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Long-Run Effects of Technological Change: The Impact of Automation and Robots on Intergenerational Mobility

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ABSTRACT

This paper examines whether advancements in automation and robotics have affected intergenerational income mobility. Using detailed data on all individuals and firms in Sweden from 1985 to 2017, we analyze how parental exposure to robots at the occupational level and the heterogeneous adoption of robots across industries influence children's outcomes in adulthood. Our results show that parents' occupational exposure to robots is associated with lower income mobility for their children. Taking into account exposure at the occupational and industry levels, we find that the negative impact on intergenerational mobility originates from industries with a relatively large increase in robot adoption. Our results also indicate that children with exposed parents are worse off with regard to several labor market and family-related outcomes, including higher risks of unemployment and being out of the labor force. Overall, our paper reveals a new determinant that shapes intergenerational mobility and highlights that advancements in automation and robotics can have long-lasting effects on society.

Keywords: Intergenerational Mobility; Automation; Robots; Matched Employer–Employee Data
JEL Codes: J24; J31; J62; O33

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1 Introduction

The degree to which children are affected by their parents' labor market outcomes influences how they can shape their future. Empirical evidence from various countries shows that intergenerational mobility is an important determinant of inequality and the future well-being of children (see Black and Devereux (2010) and Cholli and Durlauf (2022) for two literature surveys on intergenerational mobility). The vast majority of papers in this field of literature focus on income mobility. Despite significant differences across countries and time, most studies show a relatively high correlation between the incomes of parents and children.[1]

A recent stream of literature analyzes the determinants of these differences. Thus far, several determinants have been studied: genetic factors, parental education, and childhood exposure to residential segregation and school quality. These also include the impact of macroeconomic conditions and shocks to the economy, such as economic downturns, trade liberalizations, firm closures, and natural resource booms.[2] However, little attention has been given to how automation and the increased use of industrial robots, which are two of the most important structural changes affecting labor markets in recent decades, have shaped intergenerational mobility.

This paper aims to fill this gap by analyzing whether automation and robot adoption have shaped how parents influence children's earnings in adulthood. The lack of evidence in this area is surprising given the recent literature on how new technologies, such as information and communications technology (ICT), robots, and artificial intelligence (AI), have influenced different labor market outcomes (Acemoglu and Restrepo, 2020).

Currently, it is well understood that recent technological advancements have affected labor markets and the organization of jobs and production. One insight is that the increased use of

[1] A higher correlation implies lower mobility across generations; thus, countries with a high degree of intergenerational transmission also have lower economic and social mobility.

[2] See Oreopoulos, Page, and Stevens (2008); Rege, Telle, and Votruba (2011); Stevens and Schaller (2011); Chetty, Hendren, Kline, and Saez (2014); Feigenbaum (2015); Chetty and Hendren (2018); Ahsan and Chatterjee (2017); Lundborg, Nordin, and Rooth (2018); Bütikofer, Dalla-Zuanna, and Salvanes (2020); Hirvonen, Stenhammar, and Tuhkuri (2022); Nybom and Stuhler (2021).

robots and ICT has been skill-biased and that the automation of routine-intensive occupations has contributed to increased wage inequality and job polarization.[3] Recent empirical papers on automation have focused mainly on the direct effects on firms and workers.[4] While new technologies can replace workers who perform routine job tasks (the replacement effect), they can also increase the demand for non-routine workers through a productivity effect. Hence, the replacement and productivity effects suggest that there should be heterogeneous effects across occupations depending on the job tasks involved.

In this paper, we take an intergenerational perspective and study the long-run effects of automation and robot adoption on income mobility, going beyond the direct effects. We base our analysis on comprehensive and detailed register data for Sweden from 1985 to 2017. These data are merged with data on measures of automation exposure and robot usage at different aggregation levels. Since Sweden has been at the forefront of implementing new technologies, it is suitable for studying the relationship between automation and intergenerational mobility.[5]

In our main empirical analysis, we run rank–rank regression models to study whether parental exposure to robots at the occupational and industry levels impacts children's adult outcomes up to 27 years later. Hence, we can distinguish when parents are likely to have been adversely affected by automation and when they are likely to have benefited from it. At the occupational level, we study robot and software exposure using two measures created by Webb (2020). These measures are based on the overlap between patent descriptions of new technologies and specific job description texts from O*NET. At the industry level, we use information on robot adoption from the International Federation of Robotics (IFR). These data include industry information on the stock of robots for

[3] See Autor, Levy, and Murnane (2003); Autor, Katz, and Kearney (2006); Autor et al. (2003); Goos and Manning (2007); Acemoglu and Autor (2011); Autor and Dorn (2009, 2013); Goos, Manning, and Salomons (2009, 2014); Acemoglu and Restrepo (2020); Acemoglu and Loebbing (2022).

[4] See Acemoglu, Koster, and Ozgen (2023a); Bessen, Goos, Salomons, and van den Berge (2020); Aghion, Antonin, Bunel, and Jaravel (2020); Hirvonen et al. (2022).

[5] Sweden had one of the highest ratings from the EU's Digital Economy and Society Index in 2022. From a global perspective, Sweden is ranked second, after the Netherlands, on the Networked Readiness Index published by the World Economic Forum in 2021. According to statistics from the International Federation of Robots (IFR), Sweden is ranked fifth globally and second in Europe in terms of number of installed robots per 10,000 workers (IFR, 2020).

over 20 countries.

Our basic results suggest that parents' occupational exposure to robots and software is associated with lower earnings for their children later in life and that higher exposure reduces earnings mobility across generations. Comparing intergenerational income mobility based on whether parents had a high- or low-exposure occupation, we find that the rank–rank correlation is more than 10 percent higher if the parent was in a high-exposure occupation instead of a low-exposure occupation.

However, comparing intergenerational income mobility between children with parents in high- and low-exposure occupations is problematic if other underlying differences impact income mobility but have nothing to do with automation. In addition, such a comparison does not uncover if differences in mobility result from parents in occupations replaced by robots being worse off and/or parents in non-replaceable occupations gaining from robot adaption. Therefore, we apply an instrumental variable (IV) approach with exogenous industry variation in robot penetration to identify the causal impact of automation and robot adoption on intergenerational income mobility.

