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Anna Matysiak
Linus Andersson
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Technological Change, Labour Markets and Family Behaviours in Sweden

Anna Matysiak[1], Linus Andersson[2], Wojciech Hardy[1]*

[1] Interdisciplinary Centre for Labour Market and Family Dynamics, Faculty of Economic Sciences, University of Warsaw
[2] Swedish Institute for Social Research, Stockholm University
[*] Corresponding author: annamatysiak@uw.edu.pl

Abstract: This study examines whether long-term structural labour market change, driven by industrial robotization, has influenced family formation and union stability in Sweden. Linking Swedish population register data (1994–2017) with sector-level measures of robot penetration, we analyse transitions into first marriage, first, second, and third births, and divorce. We distinguish between current exposure to robotization among employed workers and residual exposure among individuals who exited employment in robotizing sectors. Event-history models are complemented by an instrumental-variable approach that exploits cross-national variation in robot adoption to strengthen causal interpretation. On average, we find only weak associations between robotization and family transitions. However, substantial heterogeneity emerges by educational attainment. Among low- and medium-educated women and men, higher exposure to automation is linked to lower birth risks, weaker marriage formation, and higher divorce risks. In contrast, highly educated individuals experience neutral or positive associations between automation and family formation, alongside greater union stability. We conclude that the aggregate contribution of structural labour market change caused by industrial automation to Sweden's post-recession fertility decline appears limited, automation contributes to widening educational disparities in family trajectories and reinforces cumulative disadvantage across labour market and family domains.

Keywords: labour market, technology, industrial robots, family, fertility

JEL codes: J31, J13, O33

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1. Introduction

Across advanced economies, fertility has been on a decline since the Great Recession and the drivers of this downward trend remain insufficiently understood (Kearney et al.2022; Gietel-Basten et al.2022). The decline has been substantial even in the Nordic countries, where fertility remained close to replacement level for two to three decades before the recession. In Sweden, the empirical setting of this study, the total fertility rate fell markedly from 1.98 in 2010 to 1.71 just before the onset of the Covid-19 pandemic and further down to 1.43 by 2024. Multiple explanations have been proposed, often referring to economic uncertainty (Comolli et al. 2021; Hellstrand et al. 2021). Yet it remains unclear what might have caused this uncertainty, especially in contexts characterized by strong employment protection and generous welfare provision, such as the Nordic countries. In this paper, we examine whether the post-recession fertility decline has been driven, at least in part, by long-term structural labour market change, linked to the diffusion of labour-replacing technologies.

Technological change has profoundly reshaped labour markets in advanced economies over the past three decades. Expansion of labour-replacing technologies, particularly industrial robots, played a central role in this process. It began in the early 1990s, i.e., well before the Great Recession, but its consequences for workers became increasingly visible from the late 2000s as automation diffused more broadly (OECD 2019). This wave of automation preceded the more recent spread of generative AI and substantially altered the structure of labour demand, especially in manufacturing and other sectors intensive in routine job tasks. Its effects have been reflected in a declining demand for workers performing easily codifiable tasks that can be substituted by technology, contributing to deteriorating employment conditions among exposed workers (Goos et al. 2014; Autor et al. 2015). At the same time, workers involved in highly cognitive tasks that are difficult to automate, or that are complementary to new technologies, have benefited from these changes, experiencing improved employment stability and earning prospects (Dauth et al. 2021; Otto and Abraham 2025).

A large body of demographic research has documented the importance of labour force participation and labour market conditions for family formation and its stability (Matysiak and Vignoli 2024; Matysiak and Osiewalska, forthcoming). Employment provides the financial resources necessary for family formation and its maintenance (Becker 1981, Oppenheimer 1988). Beyond current resources, employment stability sends signals about expected future living standards and thus affects individuals' propensity to make long-term commitments (Alderotti et al. 2021; Bastianelli and Vignoli 2022). Last but not least, labour market position shapes individuals' capacity to combine paid work and care, thereby affecting workers' fertility decisions as well as the stability of the unions (Greenberg and Landry 2011; Goldscheider et al. 2015). Consistent with this evidence, studies have shown that deteriorating labour market conditions during economic recessions led to fertility postponement (Neels et al.2013; Comolli 2017) and reduced union quality (Schneider 2017).

Similar to economic recessions, structural labour market transformations may also affect family behaviours, though with some differences. Unlike economic recessions, which typically advance rapidly, structural transformations evolve more gradually, and their demographic effects may accumulate over time. They also have a long-term character and are unlikely to recede after short-term adjustments in the economy, as recessions often do. Finally, the most recent structural labour market change, driven among others by rapid technological transformations, has not manifested in widespread unemployment, but rather resulted in wage stagnation among the exposed workers (De la Rica et al. 2020; Barth et al. 2025), heightened uncertainty (Dekker et al. 2017), and displacement into lower-status positions (Dauth et al. 2021; Cuccu and Royuela 2024). Seltzer (2019) argued that similar changes in the structure of labour demand, caused by import competition from China, resulted in fertility decline in the United States after the Great Recession, because they led to sustained deterioration in economic conditions for a large share of workers previously working in manufacturing and goods-producing industries. A similar logic motivates the present study: cumulative exposure to industrial robotization, which has progressively diffused across labour markets, may have gradually affected workers' family behaviours and, as exposure expanded to broader segments of the workforce, ultimately contributing to fertility decline at the aggregate level.

Empirical research directly linking technological change in the labour markets to family formation remains limited and has relied predominantly on macro-level analyses. These studies suggest that greater exposure to automation is associated with lower fertility and higher divorce rates. For example, Anelli et al. (2024) showed that US regions with higher robot penetration experienced increases in divorce and nonmarital childbearing, alongside a decline in marital fertility. Using European data, Matysiak et al. (2023) found that robot adoption reduced fertility in industrialized, low-skill, or technologically lagging regions and that fertility increased in more prosperous regions with higher-skilled populations. Costanzo (2025) also documented heterogeneous fertility responses, with robot exposure associated with earlier childbearing in low- and high-skilled regional labor markets, but delayed fertility in predominantly medium-skilled ones. While this evidence is informative at the population level, macro-level approaches are inherently limited: they may conceal substantial heterogeneity in how individuals experience technological change, given that robotization can simultaneously improve prospects for some workers while worsening them for others. Aggregate associations may therefore mask offsetting micro-level mechanisms and do not allow conclusions about which individuals change their family behaviours in response to technological change.

Micro-level evidence on this topic is rare, in turn. One exception is Bogusz et al. (2025), who use information on the cognitive intensity of jobs and show that workers in more cognitively demanding jobs are more likely to become parents in Germany. While this study offers valuable insight into how job task content relates to fertility, it does not directly measure technological change. Demand for cognitive work may reflect not only automation but also globalization or the broader transition toward a knowledge-based economy. Consequently, existing micro-level evidence does not allow for isolating technological change as a specific mechanism shaping family formation.

