, who focus on the content of work, contend that routine manual (low-skilled) workers are less affected by new technologies, as automation does not typically substitute or complement the low-paying service jobs in which many less-educated workers are employed (Autor et al., 1998; Autor, 2015). Consequently, it is the middle of the skill distribution that faces the greatest potential for job destruction, owing to the high risk of substitution of routine tasks, which are generally the easiest to automate (Autor et al., 2003; Goos & Manning, 2007). These routine tasks are commonly performed by middle-skilled workers in sectors such as manufacturing, clerical occupations, and sales, which are often accessible to non-college-educated individuals (Autor et al., 2003). Collectively, these processes are predicted to result in employment and wage losses for workers with medium education (Goos et al., 2014). For some, this may entail finding a new job if they are displaced by robot adoption and experience qualification downgrading (Dahlin, 2019; Cuccu & Royuela, 2024); for those who remain employed, it requires acquiring new skills to adapt to plant-level restructuring driven by robotization (Cirillo et al., 2021). Either scenario can incur significant harms, generating substantial long-term job insecurity (Furman, 2019). Moreover, adapting to robotics technology, as in other automation processes, may induce excessive cognitive load, thereby reducing job satisfaction (Nazareno & Schiff, 2021). Overall, middle-educated workers are likely to experience a decline in life satisfaction.

We now turn to the second dimension of well-being, the eudaimonic aspect. Robots can influence the meaningfulness and fulfilment derived from work by affecting workers' autonomy and discretion over their tasks, and by shaping their perception of having choices and authority over their actions (Nikolova & Cnossen, 2020). These factors provide intrinsic benefits to job quality (e.g. Green, 2005) and, by extension, to overall well-being. When considering the relationship between robot adoption and workers' eudaimonic well-being, two competing theoretical perspectives emerge.

Even when workers are not immediately unemployed, robots can potentially reduce employees' control over work content and processes (Artuc et al., 2023). Likewise, workers' ability to choose when and how to apply their skills and capabilities may be hindered (Gombolay et al., 2015). By taking over tasks traditionally performed by humans or reducing task diversity, robots could increase the risk of heteronomy—a condition in which individuals perceive their work as governed by externally imposed forces (Nikolova & Cnossen, 2020). Replacing tasks without affording workers control over these processes can diminish their sense of autonomy. Moreover, if task replacement is not accompanied by a top-down shift towards more meaningful work, workers may experience a reduced sense of purpose and a diminished perception of their agency. According to this perspective, the creative destruction inherent in robotization is likely to particularly affect those workers whose skills are most vulnerable to becoming heteronomous.

Recent sociological perspectives, however, challenge the notion that work—particularly assembly work—is becoming less meaningful and that workers are increasingly marginalised from managerial decision-making when robots are adopted (Vrontis et al., 2023). Drawing on Polanyi's concept of living human capacity (Polanyi, 1958), several scholars emphasise the importance of human capabilities in increasingly complex manufacturing processes driven by robotization and other technological advancements. Workers' tacit knowledge—comprising skills and expertise that are difficult to replicate in robots—plays a crucial role in maintaining autonomy and control during the adoption of new technologies (Lei, 2022). Researchers analysing the electronics and manufacturing industries highlight that certain tasks remain difficult for robots lacking artificial intelligence (AI) to replicate, given their limited capacity to operate in unpredictable environments—especially in roles that involve human interaction (Webb, 2020). Dahlin (2019) argues that while easily automatable manufacturing jobs have already been replaced, the remaining occupations foster a degree of symbiosis between humans and robots. Acemoglu and Restrepo (2020) further suggest that these technologies may replace human labour in certain tasks, yet they do not result in significant productivity gains. Collins (2010) notes that tasks requiring collective tacit knowledge and autonomy—attributes possessed not only by highly skilled workers but also by technicians and medium-skilled workers—are particularly resistant to automation. Certain tasks, such as those requiring dexterity, remain difficult for robots to perform (Lei, 2022). This, in turn, reinforces the agency of workers most directly exposed to robotization—particularly those with a medium level of education—in influencing managerial decisions (Vrontis et al., 2022). Consequently, workers' participation in the social organization of work and their involvement in decision-making regarding adjustments to the division of labour between humans and machines are likely to be enhanced, leading to increased job meaningfulness and autonomy.

To the best of our knowledge, the empirical evidence in this regard is both scarce and mixed. One study examining European data over the decade 1995–2005 finds no effect of robotization on workers' discretion (Anton et al., 2023), while another study, based on data from a limited number of years (2010, 2015 and 2021), reports that the introduction of robots negatively affects work meaningfulness and autonomy (Nikolova et al., 2024).

The third dimension, hedonic subjective well-being, refers to feelings typically associated with short-term circumstances—such as happiness, anxiety, and stress—and pertains to mood rather than an overall life evaluation (Steptoe et al., 2015). As studies have shown, this dimension can be influenced by technological change processes (Tirabeni, 2024), including robot adoption. On one hand, exposure to robotization is likely to increase uncertainty among workers, thereby intensifying their feelings of stress and anxiety. Workers may be concerned about the disruptive potential of technological advances (Innocenti & Golin, 2022); this fear of robotization can significantly decrease their happiness. In a country-specific study, Schwabe and Castellacci (2020) observed that, from 2016 to 2019, the introduction of industrial robots in local labour markets in Norway increased workers' fear of machine replacement. Moreover, workers might feel threatened by robots even in sectors where they have not yet been introduced (Yam et al., 2021). On the other hand, by replacing dangerous or dirty tasks and reducing physically demanding work and job intensity (Gunadi & Ryu, 2021; Gihleb et al., 2022), robots can potentially improve subjective health and other correlates of happiness (Spencer, 2018). Thus, the hedonic dimension, alongside perceived health, can significantly influence workers' overall well-being, particularly among those more directly exposed to robotization—namely, those in the middle of the skill distribution.

Given the multifaceted nature of well-being, we expect to observe the impacts of robot adoption across various outcomes, including life satisfaction, job influence, happiness, and subjective health. Our guiding hypothesis integrates two competing frameworks—the *human leverage effect* and *decreasing workers' agency*. Under the *human leverage effect*, industrial robot adoption is anticipated to enhance well-being, whereas decreased workers' agency is expected to diminish it. We hypothesize that workers in the middle of the skill distribution, being most directly involved in these processes, will be particularly affected.

It is also important to note that, consistent with the socio-tropic framework (e.g. Kinder & Kiewiet, 1981; Mansfield & Mutz, 2009), technological innovation such as robot adoption can shape the attitudes and well-being of those not directly involved. This occurs because individuals' perceptions and anxieties regarding economic shocks are informed by collective-level information rather than solely by personal self-interest. Indeed, workers may express concern about technology-induced shocks even if they are not personally exposed, provided that their collective (e.g. educational group) is exposed. Borwein and colleagues (2024) report that education is more influential in addressing individuals' anxieties than, for example, skill level.

3. Moderating factors

The debate surrounding the effects of industrial robots on well-being indicates that the mixed results in studies arise because robot adoption produces contrasting experiences for different workers. These variations depend not only on educational level but also on factors characterising the broader socio-economic environment (Nikolova et al., 2024). Consequently, it is essential to consider the role of crucial moderating factors, such as sociodemographics, industrial sectors, and institutional settings.

3.1 Gender and age

The educational gradient of the impact of robots on workers' well-being can differ by gender. Scholars have explored various mechanisms through which gender inequality in well-being may emerge when technological changes occur. On the one hand, some scholars argue that female workers are at a higher risk of job displacement during robotization because they are generally assigned more routine tasks—characterised by less flexibility, fewer learning opportunities, and greater repetitiveness—and perform fewer tasks that require analytical, interpersonal, or physical skills compared with men (Aksoy et al., 2021). This expectation is also supported by Brussevich et al. (2019) and Piasna & Drahokoupil (2017), who indicate that women in Europe are more frequently employed in medium-skilled, routine jobs, which are among the most vulnerable to robotization. Accordingly, one could expect a negative impact on life satisfaction, particularly among middle-educated women.

Following the same reasoning, scholars expect that women may experience a decrease in autonomy and a diminished sense of self-determination amid robotization, whereas men's perceptions of their competencies and the meaningfulness of their work may be enhanced (Nikolova et al., 2024). Additionally, women may perceive technological change differently, which in turn significantly influences the hedonic dimension of well-being. This issue was recently explored by Borwein et al. (2024), who argue that, because women are more sensitive to economic volatility and labour market shocks, they exhibit a less positive orientation towards workplace automation. Empirically, they show that, in a sample of 10 developed countries, women tend to perceive the fairness of automation more negatively than men.

In addition, the impact of robot adoption on well-being can differ considerably across worker age groups (Dauth et al., 2021; Deng et al., 2024). On the one hand, young workers are better positioned to adapt to the tasks demanded by new technologies (Bosma et al., 2003). On the other hand, younger production workers may be particularly vulnerable, as they often perform relatively simple routine tasks that can be easily automated (Acemoglu & Restrepo, 2020).

Empirical evidence from Deng et al. (2024) indicates that employment for young workers increases with robot adoption primarily among low- and middle-skilled individuals, whereas gains for technicians, engineers, and managers are predominantly observed among middle-aged and older workers. Accordingly, it is expected that increased robot adoption will be associated with higher levels of well-being among young workers who are middle- or high-skilled.