Our results reveal that the direct impact of having a parent who worked in an industry with a significant positive change in robot adoption is negative for the child's income. Taking into account exposure at the occupational and industry levels, we find that the negative impact of occupational exposure on intergenerational mobility in earnings originates from industries with a relatively large increase in robot adoption, where income mobility is significantly lower if the parent had a high-robot-exposure occupation (as compared to a low-robot-exposure occupation). The relationship is substantially weaker for industries with low robot adoption, supporting the idea that our estimates capture the effect of automation. Based on various specifications, our results suggest that automation and robot adoption dampen intergenerational income mobility.

To further understand the long-run effects of automation, we complement the main analysis with several extensions. First, we look at upward mobility if the parent belonged to the bottom income quartile in 1990. Our estimates show that children with parents with high-robot-exposure occupations are three percentage points less likely to reach the top quartile of the income distribution if the parent worked in an industry with high robot adoption instead of low robot adoption.

Second, we analyze a wide range of additional children's outcomes in adulthood. Looking at earnings, unemployment risk, and the probability of being out of the labor force or going into early retirement, we find that children with parents in high-exposure occupations do worse if their parents worked in a high robot adoption industry; the earnings of children with parents in high-robot-adoption industries are, on average, 17.3 percentage points lower than those of children with parents in low-robot-adoption industries. This translates to a 4.6 lower earnings percentile rank. At least some of these worse economic outcomes are explained by a higher risk of being unemployed, being out of the labor force, and living on social benefits.

Third, we show that the negative impact of parental exposure to robots on children's expected earnings rank is almost 40% larger among low-income than among high-income parents. This suggests that automation may have affected overall inequality via an intergenerational channel.

By analyzing the effects of automation on intergenerational mobility, our paper is related to the literature on intergenerational mobility and to the literature that examines labor market consequences of automation and robot investments. Based on these strands of literature, the contribution of our paper is twofold.

First, a growing body of literature explores the determinants of intergenerational mobility. In this literature, Chetty et al. (2014) and Chetty and Hendren (2018) have shown that the spatial variation in intergenerational mobility across states and commuting zones in the U.S. is systematically correlated with residential segregation, income inequality, school quality, social capital, and family quality. In addition, parental job loss is shown to be associated with children doing worse in school (Rege et al., 2011; Stevens and Schaller, 2011) and having worse outcomes in adulthood (Oreopoulos et al., 2008). Other papers have looked at how macroeconomic conditions and shocks to the economy impact intergenerational mobility. Feigenbaum (2015) and Nybom and Stuhler (2021) find that economic downturns dampen mobility in earnings. Ahsan and Chatterjee (2017) show that an exogenous tariffs reduction in India, implying greater openness to trade, increased intergenerational mobility, and Bütikofer et al. (2020) find that the Norwegian oil boom had a positive impact on intergenerational income mobility. The study that is most related to our own is Berger and Engzell (2022), who analyze the spatial patterns of intergenerational mobility in the U.S. and show that upward mobility is lower in commuting zones that are more exposed to automation.

We add to this field of literature and show that structural changes in the labor market can impact intergenerational income mobility and present new evidence on the combined impact of occupational exposure to automation and the increased use of industrial robots on intergenerational income mobility. We study a multitude of outcomes and show that the effect of automation on intergenerational mobility is not homogeneous across occupations but instead depends on the parents' specific job task, which is a result that is in line with the implications of the task-based approach.

Our second contribution is to the literature on the labor market consequences of automation and robot adoption. Worker displacement and exposure to different new technologies are essential in this literature, as machines take over tasks previously performed by humans.[6] A recent empirical literature on how technological advancements affect labor demand has focused on robots. For instance, Graetz and Michaels (2018) use differences in robot adoption across industries in different countries and find that increases in industrial robots reduce the employment of low-skilled workers but tend to increase productivity and wages. Acemoglu and Restrepo (2020) rely on the same data and find adverse effects of robots on employment and wages in the U.S. commuting zones that are most exposed to robots. In a study of Germany, Dauth, Findeisen, Suedekum, and Woessner (2021) find no evidence that robots cause overall job losses but rather affect aggregate employment composition. While industrial robots impact employment negatively in the manufacturing sector, there is a positive and significant spillover effect as employment in the non-manufacturing sectors

[6] See for instance Autor et al. (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018, 2019, 2020); Benzell, Kotlikoff, LaGarda, and Sachs (2015). Evidence for Sweden are presented in Gardberg, Heyman, Norbäck, and Persson (2020) and Edin, Evans, Graetz, Hernnäs, and Michaels (2022).

increases. The evidence on how individual workers are affected by robot adoption is mixed, with Acemoglu and Restrepo (2020), Acemoglu, Koster, and Ozgen (2023b), (Dauth et al., 2021), Barth, Roed, Schøne, and Umblijs (2020) finding negative effects on production and low-skilled workers, while Aghion et al. (2020) find positive effects and Hirvonen et al. (2022) find zero effects.

We add to this literature by taking a long-run perspective and presenting new evidence on how occupational exposure to automation and heterogeneous adoption of robots across industries affect intergenerational mobility in earnings.

The article is organized as follows. Sections 2 and 3 present the empirical strategy and data. In Section 4, we conduct the empirical analysis. Section 5 offers several extensions to the analysis. Finally, Section 6 concludes the paper.

2 Empirical strategy

The starting point for our empirical analysis is the classic intergenerational mobility regression model relating outcomes across two generations:

$$Y^c = \alpha + \beta_1 Y^p + X'\theta + \epsilon^c, \tag{1}$$

where Y^c is the average outcome for child c during 2014ó17, and Y^p is the corresponding outcome of her parent p in 1990. The vector X consists of individual controls for children and parents separately and includes birth year fixed effects and an indicator variable for being a female or not. It also includes regional and industry fixed effects for the parents. Finally, ϵ^c is the error term. To allow for regional and industry correlation over time, we adjust standard errors for clustering at the regional and industry level.[7]

When we estimate Equation (1), our main analysis focuses on the rank–rank measure of income

[7] Our analysis is based on all available observations on children and parents; thus, for a child who has two parents working in 1990, both of the parent–child combinations are included in the regressions. To account for the "treatment dose", Table IA1 presents results using the average parental outcome. This analysis is based on a sub-sample of children with two parents working in 1990.

mobility based on the position of the child and parent in their respective birth cohort earnings distributions. As discussed by, e.g., Chetty et al. (2014), using the earnings rank instead of log earnings offers two advantages; first, it circumvents the problem of how to deal with observations with zero earnings, and second, it allows the relationship in log earnings over generations to be nonlinear.[8] In the rank–rank model, β_1 is interpreted as a rank parameter where a higher value means a tighter link across generations, indicating less mobility and a lower value means a higher degree of mobility between parents and children.