In this study, we examine how exposure to robotization affects marriage formation, transitions to first, second, and third births, and divorce in Sweden, using high-quality population register data. Our focus is on the wave of automation associated with industrial robots that expanded well before the recent emergence of large language models and generative AI. To the best of our knowledge, this is the first comprehensive micro-level study which addresses the effects of robotization on multiple family transitions. Sweden is an informative case because it experienced rapid increases in robot adoption beginning in the early 1990s and is today among the most robot-intensive economies worldwide (International Federation of Robotics 2025). Our observation window spans 1993, when robotization began to accelerate, through 2017, when robot penetration had reached high levels. This long observation window allows us to capture both the early diffusion of robotization, when it may have concerned only few workers, as well as the later stage, when its diffusion was broader. At the same time, we end the analysis before the Covid-19 pandemic and the most recent expansion of AI technologies, thereby focusing on the demographic consequences of industrial robotization without confounding influences from pandemic-related disruptions or newer technological developments that may affect different social groups and whose effects on the labour market are not yet well understood.

We apply event-history models to estimate how exposure to industry-level robotization affects marriage, birth transitions, and divorce for women and men across educational groups. In addition, we examine family outcomes among individuals who exit employment in highly robotized sectors, capturing both direct and indirect effects of technological change. To strengthen causal interpretation, we follow prior research on labour market effects of robotization and employ an instrumental-variable approach based on exogenous variation in industry-level robot adoption.

We find that robot adoption affects family formation and stability in opposite directions across educational groups: downward among the low and middle educated and upward among the highly educated. At the same time, the estimated effects are not large, apply primarily to workers directly affected by automation in manufacturing, and partly offset each other in the aggregate. They are therefore unlikely to account for the substantial Swedish fertility decline observed in the post-recession period. They do, however, contribute to the ongoing reversal of the educational gradient in fertility from negative to positive.

2. Technology and Labour Market Transformations

Over the last several decades, advanced economies have experienced rapid technological change that has profoundly transformed labour markets (OECD 2019). Development of labour-replacing technologies has been key in this transformation, with industrial robots playing a central role in manufacturing by automating assembly, welding, and material-handling processes (Graetz and Michaels 2018; Acemoglu and Restrepo 2020). According to the International Federation of Robotics (2025), the number of industrial robots installed worldwide increased from 0.6 million in 1993 to more than 4 million in 2023, corresponding to a robot density of 162 industrial robots per 10,000 workers in manufacturing. Robot density is highest in East Asian countries (South Korea, Singapore, China), followed by respectively Germany, Japan and Sweden. In the latter, it grew exponentially from app. 54 robots per 10,000 manufacturing workers in 1993 to app. 279 in 2024.

The expansion of labour-replacing technologies, and industrial robots in particular, has generated extensive scientific debate about their consequences for workers' employment opportunities, earnings, and job quality. In general, research shows that automation increases productivity and may create new jobs while simultaneously eliminating certain tasks and displacing workers who are most easily replaced. Aggregate employment effects tend to be modest and often close to zero (Graetz and Michaels 2018; Acemoglu and Restrepo 2020). These effects appear to operate similarly on women's and men's employment (Acemoglu and Restrepo 2020), although some studies report a narrowing (Ge and Zhou 2020) and others slightly widening gender wage gap (Aksoy et al. 2021).

At the same time, substantial heterogeneity by educational attainment has emerged (Guarascio et al. 2025). Labour-replacing technologies have raised demand for highly skilled workers performing analytical tasks (e.g., robot programming and maintenance, data analysis, quality control) and interactive tasks (e.g., supervision of automated processes, coordination of teams, contacts with clients) that are difficult to automate and frequently complementary to robots (Autor et al. 2003). As a result of these changes, highly educated workers in automatable industries have experienced better employment opportunities (Damelang and Otto 2023) and steeper wage growth (Barth et al. 2025; Acemoglu et al. 2023; Dauth et al. 2021). Automation has also increased the complexity and variety of job tasks, opening possibilities for occupational upgrading and skill accumulation among workers able to meet the new demands (McGuinness et al. 2023). In contrast, workers performing routine, codifiable, or manual tasks, often low- and middle-educated, face worse labour market prospects. For these groups, automation is associated with lower wage growth or wage stagnation (Acemoglu and Restrepo 2020; Barth et al. 2025; Dauth et al. 2021), a higher risk of precarious, atypical, and unstable employment (Buzzelli et al.2025), and poorer access to training (Pavelea et al. 2025). Importantly, displacement does not necessarily translate into long-term unemployment (Damelang and Otto 2023). Yet, when displaced workers get re-employed, the new positions are often of lower quality in terms of earnings or stability and fall below their qualifications (Cuccu and Royuela 2024; Yakymovich 2025). Such adverse consequences are documented not only in contexts with weaker employment protection and safety nets, where they may be stronger, but also in Nordic countries characterized by high union density, strong employment protection, and generous social benefits (Buzzelli et al.2024; Barth et al. 2025; Yakymovich 2025).

Finally, the diffusion of labour-replacing technologies has consequences beyond labour market outcomes, affecting workers' physical and mental health. Some of these consequences may be beneficial as automation reduces the physical intensity of work and lowers exposure to hazardous tasks, thereby lessening physical strain and injury risks (Gihleb et al. 2022). At the same time, automation is associated with higher job insecurity (Dekker et al. 2017), elevated stress and anxiety, and poorer mental health (Lordan and Stringer 2022), as well as higher alcohol and substance abuse (Gihleb et al. 2022, Bratsberg et al. 2022), particularly among low- and middle-skilled workers.

3. Exposure to Automation and Family-related Behaviours

Automation may influence family formation and family stability through several mechanisms. The first, the income mechanism, operates through economic resources, especially income level and income stability. Paid employment provides the financial means required to secure housing, consumption, and investments in children and has therefore long been viewed as a prerequisite for family formation and its stability (Becker 1981; Oppenheimer 1988). Yet, it is not only current income that matters, but also expectations about future living standards (Ranjan 1999; Vignoli et al. 2020). Unstable employment conditions signal unpredictability, which discourages long-term commitments, such as union formation and childbearing, and strains existing unions (Alderotti et al. 2021; Bastianelli and Vignoli 2022). Since automation affects earning prospects and employment stability differently for low/middle and highly educated, it is likely to affect family formation and union stability in ways that differ by educational attainment. For highly educated workers in automatable sectors, automation may generate favourable economic conditions that support family formation and partnership stability. In contrast, for low- and middle-educated workers, who are most exposed to deteriorating employment conditions due to labour-replacing technologies, automation may reduce the capacity to enter stable unions and have children, while also increasing the risk of union dissolution.