3.2 Industries

Another moderating factor essential for unpacking the relationship between robotization and well-being is the industrial sector in which workers are employed. In theory, the impact of robot adoption should be more straightforward for workers in the manufacturing sector, who directly experience its effects on productivity, displacement, and the creation of new tasks (Chung & Lee, 2023). Empirically, Acemoglu and Restrepo (2020) and Chung and Lee (2023) have demonstrated that, in the United States, the employment effects of robots are concentrated primarily in the automotive industry. Moreover, scholars have shown that workers in sectors such as manufacturing and mining are typically middle-skilled and engaged in high-intensity routine and manual tasks—areas particularly susceptible to robotization (Hardy et al., 2018). The automotive sector, along with logistics activities, is also more prone to the so-called ‘business stealing effect’, whereby innovative adopters gain market share at the expense of non-innovators. In summary, robotization can affect manufacturing and non-manufacturing industries differently, generating heterogeneous spill-over (or cross-over) effects on well-being.

3.3 Institutional context

The relationship between robot adoption and well-being is expected to vary across societal contexts. Comparative welfare state research suggests that robot adoption has a less detrimental impact on workers in countries where institutions buffer the negative side effects of technological change. This is the case in nations where welfare states are more protective of workers' conditions and compensate for adverse effects, and where organised labour and collective bargaining have the power to mitigate a direct association between technological shocks and declining socio-economic conditions (Parolin, 2020).

During periods of rapid technological change, welfare state policies—particularly compensatory social policies (such as unemployment benefits) and protective regulatory policies (such as Employment Protection Legislation (EPL) and the minimum wage)—are expected to influence the relationship between large-scale labour market transformations and workers’ conditions (Vlandas et al., 2022; Buseymer & Tober, 2023). In line with this reasoning, one could argue that compensatory social policies, which reduce the costs associated with realised risks, together with protective policies, which prevent or mitigate the materialization of risks, can alleviate the adverse effects of robot adoption on well-being. These policies not only protect individuals facing objective risks but also mitigate the perception of risk—for example, by reducing anxiety about the potential impact of robotization.

Concerning compensatory social policies, the literature indicates that more generous unemployment benefits are associated with a nuanced impact on job loss resulting from technological change and a lower level of perceived job insecurity (Dekker et al., 2017). In countries with large, well-developed welfare states (e.g. Scandinavian countries) (Esping-Andersen, 1990), substantial unemployment benefits are likely to mitigate the adverse effects of job loss by reducing reliance on the labour market for economic survival. This may explain why individuals report lower levels of perceived job insecurity in environments characterised by higher public social spending (Mau et al., 2012).

Regarding regulatory protective policies, as conceptualised by Levy-Faur (2013, 2014), scholars have demonstrated that such measures can buffer the negative side effects of technological change (e.g. Cutuli & Tomelleri, 2023). Research suggests that employees in countries with stronger employment protection laws—such as those in Continental nations compared with Eastern or Anglosaxon countries—tend to feel more secure in their jobs (Anderson & Pontusson, 2007), as restrictive Employment Protection Legislation (EPL) prevents employers from dismissing workers (Vlandas & Halikiopoulou, 2022). However, this protective effect may not extend to contexts where welfare provision is generous only for insiders, potentially leading to precariousness for others (e.g. in Germany, France, Italy and Spain). These considerations are crucial for understanding the heterogeneous effects that the institutional context may have on well-being.

A recent study has shown that middle-educated workers who fear that their jobs will be lost due to technological change demand short-term compensatory and protective policies, such as increased unemployment benefits (Busemeyer et al., 2023). Thus, workers residing in more residual welfare states—namely, liberal and Eastern European countries—are likely to be more apprehensive about labour market risks induced by technological change and more concerned about their broader economic impact, with subsequent adverse effects on their well-being (Thewissen & Rueda, 2019).

Moreover, the literature suggests that another form of regulatory protection concerns labour relations (Anderson & Pountsson, 2007). Higher rates of union membership—and its spill-over effects on non-unionised workers—are likely to safeguard workers' conditions in the face of technological shocks (Lordan & Neumark, 2017). The adoption of robotics and other advanced digital tools, as well as the pace of their implementation, is significantly influenced by the presence of employee representation mechanisms, such as unions and works councils (Doellgast et al., 2009; Haapanala et al., 2022). Research has demonstrated that trade unions can mitigate significant occupational and structural shifts induced by technological advancements (Fernandez, 2001; Kristal & Cohen, 2017; Kristal & Edler, 2021). For example, the bargaining power of trade unions in negotiations with major automotive companies is vital for ensuring the reassignment of displaced workers, for instance by facilitating internal flexibility (Streeck, 1984). Studies indicate that employee representation increases the likelihood of receiving employer-funded training (e.g. Adolfsson et al., 2022), thereby facilitating the reallocation of tasks. Furthermore, research in Europe has shown that the presence of trade unions promotes specific work systems and practices—such as training, time management, and information-sharing—that complement the adoption of new technologies (Belloc et al., 2023). In contexts where trade unions are particularly influential, such as in Scandinavian and Western European countries, coordinated wage bargaining and the development of firm-specific skills foster incremental product innovations while maintaining a degree of job security even amidst technological advancements (Bosch & Schmitz-Kießler, 2020; Haipeter, 2020). Greater union coverage also translates into increased bargaining power in negotiations with the government and other social partners during industrial transformations.

We recognize that cross-country differences in the association between robot adoption and well-being may stem from factors beyond welfare state arrangements, such as variations in national discourses surrounding robotization and differences in the balance of objective and perceived risks associated with this transformation (e.g. Arntz et al., 2016). However, we expect that the institutional context—characterised by compensatory social policies, protective regulatory policies, and effective labour organisation—will be the most salient factor in explaining cross-national differences (see also Busemeyer & Tober, 2023). We argue that the institutional mixture is particularly influential when individuals evaluate the potential impact of robotization on their life circumstances. Therefore, we propose that a country's welfare state context—defined by its overall generosity and the balance between social investment and compensatory measures, as well as organised labour—plays a key role in workers' well-being (Di Tella et al., 2003), especially in times of technological shocks.

Given that the survey data in this study covers 24 countries with diverse welfare state arrangements, we can assess the extent to which existing institutional contexts influence individual-level well-being patterns, although a detailed quantitative analysis of cross-country differences is not feasible due to the limited number of cases. More specifically, Scandinavian countries are characterised by generous compensatory social policies and relatively lower regulatory protective policies (offset by a high prevalence of active labour market policies) alongside high to medium union density. Continental countries, in contrast, are marked by lower levels of compensatory social policies and higher levels of regulatory protective policies—particularly in terms of Employment Protection Legislation (EPL) for permanent workers—and, in some cases, minimum wage legislation (with Austria and Switzerland notably lacking a statutory minimum wage), combined with medium-high union coverage. Mediterranean countries exhibit a dualistic pattern regarding both EPL and compensatory social policies, with insiders receiving greater benefits, and generally maintain medium levels of union coverage. Finally, liberal and Eastern European countries are characterised by low levels of both compensatory and regulatory protective policies as well as generally low union coverage (Zwysen & Drahokoupil, 2024), with such policies also being fully decentralised (Haapanala et al., 2022).

4. Data

Our study utilises individual-level data from the European Social Survey (ESS ERIC, 2018a, 2018b, 2023a-2023g), a cross-sectional survey with a representative sample conducted biennially since 2002, which has involved participation from 39 countries at least once. All survey waves include consistent questions on well-being, thereby enabling a pseudo-panel analysis. We focus on the first nine rounds of the survey (2002–2018) to exclude the impacts of the COVID-19 pandemic.

To merge the individual-level ESS data with robot density—constructed using industry-level data from the International Federation of Robotics and Eurostat—we limit our ESS sample to countries that report robot stocks to the International Federation of Robotics. This approach encompasses all countries that participated in the ESS at least once, totalling 24 countries (see Table A1 in the Appendix). We restrict our sample to employed individuals aged 15 to 64, ensuring that gender, age, nationality, and the ESS-constructed analytic weights are non-missing (with less than 1% of observations discarded). Our final sample comprises 236,151 observations, with some data missing at random (up to 19% of observations, depending on the variable). To address this, we apply multiple imputation with chained equations (MICE).

We operationalize the three dimensions of well-being using distinct indicators. For the evaluative dimension, we focus on life satisfaction, while for the hedonic dimension, we focus on happiness. Both are assessed on an ordinal scale from 0 to 10, with higher scores indicating greater well-being. Respondents are asked: “How satisfied are you with life as a whole?” and “How happy are you?”. Additionally, we include an indicator of subjective health—self-reported health—which is originally measured on a Likert scale from 1 to 5 (with 1 denoting “very good” and 5 indicating “very bad”). We reverse this scale to facilitate interpretation of results.

For the eudaimonic dimension, we draw on a measure of work autonomy from the ESS. In the survey, job control is assessed by the statement: "I'm allowed to influence policy decisions about activities of the organisation," and is measured on an ordinal scale from 0 to 10, where 0 indicates no influence and 10 indicates complete control. This indicator reflects the degree of influence or power that workers have over the policy decisions within their organisations (see Huijts et al., 2017; Warr, 2017).