To analyze whether automation and robotics have affected intergenerational mobility, we augment the model in Equation (1) and allow the rank parameter to vary by parents' exposure to robots and software (automation risks) at the occupational level and changes in robot adoption at the industry level.

Using data on occupational exposure to new technologies, we estimate the following earnings rank–rank model:

$$Rank^c = \alpha + \beta_1 Rank_o^p + \beta_2 I(OccExposure_o^p) + \beta_3 Rank_o^p \times I(OccExposure_o^p) + X'\theta + \epsilon^c, \quad (2)$$

where $I(OccExposure_o^p)$ takes the value one if the underlying exposure measure $OccExposure_o^p$ is above the median and zero otherwise. We use two occupation-based measures, namely, (i) exposure to robots and (ii) exposure to software, which were created by Webb (2020) and are calculated as percentiles. Hence, the coefficient β_1 gives the rank–rank correlation when parents worked in a low-exposure occupation in 1990. The coefficient β_2 shows the average difference in children's percentile rank if the parent worked in a high-exposure occupation versus in a low-exposure occupation in 1990. Consequently, the interaction term coefficient β_3 gives the relative difference in rank mobility when the parent worked in a high-exposure occupation in 1990 versus a low-exposure occupation in 1990. If $\beta_3 > 0$, then the income mobility is lower if the parent worked

[8] Rank–rank correlations can also serve as a preferred measure if parental and child earnings are not measured at the same age (Nybom and Stuhler, 2017).

in a high-exposure occupation than in a low-exposure occupation (i.e., there is a relatively stronger relationship between the parent's and the child's earnings rank); conversely, if $\beta_3 < 0$, then the income mobility is higher if the parent worked in a high-exposure occupation. We also include the two occupational exposure measures as continuous variables as an alternative specification. Equation (2) contains the same set of parental and child controls as in Equation (1).

Comparing income mobility when parents worked in high- and low-exposure occupations is problematic if other underlying differences unrelated to automation and robotics impact income mobility. For instance, automation and digitalization have typically affected routine-intensive occupations in the middle of the income distribution (Autor and Dorn, 2013; Goos et al., 2014). At the same time, income mobility is not constant across income distributions. Palomino, Marrero, and Rodríguez (2018) find that the intergenerational income elasticity has a U-shaped pattern across the income distribution in the U.S., and Björklund, Roine, and Waldenström (2012) show that income mobility in Sweden is generally lower further up in the income distribution. Hence, in such cases, the coefficient β_3 reflects differences in both technology exposure and underlying differences across the income distribution.

To avoid the problem of underlying differences between children with parents in high- and low-exposure occupations, we utilize variation in the adoption of robots across industries in Sweden. Such an approach has been used in studies on the worker-level effects of import competition (Autor, Dorn, and Hanson, 2015; Autor, Dorn, Hanson, and Song, 2014) and on the impact of robot adoption (Dauth et al., 2021). The idea in these papers is that industry-level shocks have differential effects on workers originating from industry differences in exposure to trade and automation.

We construct the following variable that measures the change in robot adoption (operational stocks) in industry i over the period 1993–2015 relative to total employment in industry i in the pre-year 1990 ($L_{i,1990}$):

$$\Delta robots_i = \left(\frac{robots_{i,2015} - robots_{i,1993}}{L_{i,1990}}\right). \tag{3}$$

Our variable $\Delta robots_i$ varies across industries. As discussed in, e.g., Autor, Dorn, and Hanson (2013) on the impact of Chinese import competition and in Acemoglu and Restrepo (2019) and Dauth et al. (2021) on the impact of robot adoption, there is potentially a concern that this variable is correlated with domestic industry demand shocks. To address this endogeneity problem, we follow these papers and instrument Swedish robot adoption with robot adoption in other, comparable countries.[9] Here, we use the mean of robot adoption in all countries to build one instrument.

Using this approach, we estimate the following model:

$$Rank^c = \alpha + \beta_1 Rank_i^p + \beta_2 I(\Delta robots_i^p) + \beta_3 Rank_i^p \times I(\Delta robots_i^p) + X'\theta + \epsilon_i, \tag{4}$$

where $I(\Delta robots_i^p)$ is an indicator variable equal to one if $\Delta robots_i$ (the change in robot adoption per employee in industry i over the period 1993–2015) is above the median change and zero otherwise. In Equation (4), the coefficient β_1 captures the average intergenerational mobility if parents worked in an industry with relatively low robot adoption. The direct impact of $I(\Delta robots_i^p)$ is captured by the coefficient β_2, and the coefficient β_3 captures whether intergenerational mobility is different if parents worked in an industry with a high level of robot investments relative to an industry with a low level of such investments. Equation (4) includes the same set of controls as in Equation (1).

Finally, we combine Equations (2) and (4) to compare mobility when parents worked in occupations where the job task is complementary to or substitutable by robots in industries where robot adoption has developed differently:

[9] We use the same set of countries as that used in Dauth et al. (2021), exchanging Sweden with Germany. The countries used to construct the instrument are Finland, France, Germany, Italy, Norway, Spain, and the U.K. The starting year for some country–industry combinations is 1994. For those cases, we use 1994 as our first year.

$$
\begin{aligned}
Rank^c = \alpha + \beta_1 Rank^p_{oi} + \beta_2 I(\Delta robots^p_i) + \beta_3 I(OccExposure^p_o) + \beta_4 I(OccExposure^p_o) \times \\
I(\Delta robots^p_i) + \beta_5 Rank^p_{oi} \times I(\Delta robots^p_i) + \beta_6 Rank^p_{oi} \times I(OccExposure^p_o) + \\
\beta_7 I(OccExposure^p_o) \times I(\Delta robots^p_i) \times Rank^p_{oi} + X'\theta + \epsilon^c, \qquad (5)
\end{aligned}
$$

where the estimated coefficient for the triple interaction term β_7 captures whether intergenerational mobility is affected by both occupational and industry exposure. It is positive if the rank–rank correlation across generations is higher for children with parents who worked in a high-exposure occupation instead of a low-exposure occupation in an industry with a large increase in robot adoption. An advantage of this model is that it compares intergenerational mobility between high- and low-exposure occupations in high- versus low-exposure industries. Therefore, the model compares income mobility between parents with the same occupational robot exposure but with different industry exposure to robots. Alternatively, parents may be in the same industry but have different occupations.