A second pathway is the work-family mechanism, operating through opportunity costs of parenting and work-family reconciliation. High opportunity costs of parenthood, in the form of forgone earnings, slower career progression, or skill depreciation during career interruptions, have long been linked to fertility postponement (Gustafsson 2001; Nicoletti and Tanturri 2008) while difficulties in combining paid work and care to lower fertility and higher union instability (McDonald 2000; Goldscheider et al. 2015). Technological change can improve earning opportunities for some workers, but it may simultaneously reorganize work in ways that intensify cognitive demands, require continuous upskilling, and increase time and energy investments in paid work. Such demands may be difficult to reconcile with childbearing and childrearing (Luo et al. 2025) and may constrain opportunities for partner interaction and relationship maintenance (Khalil et al. 2026). Consequently, the work–family mechanism may reduce, and in some cases partially outweigh, the positive income effects of automation on family behaviours among highly educated workers.

The relative importance of the income and work-family mechanisms is likely gendered. Historically, the income mechanism has been theorized primarily with reference to men, while the work-family mechanism has been emphasized in relation to women, reflecting gendered social norms about breadwinning and caregiving (Becker 1981). In this traditional framework, men's unemployment or low and unstable earnings signal an inability to fulfil the socially prescribed provider role, undermining men's attractiveness in the marriage market (Wilson 1987) and reducing their chances of entering stable unions and having children (Kalmijn 2011, Alderotti et al.2021). Conversely, women's inactivity or employment in less demanding, though also less well-paid, occupations has been viewed as conducive to family formation and union stability by facilitating woman's role as a main care provider (Becker 1981). With rising female labour force participation and growing expectations for men to engage in care, these mechanisms have, however, increasingly converged for women and men. Women's earnings have become central to household economic security, and women's employment has gradually ceased to be associated with lower fertility (Matysiak and Vignoli forthcoming) and higher union instability (Cooke et al. 2013; Vignoli et al. 2018). At the same time, as men increase involvement in childcare, they may face growing tensions between paid work and family life (Matysiak and Nitsche 2016). These shifts are particularly pronounced in Nordic contexts, where gender equality in paid work and caregiving is institutionally supported and reflected in high maternal employment and relatively high paternal involvement (Pailhé et al. 2021; Solveig 2024). In the Swedish context, we may therefore expect work-family tensions associated with technologically advanced workplaces to weaken the positive effects of automation on family formation and stability among both women and men.

Another mechanism that may link workers' exposure to automation and their family-related behaviours is the bargaining power. Workers who gain labour market advantage as automation increases demand for their skills may acquire stronger bargaining power within the workplace, which enables them to negotiate flexible hours, remote work, or short-term leave, for instance, to care for a sick child (Greenberg and Landry 2011). Evidence suggests that such flexibility can mitigate work-family conflict and support childbearing (Osiewalska and Matysiak 2025). It may also reduce relationship tensions (Kałamucka et al. 2025). This mechanism may therefore partly weaken the negative role of work-family tensions caused by work demands among highly educated workers in highly automated settings.

Finally, automation may shape family-related behaviours through health pathways, particularly among low- and middle-educated workers. Because automation reduces physically strenuous work and because such adverse working conditions are associated with elevated miscarriage risk and other reproductive health problems (Corchero-Falcón et al.2023), automation may strengthen women's ability to conceive and avoid early miscarriage, especially among lower-educated women concentrated in physically demanding jobs. On the other hand, however, by amplifying stress and anxiety and intensifying risky behaviours, such as alcohol or drug abuse among low-and-middle educated workers, it may erode union stability and lower fertility in this social group.

Taken together, these pathways imply that robot adoption is unlikely to exert uniform effects on family formation and stability. Rather, it is expected to reinforce social stratification in family trajectories. For low- and middle-educated women and men, exposure to automation is likely to weaken union formation, reduce fertility, and increase union instability through declining income prospects, heightened uncertainty, and adverse health effects. Some adverse effects for low-educated women may, however, be partly counteracted by reductions in physical strain. For highly educated individuals, automation is more likely to support family formation through improved economic resources and potentially stronger workplace bargaining power, although these positive effects may be partly outweighed by higher opportunity costs and intensified work–family tensions in technologically advanced and demanding workplaces. In this way, robotization may contribute to widening educational differentials in family-related behaviours and a reversal of the educational gradient in fertility and union stability, possibilities we evaluate in the Swedish context. Thus, while prior literature considered the effects of robotization on family formation at the aggregate level (e.g. Anelli et al., 2024; Matysiak et al. 2023, Costanzo et al. 2025), our study considers these relationships at individual levels in order to disentangle the effects for different types of workers.

4. Data

4.1. Data Sources

In order to examine the effects of automation on family formation and its stability we make use of three data sources. Our major data source is the Swedish Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA, Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier). It is a register database prepared for research, which compiles information from otherwise separate registers, providing us with information on the Swedish population aged over 16 who registered in Sweden on December 31st. It offers a basis for constructing individual life histories, namely fertility, partnership, educational, and occupational. We had access to the data covering registers up to the end of 2017.

The other two data sources are the International Federation of Robotics (IFR), which provides us with data on operational stocks of robots, and EU KLEMS, which offers aggregate data on sector growth and employment by industry. We use IFR and EU KLEMS data to develop the robot exposure measure as proposed by Acemoglu and Restrepo (2020). The measure is sector-specific. We link it to the individual occupational histories by sector (industry) in order to model how sector exposure to automation affects family behaviours.

4.2. Individual Life Histories

Using LISA, we reconstruct fertility, partnership, and employment histories. Fertility histories are constructed based on monthly data from parent-child register which provides information on children's birthdates. Marriages and divorces are identified through marriage registers and constitute a basis for building partnership histories. Unfortunately, information on cohabitation is only available since 2011 and as such we cannot reliably identify non-married couples, which limits our study of partnerships to marriages only. Educational histories come from educational registries compiled within the LISA database. Our employment histories come from tax registers. They provide data on individual income from work, tenure within the organisation, and the industry code of the company in which the individual works in November of each year). Firms and organizations are classified using the Swedish industry code (SNI), provided by the Swedish Tax Agency, which is based on the Nomenclature of Economic Activities (NACE), i.e. the European Union's standard system for classifying economic activities. Our robot exposure measure is thus linked with individual occupational histories by industry code.

4.3. Exposure to Robotisation

In order to measure exposure to robotization, we compute the adjusted rate of penetration of robots (APR) as proposed by Acemoglu and Restrepo (2020). It measures the extent to which the adoption of industrial robots increased within an industry over time relative to the initial employment, beyond what would be mechanically implied by general industry growth, and is used as a proxy for exposure to automation. We compute it as the change in the stock of robots in sector i between year t and the baseline year $t0$=1993 (onset of automation in Sweden) relative to the sector employment in the baseline year. Dividing the change in the stock of robots by the sector's initial size makes the measure comparable across sectors. We then adjust it further for the part of robot growth which could be expected because of the output growth (and not because of the technological expansion):

$$APR_{i,t} = \frac{M_{i,t} - M_{i,1993}}{L_{i,1993}} - g_{i,(1993,t)} \cdot \frac{M_{i,1993}}{L_{i,1993}} \quad (1)$$

where M denotes the operational stock of robots, L the number of employees, and g the cumulative output growth in sector i between 1993 and year t. The APR is thus measured at the sectoral level, reflecting group beliefs about possible displacement by robots and uncertainty about future employment rather than actual situation of individual workers.