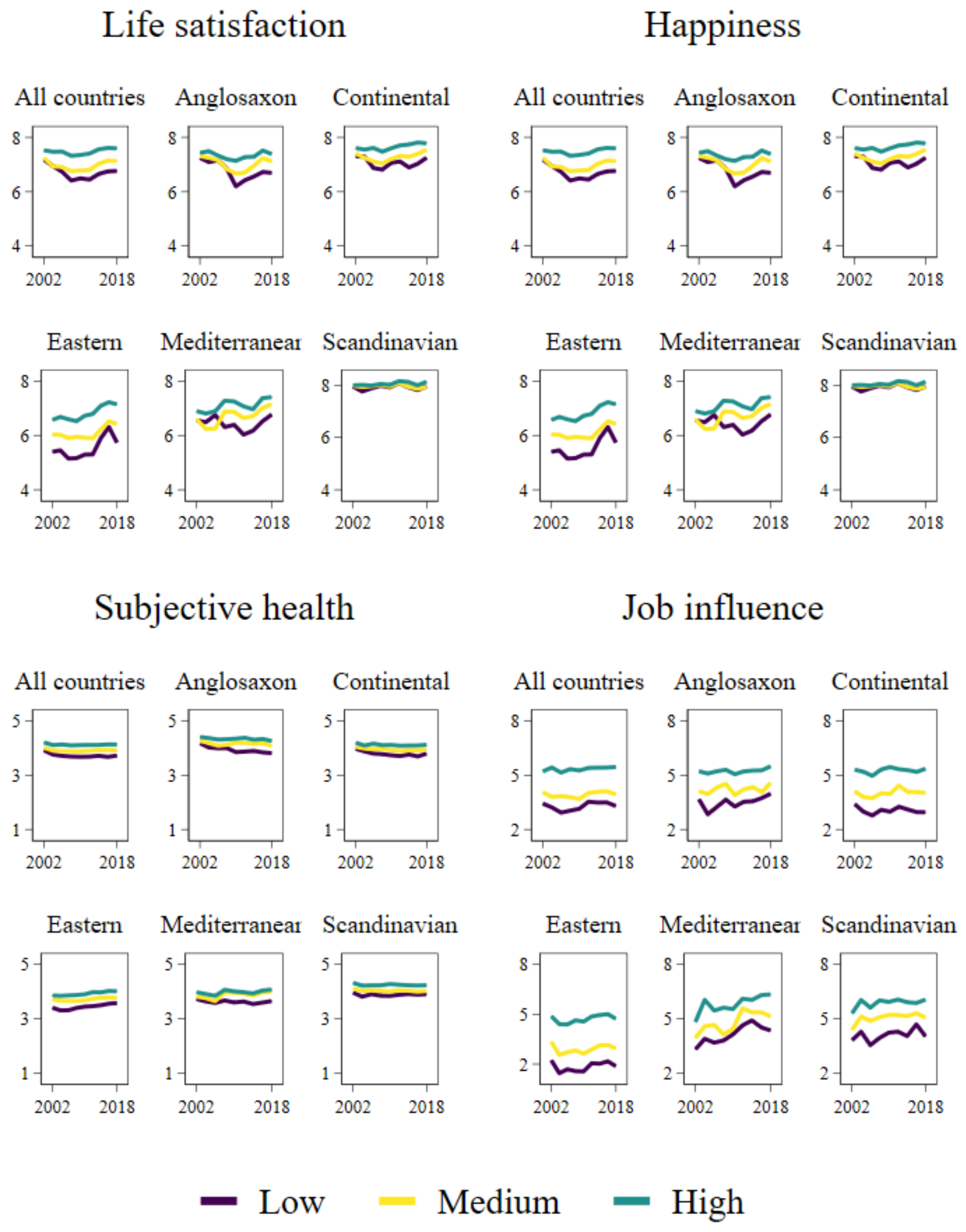
Using four measures enables us to capture the multifaceted nature of subjective well-being and confers methodological advantages. Single-measure methodologies have been criticised because variations stemming from question wording cannot be isolated (Diener, 1984). Consequently, results based on a single measure may be susceptible to biases such as acquiescence or social desirability.

Additionally, we include the following sociodemographic control variables: gender (binary, male or female, as reported in the ESS); age and age squared (in years); education (measured using ISCED and aggregated into low, medium, and high levels) as a proxy for skill (see, for example, Nikolova et al., 2024); and migration background (indicated by domestic or foreign citizenship). Education is also included as a moderator.

Figure 2 presents the average responses to the four dimensions of well-being, segmented by education level, country group, and calendar year. All measures of well-being are stratified by education level: highly educated workers report the highest levels of well-being, followed by middle-educated and then low-educated individuals. These disparities are least pronounced in Scandinavian countries, which also report the highest overall well-being among all welfare regimes (Easterlin & O'Connor, 2022). In contrast, Eastern European countries exhibit the lowest, albeit increasing, levels of well-being. Moreover, we observe a decline in certain dimensions of workers' well-being—namely life satisfaction and happiness—in Anglo-Saxon and Mediterranean countries during the Great Recession, particularly among low-educated individuals in Italy, Portugal, and Spain. This trend aligns with expectations given the rising unemployment and inactivity in these countries during the economic crisis (Biegert & Ebbinghaus, 2022; Bozio et al., 2015). Continental countries display stable trends for middle- and highly educated workers, although a noticeable decline for low-educated workers coincides with the onset of the Great Recession.

To compute robot density—a measure of workers' exposure to automation (see details in Section 5)—we utilize robot stocks data from the International Federation of Robotics (IFR). The IFR provides annual data on the operational stock of industrial robots by country and industry from 1993 to 2019 (International Federation of Robotics, 2020). Industries are classified according to the International Standard Industrial Classification (ISIC) of All Economic Activities (United Nations, 2008). This comprehensive dataset includes robot stock records at the 1-digit level for various industries, including agriculture, forestry, mining, manufacturing, electricity, gas, water supply, construction, and services. We link the robot data to employment structures by industry using the methodology detailed in Section 6. Eurostat has publicly provided country-level employment structures by 1-digit industry codes—classified according to NACE Rev. 1.1 (for periods prior to 2008)—since 1993 (Eurostat, 2023). We reclassify these data to the ISIC framework to ensure consistency with the robot stocks data.

Figure 2. Well-being of workers by measure, education, welfare regime, and calendar period.



Notes: Country groups include countries listed in Table A1.
Sources: European Social Survey 2002-2018.

5. Methods

Our methodology relies on regressing measures of well-being on robot density and a set of sociodemographic controls (as detailed in Section 4) for a sample of 24 European countries. We then perform separate analyses for each country group—Anglosaxon, Continental, Eastern

European, Mediterranean, and Scandinavian—to examine how the relationship between robot density and well-being varies across different welfare regimes.

We construct robot density at the country-industry-year level as a measure of workers' exposure to automation. Most studies on the labour market consequences of robotization rely on regional analyses, quantifying robot adoption through a Bartik instrument that decomposes country-industry robot stocks onto regions using regional employment structures (e.g. Acemoglu & Restrepo, 2020; Dauth et al., 2021). However, the measurement of workers' exposure to automation is not limited to regional analyses; for example, Graetz and Michaels (2018) employ a country-industry measure. This approach can also be applied in our study, where well-being is measured at the individual level, allowing us to merge robot density data with survey responses by country, year, and the industry in which the worker is employed.

To calculate robot density, we utilize robot stocks from the International Federation of Robotics and aggregate employment data from Eurostat. Robot density is defined as the number of industrial robots installed in a specific country *c*, in industry *i*, in a given year *t*, divided by the number of workers (in thousands) in that country-industry during a baseline period *t0*—which corresponds to the 1990s or early 2000s, depending on the country. Mathematically, this is expressed as:

$$\text{robot density}_{t}^{c,i} = \frac{\text{robot stocks}_{t}^{c,i}}{\frac{\text{workers}_{t0}^{c,i}}{1000}}.$$

This formulation provides a measure of workers' exposure to automation by standardising robot stocks relative to the employment size in the corresponding industry and country at the onset of robotization. Similarly to the regional-level Bartik instrument, the employment structure used in calculating robot density is measured before the onset of robotization, ensuring that the only potentially endogenous component is the robot stocks. We set *t0* to the earliest point in time for which employment data by country and industry are available from Eurostat. For early robot adopters such as Germany or Italy, this baseline is 1993, whereas for late adopters like Poland—where earlier industry-level employment data are unavailable—the baseline is set at 2002.

A further concern regarding the endogeneity of robot density arises if external factors simultaneously affect both robot adoption and workers' well-being. Such shocks may be continental (e.g. recession), domestic (e.g. country-level policies), regional (e.g. changes in employment structure), or sectoral (e.g. increased unionisation). To address this issue, we instrument robot density in European countries using two measures, whereby we divide robot stocks in Japan and South Korea by employment in Europe:

$$\text{instrument}_t^{JP,i} = \frac{\text{robot stocks}_t^{JP,i}}{\frac{\text{workers}_{t0}^{c,i}}{1000}};$$

$$\text{instrument}_t^{KR,i} = \frac{\text{robot stocks}_t^{KR,i}}{\frac{\text{workers}_{t0}^{c,i}}{1000}}.$$

This strategy for addressing the endogeneity of workers' exposure to robots was introduced by Acemoglu and Restrepo (2020) and has been widely adopted in other studies on robot adoption (e.g. Graetz & Michaels, 2018; Matysiak et al., 2023). We use robot stocks in Japan and South Korea because these countries (together with Germany) are forerunners of robot adoption worldwide, and robot implementation in Europe is theoretically expected to follow their patterns. At the same time, robot stocks in these countries are unlikely to have a direct impact on workers' well-being in Europe. In our methodology, we follow Dauth et al. (2021) to construct an overidentified IV model using these two instruments.