3 Data

We use data at three different aggregation levels: 1) individual-level data on parents' and children's earnings, occupations, and demographics; 2) occupational-level data on exposure to new technologies based on two different measures created by Webb (2020); and 3) industry-level data on the stock of operating robots from the IFR.

3.1 Individual-level data

The individual-level data originate from three sources. The first source is the Longitudinal Integration Database for Health Insurance and Labor Market Studies (LISA). The LISA holds yearly information on all Swedish residents older than 15 years of age for the period 1990–2017 and provides us with individual-level data on labor earnings, occupations from 2001 and onwards, employment status, and demographic characteristics such as gender, highest attained educational level, and age. Labor earnings are gross annual earnings and must be reported to the Swedish Tax Authority if they exceed 100 SEK.

The second source is the Swedish Population and Housing Census (*Folk- och bostadsräkningen*), where we get information on parents' occupations and labor earnings in 1985 and 1990. The census covers the population in Sweden with a response rate of 98.8 in 1985 and 97.5 percent in 1990. Occupations are classified according to the Nordic Standard Occupational Classification, an early version of the Swedish Standard Classification of Occupation (SSYK) used from 2001 onward. The SSYK follows the International Standard Classification of Occupation (ISCO) with some adjustments for the Swedish labor market and originates from the official Wage Statistics Survey (*Lönestrukturstatistiken*) and supplementary surveys that Statistics Sweden undertakes on employers not included in the official wage survey.[10]

The third data source is the Swedish multi-generational register. This register covers the Swedish population and links parents to children born in 1932 or later, conditional on both parents and children having been registered as living in Sweden at some point from 1961 or later. Statistics Sweden provides both the LISA and the multi-generational register data.

To minimize any life cycle bias, we create a sample where children's and parents' earnings and occupations are measured around midlife.[11] We require children to have been born between 1972 and 1983 and their parents to have been between 25 and 65 years of age in 1990. In addition, we concentrate on parents with labor earnings of at least 50,000 SEK in 1990 to ensure that they

[10]Our analysis is based on SSYK96 at the 2-digit level, which is nearly identical to ISCO88. In the context of ISCO88 and SSYK96, a "job" is defined as "a set of tasks and duties which are (or can be assigned to be) carried out by one person". Occupations are grouped together and aggregated based on the similarity of skills required to fulfill the tasks and duties of the jobs. Detailed descriptions of occupations are found on the International Labor Organization (ILO) website: http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm.

[11]The association between current and lifetime earnings varies systematically over the life cycle (Haider and Solon, 2006; Böhlmark and Lindquist, 2006). Thus, if we use current earnings, the intergenerational elasticity estimate will vary depending on when the earnings are measured, reflecting the so-called life cycle bias. Nybom and Stuhler (2016) show that life cycle bias is smallest if earnings are measured around midlife.

are working.[12] Parents' earnings are measured as the average in 1985 and 1990, while children's earnings are calculated as their four-year average between 2014 and 2017. In total, the final sample contains 892,071 parents and 1,362,605 children. Table 1 shows that earnings are, on average, measured at midlife for both parents and children (41.5 years and 38.2 years). For parents, we calculate percentile earnings ranks within the sample and for children by birth cohort.

[Table 1 about here]

3.2 Occupational-level data on exposure to automation

Information on digitization and exposure to automation at the individual level is not directly available in our data. Instead, we use two recently constructed measures of occupational exposure to robot and software technologies developed by Webb (2020).[13] These measures are based on quantifying overlaps between patent descriptions and specific job description texts from the O*NET database. To assess how occupations are affected by these technologies, the method identifies what the technologies can do and then calculates the degree to which specific occupations involve performing similar tasks. Based on the patent text, the extent to which occupations require job tasks similar to what the technologies can do determines exposure to automation based on the different technologies.

Webb (2020) calculates robot and software exposure measures based on the 2010 U.S. Standard Occupational Classification (SOC). This classification is not used in Sweden or the E.U., and there is no direct translation from the SOC 2010 categories to the Swedish counterpart SSYK96. Therefore, we translate the U.S. classifications to the European occupational code, ISCO08, which can be translated to SSYK96.[14] The U.S. code is more detailed than the E.U. and Swedish occupational classifications; i.e., some European codes include several U.S. occupations (and vice versa in some cases). We account for this by using occupational employment weights from the Bureau of Labor

[12] In December 2022, 50,000 SEK corresponds to approximately 5,000 USD.
[13] We are grateful to Michael Webb for sharing these data with us.
[14] See http://www.bls.gov/soc/soccrosswalks.htm for a translation key between ISCO08 and SOC 2010.

Statistics (BLS) and Statistics Sweden when there is no 1:1 relationship between U.S. and European occupations. Furthermore, we use the new Swedish occupational classification SSYK2012 for translating ISCO08 to SSYK96.

The finalized measure of occupational exposure to automation is expressed as score percentiles for the intensity of patenting activity in a particular technology (robots and software) directed toward the tasks in that occupation. An occupation's overall score is calculated as the average of its task scores. As with earnings, we calculate the average occupational exposure in 1985 and 1990 for parents and the four-year average between 2014 and 2017 for children.

Table 2 shows the average exposure to robots and software for the years 1990, 2001, and 2017 in the Swedish economy. For both measures, we observe declining average automation risks during this time period. We can also see that the share of the workforce in occupations with exposure above the median, i.e., the 50th score percentile, has decreased. In addition, Figures 1 and 2 show that there is a negative correlation between occupational exposure ($OccExposure$) and the change in employment shares between 1990 and 2017. This pattern is present for both robot and software exposure. In high-exposure occupations, which are defined as those for which the exposure score is above the median, the employment change is, on average, negative, while in low-exposure occupations, the average change is positive. If we take these observations together, then the pattern emerging from Table 2 and Figures 1 and 2 is consistent with automation hurting employment in high-exposure occupations and having a positive impact on low-exposure occupations.