We derive sector-level employment from the Swedish registers and sector level information on output growths g and employment[1] L from different EU KLEMS editions for comprehensiveness. The data for 1995-2017 comes from the EU KLEMS data hosted by the LUISS Lab of European Economics[2]. We extend this data to 1993 using an older, archived 2017 EU KLEMS release for Sweden[3]. Both sources follow the ISIC rev. 4 sector classification, and we combine information from both to consistently cover the same set of sectors from 1993 to 2017 (see the Appendix for details).

Next, we derive the data on the stock of robots from International Federation of Robotics (IFR) which provides annual industry-specific data on the stock of robots for Sweden since 1993. The industries are coded according to the International Standard Industrial Classification (ISIC) rev. 3. The data are available for all ISIC industries at minimum one digit level, with manufacturing industries providing information up to a three digit level. We match the IFR data with KLEMS data at the most detailed level possible. In early years, a small share of robots is reported by IFR as "unidentified" with respect to sector. Following prior work, we distribute these robots proportionally across identified sectors based on each sector's share in observed robot stocks in that year (similarly to e.g. Acemoglu and Restrepo, 2020). The unidentified category accounts for less than 10% of robot stocks throughout the period.

Table A1 in the Appendix presents unadjusted robot penetration rates (APR before adjusting for robot adoption due to output growth) as well as the APR measures across

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[1] For Sweden we utilize the register data for employment counts across sectors, but for countries used in the instrumental variable approach we use EU KLEMS for this information.

[2] EUKLEMS & INTANPROD – Release 2021: https://euklems-intanprod-llee.luiss.it/download/ (accessed: 12.07.2024)

[3] https://web.archive.org/web/20211105161700/http://euklems.net/

industries and over time. It shows substantial increases in robot penetration across most of the industries with robotization, with few industries experiencing an initial increase and stagnation or even a slight decrease in robot exposure, between 1993 and 2017. The largest increases were denoted in chemical industry (pharma cosmetics) where the robot penetration has grown by 836 robots per 10,000 workers employed in 1993; followed by automotive industry (596) and metal (294). When adjusting for the sectoral output growth, these patterns remain largely similar, although the robotization growth in plastics subdivision of the chemical industry becomes visibly more pronounced.

As a last step, we match the APR measures with the register data by years and sectors. The Swedish data follows the national SNI-schema, which is highly compatible with ISIC at aggregate levels. While matching, we follow the strategy of finding the most detailed sectoral level at which the information can be ascribed. In the end, we have APR measures attached to employees with distinct values for 10 manufacturing subsectors (or subsector groups)[4] and five broader sectors in which robots are used (Agriculture, forestry and fishing; Mining and quarrying; Electricity, gas, steam and water supply; Construction; Education), which vary over time.

4.4. Sample

As the main outcomes are childbearing and partnership behaviours, we limit the age span to those between age 18 to 45. Hence, our analytical sample includes the 1950 to 1999 birth cohort, including non-Swedish born immigrants who moved before the age of 18. Our observation period starts in 1994 given the availability of the data on operation stock of robots for Sweden. Nonetheless, this year corresponds well with the onset of the robotization in the country as well as in many other advanced economies (Chiacchio et al.2018). We thus focus on individuals who enter the risk set during our observation period, i.e. 1994 to 2017. Individuals are considered at risk of entering first marriage or first birth since they are 18, at risk of divorce since they marry and at risk of second or third conception since the birth of their youngest child. We right censor on event, death, first out-migration, after age 45 and after the last observation period (2017).

This sample is further stratified by gender (as we are not able to match cohabiting partners prior to 2011) and divided into subsamples of never married individuals for the study of

[4] Notably, the data covers all of manufacturing.

the transition into first marriage (N= 3,044,492 women and N= 3,194,278 men); married individuals for the study of the transition to divorce (N= 943,383 women and N= 1,052,766 men); childless individuals for the transition to first birth (N= 3,044,492 women and N= 3,194,278 men); parents of one child for the transition to second child (N= 1,905,918 women and N= 1,730,808 men); parents of two children for the transition to third child (N= 1,487,243 women and N=1,317,357).

5. Analytical Strategy

5.1. Base Models

We model transitions to first, second, and third conception, as well as entry into first marriage and first divorce. Because conception is not directly observed in the register data, we date it nine months prior to a live birth. The processes are estimated using piecewise constant event-history models, fitted separately for women and men.

Our main explanatory variable is exposure to robotization, measured by the adjusted penetration of robots (APR). It is standardized at the population level to have a mean of zero and a standard deviation of one, which allows the estimated coefficients to be interpreted as the effect of a one standard-deviation increase in robotization on the hazard of the respective event. Since variation in sectoral robotization is relevant only for individuals in employment, in particular for those employed in sectors in which robots are used, all models include controls for current employment status and for working in a robotized sector. Individuals who are not employed or who work in sectors without robotization are assigned an APR value of zero. This modelling strategy ensures that the estimated association between APR and family transitions is not confounded with general differences between employed and non-employed individuals or between robotized and non-robotized sectors.

Importantly, robotization may also affect the family behaviours of individuals who are no longer employed and who may have exited sectors undergoing automation. Because APR is defined only for current employment, it does not capture the experiences of those who leave employment, potentially as a consequence of robotization. To account for this, we also introduce an additional variable capturing the level of robotization in the sector of an individual's most recent job among those who are currently not employed. The APR of the last job sector serves as a proxy for the difficulties individuals may face in re-entering employment, insofar as recent experience in a highly robotized sector may signal that their skills have become redundant. As in the case of current APR, we additionally include dummy controls indicating whether the last job was in a robotized sector, ensuring that the estimated effects reflect variation in the intensity of robotization rather than differences between sectors per se.

Models that include current APR and the APR of the last job sector are denoted as Models 1a–e (with a–e referring to marriage, first, second, and third birth, and divorce). These models estimate average associations between exposure to robotization and family-related behaviours within sectors. However, prior research consistently shows that robotization disproportionately disadvantages low- and middle-educated workers, while highly educated workers may benefit. To account for this heterogeneity, in a third step we interact current APR with educational attainment. We abstain from interacting APR of the last job with educational attainment since individuals who left the robotizing sector and remain out of work are rarely highly educated (which is also reflected in our data). Educational attainment is categorized according to the ISCED 2011 classification into basic education (levels I–III), post–upper secondary education (levels IV–V), and tertiary education (levels VI–VIII). These categories correspond closely to labour market sorting by skill level and formal requirements and are commonly used in studies of educational gradients in fertility in Sweden and the Nordic countries. These interaction models are denoted as Models 2a–e.