One further concern is that Japan and South Korea primarily adopt robots in the electronics sector, whereas most European countries install robots mainly in the automotive industry. However, robot adoption in electronics has been increasing in Europe (International Federation of Robotics, 2020). Moreover, identifying a suitable instrument for robot density in Europe is challenging, as most countries with similar cultural and developmental profiles—such as the United States, Canada or Australia—adopt industrial robots to a much smaller extent than European countries (International Federation of Robotics, 2020). One strategy documented in the literature is to estimate models for each European country separately, using robot adoption in other European countries as an instrument for robotization (e.g. Matysiak et al., 2023). However, such an approach is not feasible when estimating models across multiple European countries, and one of the objectives of this paper is to compare country groups. Although it remains unclear whether Europe will indeed follow the robot adoption patterns of the two Asian forerunners, we demonstrate in the online supplementary material that these instruments are both relevant and strong in our IV regressions. To test the instruments' relevance, we compute the Kleibergen–Paap rk Wald F statistic (Kleibergen & Paap, 2006).

Our model takes the following form:

$$Y = \alpha + \beta \ (\text{robot density} \ \times \ \text{education}) + \gamma \ \text{robot density} + \delta \ \text{education} + \theta \, X + \varepsilon,$$

where X represents a set of control variables, including age, age squared, gender, migration background (native or migrant), as well as country and year fixed effects. We estimate this model using two-stage least squares (2SLS/IV) regression. The dependent variable Y denotes each of the following well-being measures—life satisfaction, job influence, happiness, and subjective health—and we estimate separate models for each outcome.

We interact robot density with education (categorised as low, medium and high) to test our hypothesis that robots exert a heterogeneous effect on workers according to their skill level. Next, we re-estimate the model separately for women, men, younger and older workers, as well as for those employed in manufacturing. This approach enables us to test expectations drawn from the literature—that women and younger workers are more affected by industrial robot adoption than men and older workers, and that the impact of automation is larger in the manufacturing sector. Finally, we run the model separately for each welfare state type to verify whether institutional safety nets can mitigate the adverse impact of robots on well-being.

6. Results

Tables 1 and 2 present the coefficients for the interaction between robot density and education. We observe a stratified impact of robot density on workers' well-being, with effects varying by education level. In a 2SLS model estimated on the full sample of countries, an increase of one robot per 1,000 workers is associated with a decrease in life satisfaction among middle-educated workers of –0.012 (SE = 0.005) on a scale from 0 to 10. The corresponding negative effects on happiness and subjective health are –0.008 (SE = 0.005) and –0.005 (SE = 0.002), respectively, while the impact on job influence is considerably larger at –0.184 (SE = 0.02).

In contrast, one additional robot per 1,000 workers increases life satisfaction and happiness among low-educated workers by 0.019 (SE = 0.005) and 0.014 (SE = 0.003), respectively, and among highly educated workers by 0.005 (SE = 0.005) and 0.003 (SE = 0.005). Moreover, an additional robot per 1,000 workers raises the subjective health of highly educated workers by 0.004 (SE = 0.002) and their job influence by 0.158 (SE = 0.019). We do not, however, find statistically significant effects of robot adoption on subjective health and job influence among low-educated workers. In summary, both high- and low-educated workers tend to experience a more favourable impact on well-being relative to middle-educated workers, holding all else constant.

These results support the hypothesis of a U-shaped relationship between robot adoption and well-being across education levels. In particular, the evidence for middle-educated workers is consistent with the *decreasing workers' agency* hypothesis: this group—whether directly or indirectly exposed to robotization, as suggested by the socio-tropic perspective—suffers more in terms of well-being. Furthermore, the effects are slightly larger for life satisfaction than for happiness or subjective health, suggesting that the implications of robot adoption extend beyond immediate economic outcomes. Notably, the effect on job influence is an order of magnitude larger, which indicates that robot adoption may substantially undermine the eudaimonic dimension of well-being among medium-skilled workers by reducing their job control and limiting their participation in the social organization of work.

Next, we investigate gender differences in the impact of robot density on well-being. The results for the overall sample are consistent with the main models, with statistical significance evident for women (see Table 1). Specifically, one additional robot per 1,000 workers is associated with a decrease in life satisfaction among medium-educated women (coefficient = –0.034, SE = 0.004). Conversely, for low-educated and highly-educated women, robot density is associated with increases in life satisfaction by 0.04 (SE = 0.004) and 0.025 (SE = 0.003), respectively. This U-shaped relationship is also observed for the other three well-being dimensions among women. In contrast, the corresponding estimates for men are generally smaller and not statistically significant, with the exception of job influence. Among middle-educated workers, the effect on job influence for men is approximately half that observed for women, although it remains significant at the 1% level. Overall, these findings suggest that middle-educated women are more sensitive to increases in robot adoption. The most pronounced gender differences are related to subjective health and, especially, life satisfaction—indicating that evaluative well-being is the primary driver of the U-shaped relationship observed in the data.

Moreover, we observe that the educational gradient does not vary substantially by age (Table 1). For all four well-being dimensions examined, medium-educated workers report a decrease in well-being with increased robot adoption, regardless of age group. Specifically, both younger workers (under 35) and older workers (35 or more) exhibit declines in job influence of a similar magnitude (–0.174 with SE = 0.015 for those under 35, and –0.188 with SE = 0.023 for those aged 35 or older), while the impact on the other well-being domains is marginally larger for the younger cohort. Notably, highly-educated workers who are relatively young also report a significant negative coefficient with respect to life satisfaction. This finding is consistent with the idea that the benefits of robotization may accrue primarily to highly skilled workers with more work experience.

Next, we restrict our sample to workers employed in manufacturing (Table 1), which represents approximately 16% of the total sample. In this sector, we observe negative effects of increased robot adoption on job influence and happiness for medium-educated workers, while no significant effects emerge for the other educational groups. In particular, for the dimension of job influence, the coefficient for medium-educated workers in the manufacturing sector is –0.174 (SE = 0.072), compared to –0.184 (SE = 0.020) for the overall sample. These findings suggest that medium-educated workers, who are arguably the most vulnerable to robotization in a sector highly susceptible to technological change, experience a substantial reduction in work autonomy. Moreover, this group reports a significant decline in the hedonic dimension of well-being, which may be explained by an upsurge in negative feelings such as stress and pain. Notably, we do not find statistically significant effects for medium-educated workers in manufacturing with respect to the other two well-being domains, namely life satisfaction and subjective health.

Finally, we examine how the overall effects of robot density on workers' well-being vary by institutional context, revealing notable heterogeneities (Table 2). With respect to the evaluative dimension, our analysis shows that robots exert a negative and statistically significant effect on the life satisfaction of middle-educated workers in Anglosaxon (–0.026) and Eastern countries (–0.028). A negative, albeit smaller, coefficient is observed in Scandinavian countries (–0.01) and in Continental countries (–0.003, not significant). In Mediterranean countries, however, the effect is positive and statistically significant for middle-educated workers (0.013), but negative for highly-educated workers (–0.021).

A clearer pattern emerges for the eudaimonic dimension: the U-shaped relationship associated with the educational gradient is evident across all country groups, with larger coefficients in Anglosaxon and Eastern European countries. In general, the U-shaped pattern also holds for the hedonic dimension. However, for highly-educated workers in Mediterranean countries, we observe a decrease in hedonic well-being, whereas middle-educated workers experience the opposite effect. This suggests that highly-educated workers in strongly dualistic labour markets may suffer a decline in hedonic well-being as robot adoption increases.

Additional analyses by age (Table A3) indicate that the non-negative effects observed in Mediterranean and Continental countries are driven primarily by workers aged under 35. In these groups, the coefficients for robot density are generally larger for younger workers than for older workers, which is consistent with previous studies reporting that labour market entrants are more affected by robot adoption. In Continental and Mediterranean countries, the impact of robot adoption on the well-being of middle-educated workers under 35 is positive, contrasting with the effects observed in other country groups. Notably, these two country groups also exhibit the highest robot density rates in our sample (see Figure 1).

A recent study by Chung and Lee (2023) demonstrated that robot adoption increases employment at advanced stages of technological progress by creating new tasks—particularly in the automotive industry, where most robots are installed in Continental and Mediterranean countries. Similarly, Deng et al. (2024) reported that young workers are most likely to benefit from the reinstatement effect of robot adoption. We interpret these findings as indicating that the positive effect of robot density on the well-being of middle-educated workers in Continental and Mediterranean countries may reflect the higher employment and task-reallocation opportunities afforded to young workers in sectors with high levels of robot adoption.

The results for the subjective health dimension generally follow the overall educational gradient, although the effects are more mixed in more liberal economies. In these contexts, highly-educated workers tend to experience a negative impact from an increase in robot adoption, whereas middle-educated workers exhibit the opposite pattern.

It is clear that, overall, middle-educated workers in Scandinavian and Continental countries experience a smaller impact from robot adoption compared to their counterparts in other European regions. One might speculate that, in Scandinavian countries, the generosity of compensatory social policies combined with robust labour organization mitigates the effects of robotization on both affective and hedonic well-being. In Continental countries, the configuration of labour organization appears particularly effective in countering the loss of work meaningfulness associated with technological transformation, thereby ensuring that middle-educated workers are not disproportionately disadvantaged.

However, even though the magnitude of the coefficients is smaller in these regions, the effects are not negligible; certain groups may still face challenges in adapting to new forms of automation and potential shifts in well-being. By contrast, in Anglosaxon countries, middle-educated workers are the most adversely affected by robot adoption—the magnitude of the coefficients is higher than in other country groups. Notably, in these countries, highly educated workers experience the most positive impact on three out of the four well-being dimensions, with subjective health being the only exception.