[Table 2 and Figures 1–2 about here]

Turning to our sample of parents, Figure 3 shows the correlations between occupational exposure to robots and software and various labor market outcomes during the period 1990-2001. The labor market outcomes are labor earnings, unemployment incidence, and whether a person is out of the labor force. The sub-figures clearly indicate that higher occupational exposure to robots among parents is associated with a worsening of their labor market outcomes. Figure 3A shows a negative correlation between occupational robot exposure and how labor earnings evolve from 1990 to 2001.

Figures 3B and 3C depict a corresponding positive correlation between occupational exposure to robots and the share of parents that were unemployed or out of the labor force in 2001. Similar negative labor market consequences for occupational software exposure are seen in Figures 3D, 3E, and 3F. In sum, all these parental outcomes indicate adversely negative effects of working in high-exposed occupations.

[Figure 3 about here]

3.3 Industry-level data on robot adoption

The data on robot usage originate from the IFR. These data include industry information on the stock of operating robots for over 20 countries (see IFR (2020) for details) and are reported by industry, country, and application. All major industrial robot suppliers report to the IFR, and this information is complemented with data from the national robot associations. We use the operational stock to measure robot penetration, where the definition of a robot is "[a]n automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". The industry classification is based on the 2-digit ISIC Rev. 4; thus, we use a crosswalk to match it with our Swedish data that use NACE Rev. 1.1.

The IFR data have been used in several recent studies. For instance, Graetz and Michaels (2018) find that industrial robots increase productivity and wages but reduce the employment of low-skilled workers. Acemoglu and Restrepo (2020) and Dauth et al. (2021) are two other recent papers that rely on the same IFR data.

Figure 4 depicts the development of the operational stock of robots per 1,000 workers in eight Western European countries. All countries except Norway and the UK have seen a significant increase in robot penetration. Germany stands out as having the largest increase from 1993 to 2018, followed by Italy and Sweden. For Sweden, Figure 4 shows an increase from approximately one robot per thousand workers in 1993 to nearly four robots in 2018.

Industry variation in robot penetration is presented in Figure 5. The figure shows the change in the stock of robots per 1,000 workers in 27 Swedish industries between 1993 and 2018. These are the industries that are matched between the IFR data and our Swedish microdata. Similarly to Dauth et al. (2021) who present evidence for Germany, we find substantial variation across industries in robot investments. The largest increase is seen in the vehicles industry, followed by other transport products. The figure also reveals that there are many industries with nearly no change in robot adoption between 1993 and 2018.

Finally, Figure 6 depicts changes in robot adoption per thousand workers across all 21 Swedish regions. The largest increase is seen in Blekinge in southern Sweden, whereas Stockholm is the region with the smallest change between 1993 and 2018.

[Figures 4–6 about here]

4 Results

Table 3 displays basic results on intergenerational mobility from Equation (1). Column 1 shows that the intergenerational income elasticity in our sample is equal to 0.19. The corresponding estimated rank-rank parameter is presented in Column 2 and is equal to 0.14, indicating that a 10-percentage-point increase in the parent's earnings rank is associated with an average 1.4-percentage-point increase in the child's earnings rank.[15] Figure 7 shows that the rank–rank relationship between parents and children is approximately linear up until the top decile of the parent's earnings distribution.

[Table 3 and Figure 7 about here]

Next, we consider the occupational rank–rank estimates using the robot and software percentile ranks created by Webb (2020). In Columns 3 and 4, we see that a 10-percentage-point increase

[15] As we include fathers, mothers, sons, and daughters in our sample, our estimates of the intergenerational elasticity and the rank–rank estimates are somewhat smaller than earlier estimates based on Swedish father–son data, where, for instance, Björklund and Chadwick (2003) estimate an elasticity of 0.24. Adermon, Lindahl, and Palme (2021) present results that intergenerational mobility is even stronger when the extended family is considered.

in the parent's robot-exposure rank is associated with a 2-percentage-point increase on average in the child's robot-exposure rank. The rank–rank correlation for software exposure is lower, at 0.65 percentage points, revealing that the correlation between parents' and their children's exposure to robots is significantly stronger than the corresponding correlation for their exposure to software. This can also be seen in Figure 8, where we plot children's exposure to robots (and software) on the y-axis against parents' exposure. Both figures show a positive relationship, but the correlation is stronger for exposure to robots than for exposure to software.

[Figure 8 about here]

Hence, having a parent who worked in a high-exposure occupation is, on average, associated with lower intergenerational mobility for exposure to robots than for exposure to software.

Last, Columns 5 and 6 in Table 3 show that there is a negative association between parental robot and software exposure and children's earnings rank later in life. Once again, the association is stronger for robots than for software. The rank–rank estimate in Column 4 indicates that a 10-percentage-point increase in parents' robot exposure rank is associated with an average 1.4-percentage-point lower earnings rank for their children.[16]

To address the question of whether new technologies have affected intergenerational income mobility, we estimate Equation (2) that compares intergenerational income mobility for parents with high- or low-exposure occupations. The results are presented in Table 4.

[Table 4 about here]

The estimates in Column 1 in Table 4 show that children whose parents worked in high-robot-exposure occupations have an earnings rank on average four percentage points lower than that of children whose parents worked in low-exposure occupations. Furthermore, the rank–rank correlation is around 10 percent higher if the parent was in a high-exposure occupation instead of a

[16]To take the "treatment dose" into consideration, we also estimate separate regressions to study the overall impact of both parents' outcomes. This analysis is based on a sub-sample of children with two parents working in 1990. In Table IA1, we show that the results are even stronger if we use the two parents' mean rank instead of each parent's individual rank.

low-exposure occupation (0.011 divided by 0.113), suggesting that exposure to robots is associated with lower income mobility. The same pattern is found for software exposure in Column 3, and the results are robust to using a continuous measure of the robot and software exposure ranking, as seen in Columns 2 and 4. However, as discussed in Section 2, comparing intergenerational mobility between parents in high- and low-exposure occupations may also reflect underlying differences other than the variation in automation and robotization.

To further shed light on whether recent technological advancements have affected intergenerational mobility, we now turn to results on the impact of changes in robot investments using data from the IFR. Table 5 displays the results using the approach represented by Equation (4) and (5). Column 1 presents ordinary least squares (OLS) results based on Equation (4), where the estimate on $I(\Delta robots_i^p)$ shows that the direct impact of having a parent who worked in an industry with a large positive change in the number of robots per employee on the child's income rank in adulthood is negative. Furthermore, the rank–rank correlation is approximately 20 percent higher if the parent was employed in an industry with a high level of robot investments in contrast to those with a low level of such investments (0.027 divided by 0.138).