In addition, all models control for age, age squared, and calendar period (1994–2006, 2007–2009, and 2010–2017). We also control for current enrolment in education and being born in Sweden. In models of divorce, we also control for marriage duration, while in models of second and third births we include controls for the age of the youngest child .

5.2. Instrumental Variable Regressions

Finally, we adopt an instrumental-variable framework to strengthen the causal interpretation of the estimated association between robotization and family formation outcomes. Although our baseline models document associations between APR and family transitions, these estimates may be biased if unobserved factors influence both sectoral robot adoption and individual family behavior. For instance, sudden shifts in demand, long-term structural changes, or unobserved changes in workplace conditions could simultaneously affect automation and workers' fertility or partnership behaviours.

To mitigate this concern, we instrument robotization in Swedish sectors with robot adoption in the corresponding sectors of another country, following a strategy widely applied in economics (e.g., Acemoglu and Restrepo 2020; Dauth et al. 2021). This approach takes advantage of cross-national differences in robot adoption that stem from global technological developments rather than domestic, country-specific forces. The identification of model coefficients relies on two assumptions. First, the exclusion restriction requires that robotization in a given sector abroad does not directly affect family behavior in Sweden, except through its relationship with robot adoption in Sweden. Second, the relevance restriction demands that sectoral patterns of robot adoption are correlated across countries because they are driven by shared global technological trends, such as declining robot costs or advances in robotic capabilities, that similarly influence firms' incentives to automate across advanced economies. Under these conditions, foreign sector-level robotization generates plausibly exogenous variation in Swedish robot adoption.

To this end, we consider two neighboring countries for which comparable robot data are available, Denmark and Finland. Due to limitations in IFR data coverage for Denmark[5], we use Finland as the source country for the instrument. We construct Finnish sector-level APR measures following the same procedure as for Sweden, with the exception that sectoral employment data are taken from EU KLEMS rather than population registers, to which we do not have access for Finland. The resulting Finnish APR varies by sector and year and is used as an instrument for the corresponding Swedish APR.

The instrumental-variable models are estimated within a survival-analysis framework using a generalized method of moments (GMM) Poisson regression, as the Poisson regression models can provide estimates equivalent to continuous-time proportional hazard models (see Rodríguez 2007, Chapter 7). This allows the instrumental-variable approach to be integrated with our event-history setup. Estimation is implemented using the *ivpoisson gmm* command in Stata, following the procedure outlined by Hogendoorn et al. (2021) and related methodological guidance (Statalist 2017). In all other respects, the instrumental-variable models, denoted as Models 3a–e and 4a–e. mirror the corresponding baseline specifications, i.e. Models 1a–e to 2a–e.

6. Results

This Section presents our empirical findings. We first briefly discuss the findings from Models 1a–e which present the overall effects of the sectoral exposure to automation on family

[5] Up until 1997, all robot stocks in Denmark are matched to the "Unspecified" sector category. Afterwards, new robot inflows are matched with specific sectors, but this categorization does not extend backwards. In other words, for the next period, most of the robots remain in the unspecified category until their eventual deprecation and substitution with newer robots.

behaviours for women and men. We then move to discussing the effects by educational attainment (Models 2a–e). Finally we present our models with instrumental variables. Since they were estimated on the whole population of workers in Sweden meeting the pre-specified criteria (e.g. age, sex), we do not report statistical significance of our estimates but rather focus on interpreting the magnitude of the estimated coefficients.

6.1. Total Effects of Robotization on Family Behaviours

Table 1 presents estimates from Models 1a–e. The coefficient labelled Current work APR captures the effect of a one standard-deviation increase in robotization on the hazard of experiencing a given event among individuals who are currently employed in a robotizing sector. The coefficient labelled Last job APR captures the corresponding association for individuals who exited employment in a robotizing sector and are currently non-employed.

Overall, the estimated associations between robotization and family transitions are small and generally close to zero for both women and men. The largest effect of current exposure to robotization is observed for men's transition to first birth, where a one–standard-deviation increase in APR is associated with a hazard ratio (HR) of 0.96, corresponding to a 4% reduction in the risk of becoming a father. For all other outcomes, effects of current APR are modest and statistically close to null.

In contrast, exposure to robotization appears more consequential for individuals who exited employment in robotizing sectors, as captured by Last job APR. Higher levels of robotization in the sector of the last job are consistently associated with lower fertility risks. Among women, a one–standard-deviation increase in robotization in the sector they exited is associated with a 10% lower risk of transition to first birth, a 4% lower risk of second birth, and an 11% lower risk of third birth. Among men, the corresponding reductions amount to 9%, 4%, and 3%, respectively.

For men, fast job APR is also associated with partnership dynamics, unlike for women. Men whose most recent job was in a more highly robotized sector exhibit lower marriage risks (HR = 0.94) and higher divorce risks (HR = 1.05). These patterns suggest that exit from highly automated sectors is linked not only to reduced fertility but also to weaker union formation and stability among men. For women, by contrast, the estimated associations between robotization in the last job sector and marriage or divorce are negligible.

Table 1. Survival regression analysis of the effects of robotisation on family formation, hazard ratios from Models 1a–e

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR	0.99 (0.00)	1.02 (0.00)	0.97 (0.01)	1.01 (0.00)	1.01 (0.01)
- Sector with robots	1.06 (0.00)	0.98 (0.00)	0.94 (0.01)	1.02 (0.00)	0.98 (0.01)
Last job (non-worker)					
- APR	0.90 (0.02)	0.96 (0.02)	0.89 (0.03)	0.99 (0.02)	1.02 (0.04)
- Sector with robots	1.31 (0.02)	0.99 (0.01)	0.94 (0.01)	1.08 (0.01)	1.02 (0.02)
Worker	1.76 (0.01)	1.07 (0.00)	0.96 (0.00)	1.04 (0.00)	1.18 (0.01)
Education					
- post upper-secondary	1.12 (0.00)	1.41 (0.00)	1.21 (0.01)	1.42 (0.00)	0.68 (0.00)
- tertiary	1.44 (0.01)	1.75 (0.01)	1.73 (0.01)	1.96 (0.01)	0.53 (0.01)
Observations	13,085,578	3,298,622	8,845,412	19,820,292	8,745,552
Men	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR	0.96 (0.00)	1.00 (0.00)	1.00 (0.00)	0.99 (0.00)	1.02 (0.01)
- Sector with robots	1.04 (0.00)	0.99 (0.00)	0.93 (0.00)	0.94 (0.00)	0.92 (0.01)
Last job (non-worker)					
- APR	0.91 (0.01)	0.96 (0.02)	0.97 (0.02)	0.94 (0.02)	1.05 (0.03)
- Sector with robots	1.41 (0.01)	1.01 (0.01)	0.93 (0.01)	1.23 (0.01)	1.06 (0.02)
Worker	2.00 (0.01)	1.30 (0.01)	0.79 (0.01)	2.21 (0.01)	0.64 (0.01)
Education					
- post upper-secondary	1.11 (0.00)	1.35 (0.00)	1.09 (0.01)	1.39 (0.00)	0.67 (0.00)
- tertiary	1.44 (0.01)	1.62 (0.01)	1.42 (0.01)	1.85 (0.01)	0.50 (0.01)
Observations	17,374,799	3,225,216	7,148,925	23,285,762	7,253,724

Note: regressions include controls for period (1994–2006, 2007–2009, 2010–2017), age, age squared, being born in Sweden, being in education. In addition, models of divorce also control for marriage duration, while models of second and third births for the age of the youngest child. Standard errors clustered at sector and ID levels.