Table 1. Effects of robot density on well-being of workers by education and demographic group. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Life satisfaction (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.019***	.007	.04***	.021***	.017***	-.019
	(.005)	(.004)	(.004)	(.005)	(.006)	(.014)
Middle-educated	-.012**	.001	-.034***	-.01	-.013***	-.069
	(.005)	(.005)	(.004)	(.006)	(.005)	(.049)
Highly-educated	.005	-.009	.025***	-.005*	.008	.024
	(.005)	(.006)	(.003)	(.003)	(.006)	(.018)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.085	.083	.087	.062	.093	.094
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Job influence (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.005	.023	-.013	.02	0	0
	(.014)	(.019)	(.011)	(.015)	(.021)	(.02)
Middle-educated	-.184***	-.171***	-.213***	-.174***	-.188***	-.174**
	(.02)	(.027)	(.013)	(.015)	(.023)	(.072)
Highly-educated	.152***	.133***	.195***	.131***	.16***	-.002
	(.019)	(.025)	(.014)	(.018)	(.02)	(.027)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.096	.097	.087	.085	.091	.135
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Happiness (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.014***	.012***	.018***	.007	.016***	-.002
	(.003)	(.003)	(.003)	(.006)	(.003)	(.012)
Middle-educated	-.008	-.001	-.017***	-.004	-.009*	-.096**
	(.005)	(.005)	(.004)	(.005)	(.005)	(.042)
Highly-educated	.003	-.006	.016***	.003	.001	.007
	(.005)	(.007)	(.003)	(.003)	(.007)	(.016)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.058	.057	.058	.04	.064	.061
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Subjective health (1-5)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	0	-.003	.004***	.003	-.001	-.003
	(.002)	(.003)	(.001)	(.003)	(.002)	(.005)
Middle-educated	-.005*	0	-.011***	-.004***	-.005*	.029
	(.002)	(.004)	(.002)	(.001)	(.003)	(.018)
Highly-educated	.004*	-.001	.011***	.002***	.004	.003
	(.002)	(.004)	(.001)	(.001)	(.003)	(.007)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.123	.125	.121	.041	.101	.139
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

Table 2. Effects of robot density on well-being of workers by education and welfare regime. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Life satisfaction (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	0	.007	-.021	.004	.019***
	(.022)	(.007)	(.023)	(.003)	(.002)
Middle-educated	-.026*	-.003	-.028***	.013***	-.01***
	(.015)	(.002)	(.01)	(.005)	(.002)
Highly-educated	.017***	.002	-.003	-.021***	.011***
	(.006)	(.005)	(.008)	(.005)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.015	.084	.112	.058	.023
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Job influence (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.003	-.046***	-.194	-.016	-.021***
	(.018)	(.012)	(.175)	(.017)	(.003)
Middle-educated	-.54***	-.106***	-.305***	-.085***	-.111***
	(.128)	(.016)	(.032)	(.005)	(.018)
Highly-educated	.518***	.054***	.209***	.052***	.079***
	(.09)	(.01)	(.045)	(.002)	(.013)
Observations	26580	73057	61492	25294	43057
R-squared	.074	.086	.077	.083	.105
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Happiness (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.017	.008***	-.015	.01***	.012***
	(.017)	(.003)	(.012)	(.003)	(.002)
Middle-educated	-.007	-.002	-.013	.01**	-.005***
	(.015)	(.002)	(.009)	(.005)	(.002)
Highly-educated	.031***	-.01*	.005	-.021***	.004**
	(.006)	(.005)	(.005)	(.006)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.015	.038	.088	.056	.017
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Subjective health (1-5)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.076***	-.003**	.008	.004***	.013***
	(.016)	(.001)	(.005)	(.001)	(.001)
Middle-educated	.026***	0	-.018***	-.008***	-.007***
	(.005)	(.002)	(.003)	(.002)	(.001)
Highly-educated	-.056***	.005***	-.007***	.003*	.01***
	(.01)	(.001)	(.001)	(.002)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.064	.106	.226	.135	.068
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Controls include: age, age squared, gender, migration background.

7. Discussion

Industrial robot adoption has significantly altered the conditions of participation in the labour market by rendering certain jobs redundant while simultaneously creating new opportunities for other workers. Previous literature has provided extensive evidence regarding the impact of robot adoption on employment, wages, and various socioeconomic phenomena, including the gender wage gap, fertility, and voting behaviour. A notable contribution of this study is its dual focus on assessing the impact of robotization on workers' subjective well-being—a hitherto overlooked outcome—and on analysing the associated socio-demographic gradients. In particular, we have estimated the effects of robot density on different dimensions of workers' well-being, taking into account heterogeneity by skill level (proxied by education), gender, age, and institutional setting.
The theoretical literature presents two contrasting scenarios. On one hand, the *human leverage effect* emphasises the unique strengths of workers relative to robots. Humans possess a clear comparative advantage owing to their adaptability and their ability to perform innovative and meaningful tasks, even as routine physical activities are increasingly delegated to automation. On the other hand, the framework we refer to as *decreasing workers' agency* highlights the adverse effects of rising robotization on job autonomy and on the sense of fulfilment derived from work. This perspective also underscores the potential for industrial robots to render certain jobs and skills obsolete, thereby heightening fears of unemployment and job insecurity.

Our results indicate that while robot adoption tends to diminish well-being among medium-educated workers, it appears to enhance well-being for both low- and highly-educated workers. This stratified effect underscores the importance of considering skill levels when discussing the consequences of automation, reflecting the hypothesis that technological changes can yield both positive and negative outcomes within the labour market. Notably, we find relatively larger estimates of the effect of robotization on well-being for the dimension related to job autonomy, compared with the other measures (even after rescaling). The eudaimonic dimension of well-being appears to be the most affected by robotization. On the one hand, this finding suggests that industrial robots may limit workers' autonomy when robots and algorithms dictate tasks and workflow (Gombolay et al., 2015). On the other hand, it indicates that the de-unionization of the workforce and the consequent weakening of labour organisations play a crucial role in explaining this decline—particularly among medium-educated workers, who are predominantly employed in the manufacturing sector. The lack of effective top-down agreements to facilitate a transition towards more meaningful work in the context of robotization may result in workers experiencing a diminished sense of purpose and a reduced perception of their own agency. In contrast, the *human leverage effect* hypothesis is confirmed for both low- and highly-educated workers. As suggested by previous studies (Dekker et al., 2017), the robotization shock appears to boost evaluative well-being among highly-educated workers, who are likely to reap the benefits of automation—for example, by experiencing a greater sense of contribution through the adoption of robots (Nikolova et al., 2024). Similarly, the impact on well-being is positive for low-educated workers; those at the lower end of the skill distribution, who are typically engaged in services that are difficult to robotise, do not experience any direct effect on their job autonomy, and may benefit from rising earnings and increased employment shares.

Furthermore, our analysis demonstrates that women's subjective well-being is far more affected by robotization than that of men. This finding is in line with previous studies indicating that women's employment is more negatively impacted by robot adoption (e.g. Aksoy et al., 2021) and that women tend to perceive automation more negatively than men (Borwein et al., 2024).

Our study raises a policy-relevant question: what can be done to mitigate the negative well-being effects experienced by medium-skilled workers? Our analysis of the moderating influence of the institutional environment provides partial answers. On the one hand, it suggests that both compensatory social policies and regulatory protection through robust labour organisation—characteristic of Scandinavian and Continental countries—are associated with better protection and support for workers, leading to less negative well-being outcomes for medium-educated workers. However, it is important to note that even in these countries the impact of robotization remains inequitable, adversely affecting medium-educated workers while enhancing the well-being of both low- and highly-educated workers. On the other hand, our findings indicate that in liberal market economies, workers with high levels of education receive greater robotization premia in terms of well-being, whereas the other educational groups experience negative, or at times negligible, impacts. In these economies, the adoption of technology appears to boost employment at advanced stages of technological development by generating new tasks particularly suited to younger, more recently trained workers.

Based on these findings, we argue that despite recent criticisms of traditional approaches—which have been accused of overlooking the convergence of liberalising trends across different capitalist models (Baccaro & Howell, 2017)—the notion that institutional heterogeneity drives significant cross-country differences in well-being in Europe remains valid. Nonetheless, a distinct yet significant convergence is emerging, leading to a polarization of workers' well-being across all institutional contexts, primarily driven by a (perceived or objective) decline in job control.

There are several limitations to this study. First, it relies on pooled cross-sectional data, making it impossible to track the labour market status of individuals over time. Consequently, the analysis had to be restricted to employed individuals, as we lack information on the last industry in which unemployed individuals worked. Although longitudinal data would be preferable to address this issue, panel surveys rarely include questions on well-being and are usually country-specific, which hinders comparative analysis. Second, we focus on industrial robot adoption due to data availability and to benchmark our study against previous literature on automation, which frequently operationalises automation through robot use. However, this approach might underestimate the extent of actual automation in some sectors, such as mechanical engineering, where automation often relies on machine tools rather than robots. This shortcoming may be resolved as more comprehensive data become available to researchers.

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Appendix

Table A1. Countries used in the analysis by country group, years they are available in the European Social Survey, and the number of observations for those countries in the restricted sample.