[Table 5 about here]

The OLS results in Column 1 are based on $\Delta robots_i$ measured as the change in robot adoption (operational stocks) in Sweden between 1993 and 2015. To address endogeneity concerns (discussed in Section 2), Column 2 presents the IV results, where we instrument Swedish robot adoption with robot adoption in other, comparable countries. Although the difference in income mobility is smaller than that estimated by OLS, the IV estimates still show evidence of muted income mobility if the parent worked in an industry with a high level of robot investments.[17]

Finally, we estimate Equation (5) to compare income mobility between parents with the same

[17] The results are robust if we estimate the regression using one instrument for each country instead of using the mean; see Table IA2. We also consider that the impact of exposure might differ by the age of the children. In Table IA3, we divide children into being below or above 12 years of age in 1990. The table shows that the results are very similar for the two groups.

occupational robot exposure but differential exposure to robots at the industry level. The results based on OLS are presented in Column 3, and the corresponding IV estimates are shown in Column 4. The main variable of interest in these specifications is the estimated coefficient for $I(OccExposure^p_o) \times I(\Delta robots^p_i) \times Rank^p_{o,i}$. This triple interaction term captures whether intergenerational mobility is affected by both occupational and industry exposure. It is positive if the rank–rank correlation across generations is higher if the parent worked in a high-exposure occupation instead of a low-exposure occupation in an industry with a large increase in robot adoption.

To ease the interpretation of the results, we calculate the rank–rank correlation for the four possible combinations of high–low occupational and high–low industry exposure based on the IV results in Column 4 in Table 5. The results are displayed in Table 6. The table paints a clear pattern. For parents in industries with low robot adoption, the intergenerational income mobility is similar whether the parents had a high- or low-robot-exposure occupation in 1990 (0.105 vs. 0.11). In industries with high robot adoption, the income mobility is significantly lower if the parent had a high-robot-exposure occupation (0.18 vs. 0.143). That the adoption of robots at the industry level matters is also apparent when we compare parents with high occupational exposure, where mobility is higher in low-robot-exposure industries (0.11 vs. 0.18). When we turn to parents in low-exposure occupations, income mobility, is again, lower in industries with high robot adoption (0.143 versus 0.105).

[Table 6 about here]

In sum, the results in Tables 5 and 6 suggest that the long-run effects of automation on intergenerational mobility depend on what type of occupation the parent had and that high occupational exposure to robots in industries with a relatively large increase in robot adoption leads to lower intergenerational mobility.

5 Robustness and extensions

5.1 The financial crisis in the early 1990s

In the early 1990s, Sweden faced its most severe economic crisis in the postwar period: Swedish firms lost global competitiveness while the state became highly leveraged. A substantial decline in GDP and increasing unemployment characterized the period of 1991–1994. Sweden experienced falling GDP for three years in a row, 1991–93, and unemployment rose from just over 2 percent in 1990 to approximately 10 percent in 1993.

One issue to consider is whether the economic crisis in the early 1990s affects our results on the impact of automation on intergenerational mobility in earnings. More specifically, could differences in unemployment experience in the early 1990s for the parents in our sample bias the results on how exposure to robots affects intergenerational mobility? Nybom and Stuhler (2021) find that intergenerational income mobility is weaker in Swedish municipalities that were more heavily exposed to the crisis in the early 1990s.

To address the impact of the 1990s crisis in Sweden, we divide our sample of parents into those who experienced unemployment during the period 1991 to 1994 and those who did not.[18] We then re-estimate Equation (5) separately for these two groups and compare income mobility between parents with the same occupational robot exposure but differential exposure to robots at the industry level.

The results are presented in Columns 1 and 2 in Table 7. The overall estimate of the triple interaction term in Column 5 in Table 5 (0.032) is similar to the estimate for children of parents who were not unemployed (0.038). This suggests that the negative impact of occupational exposure on intergenerational mobility in earnings that originates from industries with a relatively large increase in robot adoption is not systematically related to parents having a history of unemployment during the 1990s crisis in Sweden. Instead, automation and investments in robotics seem to have affected

[18]For this period, our data allow us to identify unemployment via unemployment benefits.

intergenerational mobility, irrespective of exposure to the crisis in the early 1990s.

Our second approach to addressing the Swedish crisis in the early 1990s is to re-estimate Equation (5) on the change in robot adoption during the post-crisis period 1996–2015. The results are shown in Column 3. The estimates are very similar to the corresponding ones in Column 4 in Table 5. This indicates that studying changes in robot adoption during a period after the 1991–94 crisis in Sweden does not affect our previous finding that high occupational exposure to robots in industries with a relatively large increase in robot adoption leads to lower intergenerational income mobility.

[Table 7 about here]

5.2 Expected earnings rank across income distribution

Next, we address whether the impact of automation on intergenerational income mobility is constant across the parentsí income distribution. The analysis can shed light on whether automation has affected overall inequality. Acemoglu and Loebbing (2022) present evidence that a substantial part of the increased wage inequality in the U.S. since 1980 can be explained by automation, as relative wages have fallen for workers performing routine job tasks.

Panel A in Figure 9 displays children's mean earnings rank by their parents' earnings rank depending on whether the parents worked in high- or low-robot-exposure occupations. The slopes are similar for the two groups up to approximately the 75th percentile of the distribution, where the slope becomes steeper for children with parents who worked in high-exposure occupations. In addition, the intercept is lower for high-exposure parents, indicating that the expected earnings rank is lower relative to that of children with parents in low-exposure occupations. The same pattern can also be seen in Panel B, where we split the sample based on whether parents worked in a high- or low-exposure industry. Here, we compare industries with large and small changes in the adoption of robots.

[Figure 9 about here]

Panel C combines Panels A and B and reveals a striking pattern. In the upper half of the distribution, the difference in expected earnings between children with parents in high- versus low-exposure occupations does not depend on the robot adoption at the industry level. However, in the lower part of the distribution, up to around the fourth decile, we see that the expected earnings gap between high- and low-exposure occupations is larger (more negative) in high-exposure industries, i.e., where there has been higher robot adoption. Table IA4 confirms this pattern, as the interaction term I(OccExposure) $\times$ I(Δrobots) in the IV-model is around 35% more negative in the lower part of the income distribution (-2.783 vs. -2.069).