6.2. Heterogeneity by Educational Attainment

Not all workers are vulnerable to robotization in the same way. Prior studies have highlighted that technological change affects non-routine cognitive jobs – typically associated with higher-skilled labour – differently to routine and manual jobs, which are typically associated with lower-skilled labour. Thus, in Models 2a–e we have allowed for the Hazard Ratios (HR) for robotization to vary across education levels. The results are reported in Table 2.

We find that the overall negligible effect of robotization can be attributed to high heterogeneity of the effects across different populations of workers. Those with tertiary education are, in fact, more likely to have children in connection with robotization in their sectors. They are also more likely to marry and less likely to divorce. The opposite can be often said of those with basic or secondary education who seem to suffer the brunt of the effects of robotization.

For women with basic education the HR of giving birth or entering first marriage remain close to 1. At the same time, they experience an increase in the risk of divorce with an increase in automation (HR: 1.05). In case of secondary-educated women, an increase in automation by is related to a decline in the of 1st (HR: 0.97) and 3rd birth risks (HR: 0.95) and a rather negligible increase in the risk of divorce (HR: 1.03). These estimates are especially considerable when compared with those for tertiary-educated women who have higher risks of both first and second parities (1.03 and 1.05, respectively), higher risks of marriage (1.03) and much lower risks of divorce (0.86) when the robotization of their sector increases.

These differences are even stronger among male workers. Men with basic education become less likely to have 1st child (HR: 0.94) and or marry (HR: 0.98) as robotization in their sectors increases. They are, however, more likely to get divorced (HR: 1.06). These effects are smaller for those with secondary education and reversed for those with tertiary education. A one SD increase in robotization for highly educated corresponds to a 1st parity HR of 1.05, marriage HR of 1.03 and divorce HR of 0.88.

Table 2. Survival regression analysis of the effects of robotisation on family formation, Models 2a–e

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR # Basic educ.	1.01 (0.01)	0.99 (0.01)	0.98 (0.01)	1.02 (0.01)	1.05 (0.01)
- APR # Post up/sec.	0.97 (0.01)	1.02 (0.01)	0.95 (0.02)	1.01 (0.01)	1.03 (0.02)
- APR # Tertiary	1.03 (0.01)	1.05 (0.01)	1.01 (0.02)	1.03 (0.01)	0.86 (0.02)
- Sector with robots	1.01 (0.01)	0.93 (0.01)	0.87 (0.01)	0.99 (0.01)	1.05 (0.02)
Last job (non-worker)					
- APR	0.90 (0.02)	0.96 (0.02)	0.89 (0.03)	0.98 (0.02)	1.02 (0.04)
- Sector with robots	1.31 (0.02)	0.99 (0.01)	0.94 (0.01)	1.08 (0.01)	1.02 (0.02)
Worker	1.76 (0.01)	1.07 (0.00)	0.95 (0.00)	1.04 (0.00)	1.18 (0.01)
Education					
- post upper-secondary	1.08 (0.00)	1.40 (0.00)	1.20 (0.01)	1.38 (0.00)	0.68 (0.00)
- tertiary	1.44 (0.01)	1.77 (0.01)	1.77 (0.01)	1.95 (0.01)	0.51 (0.01)
Observations	13,085,578	3,298,622	8,845,412	19,820,292	8,745,552
Men	(6) 1st parity	(7) 2nd parity	(8) 3rd parity	(9) marriage	(10) divorce
Current work					
- APR # Basic educ.	0.94 (0.00)	0.99 (0.00)	1.02 (0.01)	0.98 (0.00)	1.06 (0.01)
- APR # Post up/sec.	0.99 (0.01)	1.01 (0.01)	0.98 (0.01)	1.00 (0.01)	0.95 (0.01)
- APR # Tertiary	1.05 (0.01)	1.03 (0.01)	0.97 (0.01)	1.03 (0.01)	0.88 (0.02)
- Sector with robots	0.95 (0.01)	0.96 (0.01)	0.89 (0.01)	0.94 (0.01)	0.94 (0.02)

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Last job (non-worker)					
- APR	0.91 (0.01)	0.96 (0.02)	0.97 (0.02)	0.94 (0.02)	1.05 (0.03)
- Sector with robots	0.95 (0.01)	1.01 (0.01)	0.93 (0.01)	1.22 (0.01)	1.06 (0.02)
Worker	2.00 (0.01)	1.30 (0.01)	0.79 (0.01)	2.21 (0.01)	0.64 (0.01)
Education					
- post upper-secondary	1.11 (0.00)	1.36 (0.01)	1.08 (0.01)	1.38 (0.00)	0.67 (0.01)
- tertiary	1.48 (0.01)	1.64 (0.01)	1.44 (0.01)	1.85 (0.01)	0.49 (0.01)
Observations	17,374,799	3,225,216	7,148,925	23,285,762	7,253,724

Note: regressions include controls for period (1994–2006, 2007–2009, 2010–2017), age, age squared, being born in Sweden, being in education. In addition, models of divorce also control for marriage duration, while models of second and third births for the age of the youngest child. Standard errors clustered at sector and ID levels.

6.3. Instrumental Variable Approach

To assess the robustness of our findings and to strengthen causal interpretation, we additionally estimated analogous models using an instrumental-variable approach (Tables 3 and 4). Overall, the IV estimates closely mirror the results from the baseline survival regressions, both in terms of direction and magnitude of the effects. In some cases, the IV results point to slightly stronger negative effects of robotization on family-related behaviours, particularly for transitions to first birth and first marriage among men who exited employment in robotizing sectors.

The main divergence between the two approaches concerns the estimated effect of robotization on divorce among women who left robotizing sectors. While the baseline survival models indicate virtually no association between sectoral automation and divorce risks for these women, the IV estimates suggest a modest negative effect (HR = 0.95). Apart from this difference, the substantive conclusions remain unchanged, with only minor variations in effect sizes across specifications.