Country group	Country	Years available	Observations
Anglosaxon	Ireland	All (2002-2018)	13,515
Anglosaxon	United Kingdom	All (2012-2018)	13,065
Continental	Austria	All except 2012	11,866
Continental	Belgium	All (2012-2018)	10,573
Continental	France	All (2012-2018)	10,196
Continental	Germany	All (2012-2018)	13,888
Continental	Netherlands	All (2012-2018)	11,764
Continental	Switzerland	All (2012-2018)	10,759
Eastern	Bulgaria	2006-2012, 2018	6,450
Eastern	Czech Republic	All except 2006	11,357
Eastern	Estonia	All except 2002	10,070
Eastern	Hungary	All (2012-2018)	7,433
Eastern	Lithuania	2008-2018	5,980
Eastern	Latvia	2006, 2008, 2014, 2018	1,944
Eastern	Poland	All (2012-2018)	10,340
Eastern	Romania	2006, 2008, 2018	1,126
Eastern	Slovakia	2004-2012, 2018	6,335
Mediterranean	Italy	2002, 2004, 2012, 2016, 2018	4,129
Mediterranean	Portugal	All (2012-2018)	9,331
Mediterranean	Spain	All (2012-2018)	9,894
Scandinavian	Denmark	All except 2016	8,600
Scandinavian	Finland	All (2012-2018)	11,788
Scandinavian	Norway	All (2012-2018)	10,795
Scandinavian	Sweden	All (2012-2018)	10,006

Table A2. Effects of robot density on well-being of workers by education and demographic group. Estimates from ordinary least squares (OLS) regression where robot density is interacted with education.

	Life satisfaction (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.009*	.007*	.009**	.015***	.007	-.011**
	(.004)	(.003)	(.002)	(.003)	(.005)	(.005)
Middle-educated	.004	.007	.001	.007*	.003	.016*
	(.004)	(.005)	(.002)	(.003)	(.005)	(.009)
Highly-educated	.002	-.003	.007**	-.003*	.003	-.003
	(.002)	(.002)	(.002)	(.001)	(.003)	(.006)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.085	.083	.088	.063	.094	.096
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Job influence (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	-.004	.025**	-.044***	.013*	-.009	.018**
	(.007)	(.009)	(.007)	(.006)	(.01)	(.008)
Middle-educated	-.081***	-.084***	-.079***	-.066***	-.088***	-.022*
	(.006)	(.007)	(.003)	(.004)	(.007)	(.013)
Highly-educated	.044***	.036***	.065***	.024***	.05***	-.034***
	(.007)	(.008)	(.007)	(.006)	(.008)	(.009)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.103	.104	.095	.093	.098	.138
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Happiness (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.008**	.014***	-.004**	.007**	.009**	-.002
	(.002)	(.002)	(.001)	(.002)	(.002)	(.004)
Middle-educated	.002	.003	.003*	.005**	.001	.003
	(.003)	(.004)	(.001)	(.002)	(.004)	(.008)
Highly-educated	-.004	-.005	-.005**	-.007***	-.003	-.01*
	(.003)	(.003)	(.002)	(.001)	(.004)	(.005)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.058	.057	.059	.04	.064	.066
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Subjective health (1-5)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	0	.003***	-.008***	.003**	-.001	-.002
	(.001)	(.001)	(0)	(.001)	(.001)	(.002)
Middle-educated	-.002	-.001	.001	0**	-.002	-.005
	(.001)	(.001)	(0)	(0)	(.001)	(.003)
Highly-educated	.003**	.004***	0	.001**	.004**	.004*
	(.001)	(.001)	(.001)	(0)	(.001)	(.002)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.123	.125	.122	.042	.102	.141
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

Table A3. Effects of robot density on well-being of workers by education and welfare regime for workers aged under 35 years old. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Life satisfaction (0-10)					
Low-educated	.341***	.006	-.029	.003	.026***
	(.015)	(.011)	(.02)	(.009)	(.002)
Middle-educated	-.167***	.003*	-.005	.03***	-.02***
	(.024)	(.001)	(.027)	(.004)	(.004)
Highly-educated	.096***	-.004	-.034***	-.049***	.01***
	(.035)	(.005)	(.012)	(.003)	(.003)
Observations	8659	23127	18542	7983	14866
R-squared	.015	.065	.092	.042	.025
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Job influence (0-10)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	.099**	-.042***	-.096	.03*	-.051***
	(.041)	(.01)	(.077)	(.016)	(.005)
Middle-educated	-.438***	-.11***	-.327***	-.09***	-.078***
	(.08)	(.012)	(.03)	(.009)	(.014)
Highly-educated	.271***	.094***	.176***	-.004	.031***
	(.071)	(.012)	(.049)	(.006)	(.011)
Observations	8659	23127	18542	7983	14866
R-squared	.082	.081	.068	.072	.094
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Happiness (0-10)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	.263***	-.005	-.001	-.011	.001
	(.017)	(.009)	(.013)	(.007)	(.003)
Middle-educated	-.122***	.001	.02	.029***	-.011***
	(.018)	(.002)	(.019)	(.003)	(.003)
Highly-educated	.118***	-.004	-.034***	-.028***	.002
	(.04)	(.003)	(.008)	(.003)	(.003)
Observations	8659	23127	18542	7983	14866
R-squared	.013	.031	.056	.055	.016
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Subjective health (1-5)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.068***	-.003	0	-.002	.017***
	(.006)	(.005)	(.006)	(.002)	(.001)
Middle-educated	.045***	.001	-.027***	.003***	-.012***
	(.011)	(.002)	(.003)	(.001)	(.001)
Highly-educated	-.047***	.006***	-.004***	-.007***	.006***
	(.012)	(.001)	(.002)	(.001)	(.001)
Observations	8659	23127	18542	7983	14866
R-squared	.024	.049	.062	.041	.029
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

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ISSN 2957-0506

Conclusions

3.1 Discussion of findings

This dissertation has examined the socio-economic consequences of technology- and globalization-driven structural labor market changes in Europe, focusing on fertility, return to work after the first childbirth, and well-being. While labor economics has provided ample evidence on the impact of technology and globalization on labor, much less attention has been given to the broader societal consequences of these forces beyond the labor market. Conversely, the demographic and sociological literature on fertility and well-being has largely overlooked the role of structural labor market changes, which reshape industrial relations and can be a powerful predictor of various personal outcomes. This thesis aims to fill this research gap by providing the first evidence on the interplay between technology, globalization, labor, and their ripple effects on family behavior and well-being. The methodology employed in this dissertation is skewed towards the impact of technology, investigating several specific outcomes: fertility rates in Paper I, entry to parenthood in Paper II, transition to work, unemployment, or the second birth in Paper III, and individual well-being (across its three dimensions: evaluative, eudaimonic, and affective) in Paper IV. Three main conclusions can be drawn from the paper series.

First, structural labor market changes clearly have a stratified impact on family behavior and well-being across different social groups. Paper I shows that industrial robot adoption increases fertility in more technologically advanced European regions with better-educated populations, while decreasing fertility in less-developed regions with lower-educated populations. Paper II demonstrates that German workers in highly cognitive jobs—those performing complex tasks in high demand and less vulnerable to automation or offshoring—are the least likely to remain childless by the end of their reproductive lives. Paper III finds that German mothers with highly cognitive jobs are most likely to return to employment after the first childbirth, while those in highly routine jobs are the most likely to transition to unemployment. In line with Paper II, it also shows that mothers in highly cognitive jobs are more likely to transition to a second birth. Finally, Paper IV shows that industrial robot adoption negatively impacts the well-being of middle-educated workers in Europe, while having a positive effect on those with low- or high-level education. These findings suggest a socio-economic gradient, where structural labor market changes improve fertility and return-to-work conditions for individuals with cognitive jobs or tertiary education, while worsening conditions for those with routine jobs or low-to-medium education. Importantly, these changes not only affect fertility conditions but also create risks of job loss for new mothers in routine jobs. Even if these women enter parenthood (less likely than women with cognitive jobs), they face subsequent disadvantages in the labor market. Whether these impacts align with the upskilling or polarization theory remains unclear, but the consequences for social inequality are evident, as higher-SES individuals clearly benefit from these structural changes.

These findings align with research in labor economics, which predicts that technological progress and globalization deepen economic inequalities (e.g. Acemoglu & Johnson, 2023). They also provide new insights into socio-economic differences in childbearing. Recent studies show that the negative educational fertility gradient is weakening (Nisén et al., 2021, 2024), and that fertility is now more positively associated with women's and men's social class (Kreyenfeld et al., 2023) and income (van Wijk, 2024). My dissertation, particularly Paper II, contributes to this literature by finding that women and men with low cognitive task intensities are now more likely to remain childless than other workers. This suggests that technology- and globalization-driven structural labor market changes create uneven conditions for family formation across different workers and may contribute to contemporary low fertility rates.

The second main conclusion relates to the gendered impact of structural labor market changes (except for Paper III, where studying men is impossible due to data limitations). For example, Paper I finds that robot adoption has larger negative effects on fertility rates in European regions where a higher share of women, compared to men, is employed in manufacturing. Paper II shows almost no gender differences in the relationship between individual task content at work and entry to parenthood in Germany. Paper IV demonstrates that industrial robot adoption has larger negative effects on women's well-being than on men's. Contrary to the commonly held view that automation predominantly harms men's employment in manufacturing (e.g. Acemoglu & Restrepo, 2020; Anelli et al., 2024), my findings suggest that women may be more affected, at least in Europe, in terms of social inequality. These findings align with some European studies, which indicate that structural labor market changes have more adverse effects on women's labor market outcomes than on men's (e.g. Aksoy et al., 2021; Brussevich et al., 2019).

The final conclusion pertains to the institutional variation in the effects of robot adoption on well-being reported in Paper IV. We generally find smaller effects in Continental and Scandinavian countries compared to Anglo-Saxon, Eastern European, and Mediterranean countries. These findings suggest that countries with strong social safety nets and labor protections—typical of Scandinavian and Continental models—provide better support for workers, helping to mitigate the negative effects of robotization for medium-educated workers. However, it is important to note that even in these countries, the consequences of robot adoption are still uneven, with medium-educated workers facing adverse outcomes, while both low- and highly-educated workers experience well-being benefits. In contrast, our results show that in liberal market economies, highly educated workers benefit the most from robotization, while workers in other educational categories face either negative or minimal effects.