5.3 Upward mobility

An important question is how upward mobility along the earnings rank distribution across generations is affected by automation and robot adoption. To this end, we estimate the following regression:

$$\begin{aligned} Upward^c = \alpha + \beta_1 I(OccExposure_o^p) + \beta_2 I(\Delta robots_i^p) + \\ \beta_3 I(OccExposure_o^p) \times I(\Delta robots_i^p) + X'\theta + \epsilon^c \end{aligned} \quad (6)$$

where the dependent variable is an indicator variable for intergenerational mobility of earnings. $Upward^c$ is equal to one if the child has a higher earnings rank than her parent, allowing us to analyze the cases where the parent was in the bottom 25 percent on the earnings rank distribution in 1990 and the child is (i) in the top 25 percent in 2014–17 or (ii) in the top 50 percent in 2014–17. The results are presented in Table 8.

[Table 8 about here]

We start by studying the general relationship between parents' robot exposure and upward earnings mobility. The results for upward mobility to the top 25 percent and top 50 percent are presented in Columns 1 and 4, respectively. For both cases, the estimated coefficient for $I(OccExposure_o^p)$ is negative and significant, indicating that children of parents with high-exposure occupations are less likely to reach a higher earnings rank than their parents'. Hence, for these parent–child pairs, we observe less upward mobility in earnings. Quantitatively, the estimated coefficient in Column 1 suggests that the child of a parent with a high-robot-exposure occupation instead of a low-exposure occupation is, on average, 8 percentage points (equivalent to 18 percent) less likely to be in the top 25 percent of the income distribution as an adult.

Continuing with the results for the full model in Column 2, we see that the coefficient for the interaction term $I(OccExposure_o^p) \times I(\Delta robots_i^p)$ shows that children to parents with a high-exposure occupation are 2 percentage points less likely to be in the top 25 percent of the income distribution if the parent was in an industry with a high level of robot investments rather than an industry with a low level of robot investments. This difference is even larger, i.e., 3.2 percentage points when we use the IV model (Column 3). The result that higher automation exposure leads to lower upward mobility is confirmed when we analyze the likelihood of ending up in the top half of the income distribution in Columns 4 to 6.

We end this section on upward mobility by showing figures on transition patterns for mobility across income groups. Panel A in Figure 10 shows that having a parent with a high-robot-exposure occupation decreases a child's probability of being in the top quartile of the income distribution. At the same time, the probability of ending up in the first three quartiles increases. This is true across the entire parental income distribution. The same pattern is also seen in Panel B, where we differentiate by high and low IFR robot adoption. However, combining Panels A and B reveals that this pattern is present only in the lower half of the parental income distribution, once again showing the importance of taking the combined exposure into account.

[Figure 10 about here]

5.4 Additional outcomes

We have thus far analyzed how parents' exposure to robots at the occupational and industry level affects intergenerational mobility in earnings. However, are other individual outcomes also affected by parental exposure to new technologies? We address this question by examining various alternative outcomes and their relationship to our exposure measures. Addressing these outcomes could shed light on additional effects of automation on intergenerational mobility and on many different long-lasting effects of robot adoption.

Based on the IV approach, we estimate the following model using robot adoption in comparable countries as an instrument for Swedish robot adoption:

$$Y^c = \alpha + \beta_1 I(OccExposure_o^p) + \beta_2 I(\Delta robots_i^p) + \beta_3 I(OccExposure_o^p) \times I(\Delta robots_i^p) + X'\theta + \epsilon^c, \quad (7)$$

where Y^c is the average outcome Y for child c during 2014–17. We study a wide range of outcomes that reflect both labor market status and family status. The labor market outcomes are unemployment, whether a person is out of the labor force, whether a person has taken early retirement, whether a person has had a case of long-term sickness, and whether a person receives social security benefits. These are all indicator variables.[19] The family-related outcomes are whether a person is married or is living in a single household. The results are presented in Table 9.

[Table 9 about here]

We start by looking at unemployment in Column 1, Panel A, where children with a parent in a high-robot-exposure occupation are more likely to be unemployed in adulthood than children with a

[19] A person is defined as unemployed if she has at least one day of unemployment compensation in at least one year during 2014–17. A person is defined as out of the labor force if she has no employment, wage income, or unemployment days in a given year. Early retirement is when a person is less than 65 years of age (i.e., below the normal pension age in Sweden) and her pension payments exceed her labor earnings. A long-term sick leave spell is defined as a spell of at least 14 days. The variable social benefits is a dummy that takes the value one if a person has received social security benefits at any point between 2014 and 2017 and zero otherwise.

parent in a low-robot-exposure occupation. In addition, among children with parents in high-robot-exposure occupations, the unemployment risk is around 14 percent higher if the parent worked in an industry with a high level of robot investments instead of a low level of robot investments.[20]

That automation can have long-term adverse effects that spill over from parents to children is also seen when we look at the incidence of being out of the labor force (Column 2, Panel A), taking early retirement (Column 3, Panel A), having a long-term sick spell (Column 4, Panel A) and receiving social benefits (Column 5, Panel A). All these additional outcomes point to negative labor market effects for children with parents who worked in high-robot-exposure occupations. In addition, the estimate for the interaction term, $I(OccExposure_o^p) \times I(\Delta robots_i^p)$, shows that the adverse effects are exacerbated if the parent worked in an industry with a relatively large increase in robot adoption. In terms of magnitudes, we see that the negative effect of parental occupational exposure in high-robot industries is especially severe for the incidence of taking long sick leaves and receiving social benefits.

Finally, we also find adverse effects on children from parental exposure to automation when we analyze family-related outcomes, namely, being married and living in a single household. Previous research has presented evidence that there is a positive marriage wage premium and a negative relationship between wages and living in a single household and that unemployment is associated with higher divorce risk (see, e.g., Pilossoph and Wee (2021) for evidence on the wage premium and Eliason (2012) on the economic consequences of lost marriages). Column 1 in Panel B shows that the marriage rate among children of parents with high-exposure occupations, and relative to that of children of parents in low-robot-exposure occupations, is considerably lower when the parent worked in an industry with high robot investment levels. Column 2 in Panel B confirms this result by looking at the shares who are single (i.e., not married or cohabiting).