Table 3. Instrumental variable Poisson regression of the effects of robotisation on family formation

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR	0.98 (0.04)	1.03 (0.02)	0.97 (0.02)	1.01 (0.03)	1.02 (0.02)
- Sector with robots	1.05 (0.13)	0.98 (0.05)	0.94 (0.05)	1.02 (0.12)	0.98 (0.03)
Last job (non-worker)					
- APR	0.88 (0.07)	0.94 (0.04)	0.91 (0.06)	0.97 (0.07)	0.95 (0.06)
- Sector with robots	1.30 (0.19)	0.98 (0.06)	0.94 (0.07)	1.08 (0.14)	1.00 (0.04)
Worker	1.76 (0.31)	1.07 (0.08)	0.96 (0.09)	1.04 (0.18)	1.18 (0.06)
Education					
- post upper-secondary	1.12 (0.19)	1.41 (0.11)	1.21 (0.10)	1.42 (0.21)	0.68 (0.03)
- tertiary	1.44 (0.27)	1.75 (0.15)	1.73 (0.16)	1.96 (0.32)	0.53 (0.02)

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Men	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR	0.94 (0.04)	1.00 (0.02)	1.02 (0.02)	0.99 (0.04)	1.03 (0.02)
- Sector with robots	1.04 (0.14)	0.99 (0.05)	0.93 (0.05)	0.94 (0.12)	0.92 (0.04)
Last job (non-worker)					
- APR	0.83 (0.06)	0.94 (0.03)	0.94 (0.04)	0.87 (0.06)	1.07 (0.05)
- Sector with robots	1.39 (0.20)	1.01 (0.06)	0.92 (0.05)	1.21 (0.16)	1.07 (0.05)
Worker	2.00 (0.35)	1.30 (0.09)	0.79 (0.06)	2.21 (0.35)	0.64 (0.04)
Education					
- post upper-secondary	1.11 (0.16)	1.35 (0.09)	1.09 (0.07)	1.39 (0.21)	0.67 (0.03)
- tertiary	1.44 (0.24)	1.62 (0.12)	1.42 (0.11)	1.85 (0.30)	0.50 (0.02)

Note: regressions include controls for period (1994–2006, 2007–2009, 2010–2017), age, age squared, being born in Sweden, education levels and studying. Models estimated using the generalized method of moments. Standard errors clustered at sector and ID levels.

Table 4. Instrumental variable Poisson regression of the effects of robotisation on family formation, by education levels

Women	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR # Basic educ.	1.01 (0.05)	0.99 (0.02)	1.00 (0.03)	1.04 (0.05)	1.08 (0.02)
- APR # Post up/sec.	0.95 (0.05)	1.04 (0.02)	0.92 (0.03)	1.00 (0.05)	1.05 (0.02)
- APR # Tertiary	1.05 (0.04)	1.07 (0.02)	1.01 (0.03)	1.04 (0.04)	0.83 (0.03)
- Sector with robots	1.02 (0.19)	0.93 (0.08)	0.87 (0.08)	1.00 (0.17)	1.03 (0.05)
Last job (non-worker)					
- APR	0.87 (0.07)	0.95 (0.04)	0.91 (0.06)	0.97 (0.07)	0.95 (0.06)
- Sector with robots	1.30 (0.19)	0.98 (0.06)	0.94 (0.07)	1.08 (0.14)	1.00 (0.04)
Worker	1.76 (0.31)	1.07 (0.08)	0.95 (0.09)	1.04 (0.18)	1.18 (0.06)
Education					
- post upper-secondary	1.08 (0.21)	1.40 (0.12)	1.20 (0.11)	1.38 (0.24)	0.68 (0.03)
- tertiary	1.44 (0.35)	1.77 (0.17)	1.77 (0.20)	1.95 (0.41)	0.51 (0.03)
Men	(a) 1st parity	(b) 2nd parity	(c) 3rd parity	(d) marriage	(e) divorce
Current work					
- APR # Basic educ.	0.91 (0.05)	0.98 (0.02)	1.04 (0.02)	0.98 (0.05)	1.08 (0.02)
- APR # Post up/sec.	0.98 (0.05)	1.02 (0.02)	0.97 (0.03)	1.01 (0.05)	0.94 (0.03)
- APR # Tertiary	1.06 (0.06)	1.04 (0.02)	0.95 (0.03)	1.04 (0.05)	0.82 (0.03)
- Sector with robots	0.95 (0.18)	0.96 (0.08)	0.88 (0.08)	0.94 (0.18)	0.93 (0.05)
Last job (non-worker)					
- APR	0.83 (0.06)	0.94 (0.03)	0.94 (0.04)	0.87 (0.06)	1.07 (0.05)
- Sector with robots	1.39 (0.20)	1.01 (0.06)	0.92 (0.05)	1.21 (0.16)	1.07 (0.05)
Worker	2.00 (0.36)	1.30 (0.10)	0.79 (0.06)	2.21 (0.36)	0.64 (0.04)
Education					
- post upper-secondary	1.11 (0.22)	1.36 (0.13)	1.08 (0.10)	1.38 (0.29)	0.67 (0.04)
- tertiary	1.48 (0.36)	1.64 (0.18)	1.45 (0.16)	1.85 (0.45)	0.49 (0.03)

Note: regressions include controls for period (1994–2006, 2007–2009, 2010–2017), age, age squared, being born in Sweden, education levels, studying and interactions between education levels and working in sectors with robots. Models estimated using the generalized method of moments. Standard errors clustered at sector and ID levels.

7. Discussion

In this paper, we examined whether long-term structural labour market change driven by the adoption of labour-replacing technologies, specifically industrial robots, has contributed to changes in family formation and union stability. Our starting point was that the implementation of labour-replacing technologies may generate anxiety and psychological distress among exposed workers, predominantly those with low and medium levels of education, and lead to a deterioration of their working conditions, thereby undermining workers' attractiveness on the marriage market and constraining their opportunities for family formation. We situated our analysis in Sweden, a country that ranks among the global leaders in robot adoption—following East Asian economies such as Singapore, South Korea, and China, as well as Germany. Using population-wide register data linked to sector-level measures of robot penetration between 1994 and 2017, we analysed transitions into first marriage, first, second, and third births, and divorce. We distinguished between current exposure to robotization among employed workers and residual exposure among individuals who had exited employment in robotizing sectors. Given strong evidence that the labour market consequences of automation differ by skill level, we further examined heterogeneity in family responses by educational attainment. In addition to standard event-history models, we implemented an instrumental-variable strategy to strengthen causal interpretation.

Our findings suggest that, on average, sectoral exposure to robotization is only modestly linked to fertility and partnership transitions in Sweden. Associations between current exposure to automation and transitions to first, second, and third births are generally small and close to zero for both women and men. More substantial effects emerge among individuals who exited employment in robotizing sectors, particularly with respect to entry into parenthood. A one–standard-deviation increase in robotization in the exited sector is associated with a 12% reduction in first-birth risks among women and a 17% reduction among men. Among men, we additionally observe pronounced negative effects of sectoral robotization on marriage formation and marital stability, amounting to a 13% lower risk of marriage and a 7% higher risk of divorce. These findings are consistent with prior evidence for Sweden showing that post-recession fertility decline has been driven primarily by falling first-birth rates (Ohlsson-Wijk and Andersson 2022), and they resonate with evidence from the United States demonstrating that exposure to automation undermines men's attractiveness on the marriage market (Autor et al. 2019). Notably, our results indicate that such mechanisms may also operate in a highly gender-egalitarian context such as Sweden.