This dissertation has several limitations that shape future research in this area, which I summarize in the following section. These limitations make it challenging to draw more overarching conclusions from the dissertation. While this thesis represents an initial step in understanding how structural labor market changes affect family outcomes and well-being in Europe, the limitations outlined below indicate that further research is needed for a more comprehensive understanding of the topic.

3.2 Limitations and future research agenda

The first limitation is the focus on selected contexts within Europe (except for Paper IV, which covers most European countries). This focus is driven by both methodological and practical considerations. For instance, Paper I investigates the effects of robot adoption on regional fertility rates in a select few European countries, rather than across the entire continent, due to constraints in constructing exposure instruments for robot adoption. Typically, exposure to robots is instrumented for one country, using similar measures for other countries with comparable robotization patterns and levels of economic development—this strategy was used in Acemoglu and Restrepo (2020) for the U.S. and in Dauth et al. (2021) for Germany. However, because robot stocks in other European countries are often used as instruments, this approach prevents a pooled analysis of all European countries, necessitating a focus on a selected sample. This limitation was addressed in Paper IV, where robot density in Japan and South Korea was used as instruments for robot adoption in Europe. In that case, these instruments proved strong and relevant, which was not the case in Paper I, where similar instruments were tested but turned out to be invalid in the regional analysis. Additionally, practical considerations involve the industrial relations specific to each country. For example, in 2023, approximately 20% of Germany's workforce (ages 15-64) was employed in industry (NACE B-E), compared to only 12% in Greece (Eurostat, 2024a). Moreover, Germany installs industrial robots at a much larger scale than Greece (International Federation of Robotics (IFR), 2020a). Investigating the impact of robot adoption on social inequalities in countries where it is still in its early stages makes little sense. While service-based economies are undoubtedly affected by automation, alternative measures, such as changes in task content of work or the spread of information and communication technologies, should be applied in those contexts.

Papers II and III, which are based on individual-level data, face an even greater challenge with generalizability. The focus on Germany in these papers is primarily driven by data limitations. The BIBB Employment Survey allows for longitudinal quantification of task content, and the German Socioeconomic Panel and administrative data from the German Pension Fund provide sufficiently large samples to study fertility. Worldwide, there are few data sources that allow researchers to assess task content, with the American O*NET being the most prominent (Acemoglu & Autor, 2011; Gradín et al., 2023). However, task measures derived from O*NET and recoded to match European datasets, like the European Labor Force Survey, face two significant limitations. First, they are cross-sectional, capturing only a snapshot of occupational and task structures, and assuming no dynamics in task content when matched to panel data. Second, they assume that the task structure in European occupations is analogous to the U.S., which is likely not the case. In contrast, the BIBB Employment Survey provides task measures designed specifically for Germany, is longitudinal, and has clear guidelines for their computation (Rohrbach-Schmidt & Tiemann, 2013). These task measures can also be easily merged with other data sources based on occupational codes. Furthermore, Papers II and III rely on task measures at the occupational level (rather than individual), which requires sufficient statistical power to model variables at the three-digit occupational level. Germany's large population makes this feasible, and the German Socioeconomic Panel and two percent administrative sample from the German Pension Fund provide sufficiently large samples that also contain fertility data, which is essential for this dissertation. Furthermore, Germany is a European country where structural labor market changes are particularly pronounced, including the labor-replacing effects of automation (Dauth et al., 2017) and trade competition (Baumgarten et al., 2013; Keller & Utar, 2023), alongside growing demand for non-routine cognitive tasks (Rohrbach-Schmidt & Tiemann, 2013). These patterns make Germany a suitable starting point for this type of research. However, if data limitations can be addressed, individual-level studies in other countries should follow.

The second limitation of this thesis is its failure to account for the couple perspective. Since childbirth typically occurs within couples, all theories on the gendered relationship between labor market outcomes and fertility, discussed in Section 1.2, suggest that partners pool resources, and both of their labor market outcomes—and their intersection—matter for fertility decisions (Becker, 1993; Goldscheider et al., 2015; Oppenheimer, 1997). This perspective has been frequently considered in empirical research on family outcomes (e.g. Di Nallo & Lipps, 2023; Huttunen & Kellokumpu, 2016; Matysiak et al., 2024b), and even in one study on structural labor market changes, which showed that partners share risk when exposed to trade shocks (Huber & Winkler, 2019). Among the data sources used in this dissertation, partner matching is only possible with the German Socioeconomic Panel in Paper II. However, I chose not to match partners, as doing so would significantly reduce the sample size and exhaust the already limited statistical power available. If data limitations can be addressed in future research, a dyadic approach to studying the impact of structural labor market changes on fertility would provide potentially clearer and more comprehensive findings.

Third, this dissertation does not analyze the mechanisms through which structural labor market changes affect family outcomes and well-being. For example, Paper II shows that women and men with highly cognitive jobs are the least likely to remain childless by the end of their reproductive lives. These individuals could have higher first-birth rates due to the income effect associated with their high-demand jobs, or they may enjoy better conditions for childbearing because of the flexibility that cognitive workers typically have. Whether one or both of these mechanisms, or another entirely, drives the result is unclear. Testing mechanisms in Papers II and III was not feasible for several reasons. First, there is currently no method for incorporating mediation in event history analysis. Second, the administrative data used in Paper III has limited information. Third, as explained in Paper III, income and education are bad controls when analyzing the task content of work and birth events. Papers I and IV also do not explicitly investigate mechanisms, but they do offer some clues. For example, Paper I identifies negative effects of robot adoption on fertility in highly industrialized European regions, suggesting that fertility decline may result from the loss of manufacturing jobs. Conversely, highly technologically advanced regions experience fertility increase from automation, indicating their greater capacity to absorb new technologies for broader benefit. Additionally, Paper IV shows that industrial robot adoption has a consistently smaller effect on workers' well-being in Continental and Scandinavian countries compared to Anglo-Saxon, Mediterranean, or Eastern European countries, suggesting that stronger compensatory social policies may help shield workers from the impact of labor-replacing technologies. An explicit analysis of mechanisms in that paper was not possible due to methodological constraints. In principle, causal mediation analysis in IV regressions could be conducted (Dippel et al., 2020), but this method requires using the same instrument for both the mediator(s) and the endogenous variable—in this case, robot density. While robot adoption in Japan and South Korea works as an instrument for robot density in Europe, it is unlikely to be an effective instrument for feasible mediators, such as unionization or collective bargaining agreements. Overall, analyzing the mechanisms through which structural labor market changes affect family outcomes and well-being is a worthwhile area for future research, potentially providing a more nuanced understanding of how technology and globalization influence social inequalities. However, it is currently challenging due to data and methodological limitations.

The fourth limitation of this dissertation is its failure to investigate the interplay between well-being and fertility, despite both being analyzed as outcomes. I decided to include well-being in the dissertation because, while working on studies about structural labor market changes and fertility, I found no research on how these factors might impact subjective experiences related to the labor market, such as well-being. Upon realizing that it was possible to explore this connection with the available data and methods, I decided that doing so would provide a more comprehensive view in this thesis. As mentioned earlier, well-being is both as a mediator between labor market outcomes and fertility (Vignoli et al., 2020b) and an outcome influenced by previous fertility (Luppi & Mencarini, 2018). Modeling such a complex relationship properly is not trivial and would likely require a structural model. This complicated exercise would be a natural extension of the research presented in this dissertation.

Fifth, this dissertation focuses on two measures of the impact of structural labor market changes: industrial robot adoption and task content of work. As noted in Section 1.1, this means the work presented here is somewhat skewed toward the topic of automation. However, it does not explore the occupational impact of artificial intelligence (AI). AI is undoubtedly another transformative technology in the world of work, and scholars have been debating its implications since before the emergence of large language models like ChatGPT (Brynjolfsson & McAfee, 2014; Brynjolfsson & Mitchell, 2017). Acemoglu and Johnson (2023) predict that, if left unregulated, AI will likely deepen social inequalities more than previous technological revolutions. However, empirical research on the impact of AI on jobs remains limited. A few early studies have identified occupations most *exposed* to AI (Eloundou et al., 2023; Felten et al., 2023; Gmyrek et al., 2023), but exposure does not necessarily equate to displacement and may also imply complementarity. This issue was a major point of debate at the last American Economic Association conference I attended (2025, San Francisco), where economists agreed that the impact of large language models on jobs remains uncertain. While it is clear that these technologies will profoundly affect workers and families, it is too early to study their effects on family outcomes, and no data currently exists to assess their impact on well-being.

Sixth, like most social science research, this dissertation unfortunately presumes heteronormativity and cisnormativity, implicitly assuming that all individuals are heterosexual (i.e., attracted exclusively to people of a different gender) and cisgender (i.e., their gender aligns with their sex assigned at birth). However, sexual and gender minorities exist and often have distinct labor market experiences and family trajectories compared to their heterosexual and cisgender counterparts. For example, women in same-sex couples typically have a much higher labor supply than women in different-sex couples, while only up to 10% of male same-sex couples raise children (Bogusz & Gromadzki, 2024). Research in LGBTQ+ economics and queer demography has advanced significantly in recent years (Badgett et al., 2021; Badgett et al., 2024) and increasingly includes non-binary gender perspectives (Coffman et al., 2024; Mittleman, 2022). However, severe data limitations still hinder studies of LGBTQ+ populations. Among the data used in this dissertation, only the German Socioeconomic Panel includes information about sexual orientation, identifying approximately 1,000 homosexual or bisexual individuals (Bohr & Lengerer, 2024), a sample size too small to analyze occupational variety. If larger LGBTQ+ samples can be collected, future research on structural labor market changes and social inequality should include sexual and gender minorities, as they may have distinct labor market experiences and determinants of family outcomes and well-being.

Finally, this dissertation does not investigate the diverse family-related outcomes that migrants might experience as a result of structural labor market changes. Migration is generally associated with occupational downgrading (Dustmann et al., 2008; Lebow, 2024). A recent study of Ukrainian war refugees in Poland found that those transitioning to lower-skilled jobs faced significant increases in routine task intensity, often equivalent to shifts from managerial to clerical roles (Lewandowski et al., 2025). Thus, migrants and refugees may be disproportionately and adversely affected by technology- and globalization-driven structural labor market changes. While their experiences certainly warrant further scholarly attention, incorporating migration into this dissertation was infeasible for two reasons. First, the goal of the dissertation was to shed light on an unexplored issue, and including migration could have complicated the analysis at this stage. Second, most migrants in Europe have distinct family trajectories compared to European nationals (Milewski, 2010), requiring special attention when studying their experiences. Future research should address this gap.

3.3 Policy relevance

The limitations discussed above make it difficult to formulate specific policy recommendations. However, given that structural labor market changes exacerbate inequalities, which appear to affect family and well-being outcomes, there are some valuable policy directions to consider. These policies should address reducing inequalities at the education and labor market stage of the life course, as well as inequalities in family outcomes and well-being *given* individuals' labor market situations.

The implications of structural labor market changes for labor policy are outlined by Autor et al. (2022) and Autor (2022), who categorize these policies into three areas: education and training, labor market institutions, and innovation policy. However, the authors note that "the question is so broad that almost any answer is bound to appear vague and inadequate" (Autor, 2022, p. 26). First, expanding access to education and skills training is crucial to help workers adapt to the changing labor market. Specifically, fostering cognitive and technological skills among vulnerable populations could mitigate the negative effects of automation and trade competition. However, skill upgrading does not necessarily lead to wage growth, and there is considerable literature on overeducation in Europe (International Labour Organization, 2014). Thus, policies should not only target upskilling, but also simultaneously improve the quality of low-skilled jobs.

This leads to the second policy domain: labor market institutions. Strengthening institutions that translate rising productivity into shared prosperity is essential. This might involve updating and enforcing labor standards, systematically raising the minimum wage, expanding unemployment insurance systems, or strengthening broadly defined social safety nets, such as public healthcare and education, which tend to have pre-distributive effects (Blanchet et al., 2022). Findings from Paper IV suggest that bolstering such institutions could reduce inequalities in well-being caused by structural labor market changes, as the effects of robot adoption on well-being were smaller in countries with more robust social policies. Failing to strengthen these institutions may have dire consequences; for example, Anelli et al. (2021) shows that individual vulnerability to industrial robots increases support for far-right parties, undermining social cohesion. Political science research also suggests that comprehensive welfare systems can buffer the adverse effects of automation on well-being and fertility, particularly for low- and medium-skilled workers who are disproportionately affected by job displacement (Busemeyer & Sahm, 2022; Thewissen & Rueda, 2019).

The third and final policy domain focuses on shaping innovation in a way that complements the skills of the labor force and drives productivity growth (Autor, 2022). This approach advocates for innovation in areas where Europe already has a comparative advantage and where workers' skills can be directly applied. Such an innovation system would likely benefit society as a whole.

The second strand of policies suggested here aims at supporting parents and lowering the cost of parenthood. Papers I and II presented in this dissertation showed that both women's and men's labor market situations matter for fertility decisions. Thus, childcare expansions, as well as paid parental leaves (for both mothers and fathers) are crucial to help individuals reconcile work and family life. A systematic review of quasi-experimental literature on family policies in high-income countries by Bergsvik et al. (2021) shows that childcare expansion increases completed fertility and has long-term redistributive effects. In contrast, universal transfers and earnings-related parental leave programs tend to redistribute wealth more toward well-off families. Paternal leave take-up is positively associated with parity progression (Duvander et al., 2019), but its causal effect is null or negative, as it depends on whether fathers increase their involvement at home permanently[1]. Finally, as women's age at first birth continues to rise, the potential impact of assisted reproduction on total fertility rates (TFRs) also increases. Relatedly, Paper II in this dissertation shows that women in highly cognitive jobs are the least likely to remain childless, though they tend to delay fertility and accelerate it their late thirties. Therefore, greater access to assisted reproduction services may help these individuals achieve their fertility goals.

To sum up, counteracting the socio-economic inequalities created or exacerbated by technology- and globalization-driven labor market changes is possible, but it requires broad political action. Policies are likely to be effective only if multiple interventions are made at various stages of individuals' life courses: in education, the labor market, and family dynamics. Whether European countries will take action in this regard remains a political decision.

[1]Bergsvik et al. (2021) note that evidence on this is still scarce.

Other research activity

A.1 Published

Bellani, D., & Bogusz, H. (2024). 49: Automation and wellbeing. In H. Brockmann & R. Fernandez-Urbano (Eds.), *Encyclopedia of Happiness, Quality of Life and Subjective Wellbeing* (pp. 370–376). Edward Elgar Publishing. https://doi.org/10.4337/9781800889675.00060

ABSTRACT: This entry provides an overview of empirical evidence and theoretical perspectives on the relationship between automation and subjective wellbeing. Authors identify different spheres of influence of automation on individual wellbeing, emphasizing several dimensions associated with working and personal life. Additionally, authors discuss the main limitations in the existing literature on the topic and conclude by drawing research implications and new avenues for future.

Bogatyrev, K., & Bogusz, H. (2025). On the verge of progress? LGBTQ+ politics in Poland after the 2023 elections. *European Journal of Politics and Gender*, **8**, 242–248. https://doi.org/10.1332/25151088Y2024D000000024

ABSTRACT: The 2023 parliamentary elections marked a change in Polish politics, putting an end to the government of the radical-right Prawo i Sprawiedliwość ('Law and Justice' [PiS]) party. Over its eight-year rule, PiS made international headlines with its rhetoric and initiatives against the lesbian, gay, bisexual, transgender, queer and other (LGBTQ+) community (Korolczuk, 2020). As Poland draws a line under PiS rule, we take stock of Polish LGBTQ+ politics, analysing the institutional legacy of the previous government, highlighting the trends in public attitudes towards LGBTQ+ citizens and exploring the policy prospects under the new coalition government, led by centre-right Prime Minister Donald Tusk.

Bogusz, H., Winnicki, S., & Wójcik, P. (2025). What factors contribute to uneven suburbanisation? Predicting the number of migrants from Warsaw to its suburbs with machine learning. *The Annals of Regional Science*, **72**, 1353–1382. https://doi.org/10.1007/s00168-023-01245-y

ABSTRACT: This article investigates the spatially uneven migration from Warsaw to its suburban municipalities. We report a novel approach to modelling suburbanisation: several linear and nonlinear predictive models are applied, and Explainable Artificial Intelligence methods are used to interpret the shape of relationships between the dependent variable and the most important regressors. The support vector regression algorithm is found to yield the most accurate predictions of the number of migrants to the suburbs of Warsaw. In addition, we find that migrants choose wealthier and more urbanised municipalities that offer better institutional amenities and a shorter driving time to Warsaw's city centre.

Waszkiewicz, R., & Bogusz, H. (2025). Lekarstwo na prokrastynację: kontrakty na zobowiązania [The cure for procrastination: commitment contracts] [Popular science article in Polish.]. *Delta*. https://www.deltami.edu.pl/2025/03/lekarstwo-na-prokrastynacje-kontrakty-na-zobowiazania/

A.2 Pre-prints

Bogusz, H., & Gromadzki, J. (2024). Labor Market Outcomes of Same-Sex Couples in Countries with Legalized Same-Sex Marriage. *IZA Discussion Paper*, **17107**. https://www.iza.org/publications/dp/17107/labor-market-outcomes-of-same-sex-couples-in-countries-with-legalized-same-sex-marriage

ABSTRACT: We study the labor market outcomes of same-sex couples using data from large household surveys that represent more than two-thirds of the world's population with access to same-sex marriage on three continents. Same-sex couples are less likely to be inactive and work more hours than different-sex couples, largely due to the differences in the probability of having a child. Men in same-sex couples are up to 60 percent more likely to be unemployed than men in different-sex couples. These unemployment gaps cannot be explained by occupational sorting or other observable characteristics.

Waszkiewicz, R., & Bogusz, H. (2023). The Impact of Parenthood on Labour Market Outcomes of Women and Men in Poland. *arXiv preprint.* https://doi.org/10.48550/arXiv.2306.12924

ABSTRACT: We examine the gender gap in income in Poland in relation to parenthood status, employing the placebo event history method adapted to low-resolution data (Polish Generations and Gender Survey). Our analysis reveals anticipatory behavior in both women and men who expect to become parents. We observe a decrease of approximately 20 percent in mothers' income post-birth. In contrast, the income of fathers surpasses that of non-fathers both pre- and post-birth, suggesting that the fatherhood child premium may be primarily driven by selection. We note an increase (decrease) in hours worked for fathers (mothers). Finally, we compare the gender gaps in income and wages between women and men in the sample with those in a counterfactual scenario where the entire population is childless. Our findings indicate no statistically significant gender gaps in the counterfactual scenario, leading us to conclude that parenthood drives the gender gaps in income and wages in Poland.

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