These average effects conceal substantial heterogeneity. Once we allow the effects of robotization to vary by educational attainment, a clear pattern emerges: automation appears to widen educational differentials in family formation and stability. Among low- and medium-educated women and men, higher sectoral exposure to robotization is associated with lower first-birth risks, weaker marriage formation, and elevated divorce risks. In contrast, among highly educated individuals, exposure to automation is either unrelated or positively associated with fertility and partnership stability. These patterns are robust across baseline and instrumental-variable specifications and contribute to the ongoing reversal of the educational gradient in fertility (Jalovaara et al.2019, 2022) and partnership stability (Härkönen and Dronkers 2006; Matysiak et al. 2014). Our findings thus suggest that workers with lower educational attainment, who are more exposed to deteriorating labour market prospects under automation, face not only restricted access to stable employment and income but also diminished opportunities for stable partnerships and parenthood. In this sense, technological change contributes to cumulative disadvantage, whereby labour market marginalization spills over into the family domain.

Despite these widening educational disparities, the overall contribution of robotization to the Swedish post-recession fertility decline appears limited. Although we argued that ongoing robotization might have contributed to the downward trend in aggregate fertility by becoming more widespread by the end of 2010s, our findings illustrate that the effects of sectoral exposure to automation on family behaviours are in general small and apply primarily to workers directly affected by automation in manufacturing, which makes their contribution to aggregate fertility decline negligible. Even the larger effects observed among individuals who exited robotizing sectors are unlikely to have played a major role in aggregate fertility trends, given that robotization rarely leads to long-term unemployment but more often to re-employment in lower-quality jobs. Nevertheless, the Swedish context is distinctive. Generous unemployment benefits, active labour market policies, strong union density, collective bargaining, and strong employment protection, typical of the Swedish institutional setting, may buffer workers from the most severe consequences of technological displacement and thereby attenuate its demographic effects. It is therefore plausible that similar processes could have more pronounced family consequences in institutional settings with weaker social protection. Future research should extend this line of inquiry to other policy contexts to assess the generalisability of our findings.

Our study focuses on one type of labour-replacing technology that has been particularly prevalent in manufacturing: industrial robots. It may therefore be questioned whether our findings remain relevant in light of the rapid expansion of generative AI. We argue that they do, for two reasons. First, advances in AI are likely to further accelerate robot diffusion by expanding robots' functional capabilities (i.e. enabling real-time responses), and by reducing robot costs, thereby broadening their application beyond manufacturing. Second, there is preliminary evidence that generative AI disproportionately limits employment opportunities for labour market entrants and young graduates by substituting tasks typically performed by inexperienced workers (Brynjolfsson et al., 2025). Given that our study demonstrates that automation affects family behaviours of workers by affecting their labour market outocomes and that early-career labour market prospects strongly determine family formation (Adsera 2004, Vignoli and Guetto 2025), we can expect generative AI to lead to further substantial postponement of family formation. Structural labour market change should therefore remain a central concern of demographic research.

Finally, this study is not without limitations. Although we draw on high-quality population register data covering the entire Swedish population, the data do not allow us to observe cohabiting unions prior to 2011. We were therefore unable to examine transitions into cohabitation, which is a central form of partnership in Sweden. It remains possible that robotization discourages marriage while encouraging cohabitation, a pattern we cannot assess. Moreover, we were unable to account for partners' joint exposure to automation, which could potentially amplify effects on childbearing. Finally, our measure of automation operates at the sectoral level. While widely used in the economic literature, sector-level measures cannot capture firm-level heterogeneity in automation exposure, which may more directly shape displacement risks for individual workers. This limitation is common to much of the existing literature and does not undermine our central conclusion: structural technological change reshapes workers' labour market trajectories and, through them, their family behaviours.

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Annexes

Robot penetration rates

Table A1. (Adjusted) robot penetration rate by year and industry

Sector	Robot penetration rate (per 10,000 workers in 1993)			Adjusted robot penetration rate		
	1994	2005	2017	1994	2005	2017
Food, beverage & tobacco	0,0	32,8	99,1	0,0	32,8	99,1
Textiles	0,0	0,4	2,0	0,0	0,4	2,0
Wood and paper	0,0	3,0	68,6	0,0	9,0	20,6
Chemical: pharma costmetics	0,0	66,6	835,7	0,0	66,6	835,7
Chemical: unspecified	0,0	0,0	1,1	0,0	0,0	1,1
Chemical: plastics & other	0,0	21,1	11,8	0,0	28,1	170,9
Metal:basic	0,1	165,4	293,5	0,5	127,2	232,3
Electronics	0,2	60,6	17,9	0,2	60,6	17,9
Metal: industrial	0,3	32,7	147,7	0,3	32,7	147,7
Automotive	1,6	420,1	596,0	1,2	304,4	423,0
Other manufacturing	0,9	61,7	184,4	0,9	61,7	184,4
Agriculture & forestry	0,0	0,1	2,5	0,0	0,1	2,5
Mining & quarrying	0,0	0,0	46,9	0,0	0,0	46,9
Electricity, Gas, water	0,0	0,3	2,5	0,0	0,3	2,5
Construction	0,0	1,6	0,6	0,0	1,6	0,6
Education, R&D	0,0	3,4	2,7	0,0	3,4	2,7

Deriving sectoral data

The EU KLEMS data used in this study comes from two sources. The data for 1995–2017 comes from LUISS Lab of European Economics[6]. We extend this data to 1993 using an older, archived 2017 EU KLEMS release for Sweden[7]. While both sources follow the same general sectoral classification, some of the information is provided at different levels of detail in both datasets. In cases where the older release years have less detailed information, we calculate shares of subsectors in a group in 1995 and use these shares to disaggregate the older release data for years 1993–1995.[8] While both data releases cover 1995, the values are not a 100%

[6] EUKLEMS & INTANPROD – Release 2021: https://euklems-intanprod-llee.luiss.it/download/ (accessed: 12.07.2024)

[7] https://web.archive.org/web/20211105161700/http://euklems.net/

[8] For example, the 1993-1994 data have a joint "26-27" category, but the newer dataset splits the values between "26" and "27". We calculate the shares of the individual sectors in the broader category, and split the broader category in earlier years accordingly. We do the same for sectors: "68A" (broader sector "L"); "86" and "87-88" (broader "Q"); "D" and "E" (broader sector "D-E"); "M" and "N" (broader sector "M-N"); from "49" to "51" (broader sector "H").

match. Thus, for each sector, we calculate the relationship between the values for 1995 in both releases and adjust the older release values for 1993–1994 by the same factor. Finally, the EU KLEMS data lacks information on output growths for sectors “20” and “21” in Sweden. We impute these values from the data for Denmark. The resulting data consistently cover the same set of sectors across 1993–2017.

University of Warsaw
Faculty of Economic Sciences
44/50 Długa St.
00-241 Warsaw
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