[20]The value for parents with high occupational exposure and high industry robot adoption equals 0.105+0.024+0.006+0.018=0.147. The corresponding value for parents with high occupational exposure and low industry robot adoption is 0.105+0.024=0.129.

5.5 Earnings effects

In line with the current research on intergenerational mobility in earnings, we have thus far focused on relative mobility, presenting evidence that automation and technology shocks dampen intergenerational mobility. In this section, we complement these results and the findings in the previous section on the negative effects on a variety of other outcomes by providing further evidence on direct intergenerational earnings effects of exposure to automation and changes in robot penetration across generations.

Based on Equation (7), Columns 4 and 5 in Table 9, Panel B, present the results on earnings. In accordance with our results on additional outcomes in Section 5.4, we find negative effects of automation across generations. Looking at log earnings in Column 4, we see that children of parents with high robot exposure occupations have lower wages than children of parents with low exposure. The effect is even stronger for children with parents who worked in industries with high robot adoption. Our estimates suggest that wages are around 4 percent lower for these children than for children with low-exposure parents who worked in industries with a low level of robot investments. Similar negative effects on earnings are seen in Column 4, where absolute mobility is calculated in terms of rank–rank regressions.

When we take these results together, the main message from Sections 5.4 and 5.5 is that the effects of occupational exposure to automation and heterogeneous adoption of robots across industries spill over from parents to children in many different ways. Our findings of negative labor market effects, such as higher unemployment risk and higher probabilities of being out of the labor force, taking early retirement, having lower earnings, and living on social benefits, complement our previous findings on how automation affects intergenerational mobility in earnings.

5.6 Gender differences

Intergenerational mobility in earnings has been extensively researched, but most studies have focused on fathers and sons. This is partly due to women's historically low labor market participation in many countries, which has limited opportunities to analyze earnings mobility across generations for females. However, a small body of literature explores gender differences in intergenerational earnings mobility (see, e.g., Chadwick and Solon (2002) and Mazumder (2005) for two seminal papers). A common result in this literature is that women experience higher levels of intergenerational mobility than men. For instance, Jantti, Bratsberg, Roed, Raaum, Naylor, Osterbacka, Bjorklund, and Eriksson (2006) analyze and compare intergenerational earnings mobility in the United States, the United Kingdom, and the Nordic countries and examine earnings mobility among combinations of fathers, sons, and fathers and daughters. Their results on gender differences suggest higher mobility for daughters than for sons.

In our setting, the children can be influenced by both of their parents. Thus, identifying the effects separately by fathers and mothers is not straightforward. Consequently, we concentrate on the disparities between sons and daughters. Table 10 presents results on gender differences. More specifically, Columns 1-4 replicate the results from Columns 4 and 5 in Panel B in Table 9 separately for sons and daughters. These columns compare the earning effects for sons and daughters with parents in high- or low-exposure occupations in industries with high and low robot adoption. Consistent with the results in Table 9, we find that both sons and daughters experience adverse effects of automation across generations if their parents were directly affected in a high-exposed industry. Notably, for log earnings and highly exposed parents, the estimated effects are very similar across gender, indicating no significant differences between sons and daughters in how parents' exposure to robots affect them. Columns (3) and (4) show corresponding rank–rank estimates results. Here we note significantly lower rank–rank estimates for sons than daughters when we compare children with parents in highly exposed occupations in industries with high and low robot adoption. Columns 5 and 6 show estimates where we replicate the IV specification in Column 4 in Table 5 separately by sons and daughters. The estimated coefficients for the triple interaction term, $I(OccExposure^p_o) \times I(\Delta robots^p_i) \times Rank^p_{o,i}$, are very similar across sons and daughters (0.036 versus 0.029).

Moreover, Table IA5 replicates the non-earnings results in Table 9, separately by sons and daughters. The message from Table 9 holds when we distinguish between sons and daughters. That is, we note that the adverse effects in terms of higher risk for (i) unemployment, (ii) being out of the labor force, (iii) going into early retirement, (iv) having a long-term sick spell, or (v) living on social benefits are all exacerbated by having a parent in a high exposed occupation in industries with a relatively large increase in robot adoption, irrespective of child gender.

6 Concluding remarks

How are labor market outcomes, such as earnings, transmitted across generations? Are there long-term effects of parents' labor market experience on future generations? How does early childhood exposure shape the future well-being of children and the correlation between the earnings of parents and their children? These basic—but, from a welfare perspective, fundamental—questions are addressed in an extensive literature that studies different aspects of intergenerational mobility. In economics, the focus has mainly been on examining intergenerational mobility in earnings. Despite differences in the magnitude of estimates of intergenerational mobility across countries and time, the common result from this literature is that transmission across generations is an essential component for children's expected future earnings.

In this paper, we have departed from the literature above to study whether recent technological advancements have affected intergenerational mobility in earnings. More specifically, we have analyzed how differences in exposure to robots and software at the occupational level and shocks to robotization at the industry level are related to intergenerational mobility. The analysis is based on detailed matched employer–employee data for Sweden combined with data from IFR and Webb (2020).

We find that parents' occupational exposure to automation is negatively related to the earnings of their children and that higher exposure reduces earnings mobility across generations, indicating that parental exposure to new technologies is transmitted to children.

To identify the causal impact of automation and robot investments on intergenerational mobility, we use industry variation in robot adoption, which allows us to adopt an IV approach to estimate the causal effect of changes in robot exposure on intergenerational mobility.

Our results suggest that the impact on the child's income of having a parent who worked in an industry with a high positive change in robot usage is negative. Considering both occupational exposure and aggregate changes in robot investments, we find that the negative impact on intergenerational mobility in earnings originates from industries with a relatively large increase in robot adoption, where income mobility is significantly lower if the parent had a high-robot-exposure occupation. No such relationship is found for industries not exposed to robot adoption, supporting the idea that our estimates capture the effect of automation.

To further understand the long-run effects of automation, we complement the main analysis with several extensions. First, we show that the negative impact of parental exposure to automation on children's expected earnings is larger among low-income than among high-income parents. This suggests that automation may have affected overall inequality via an intergenerational channel.

Second, we look at upward mobility measured as the probability of a child reaching the top income quartile if the parent was in the bottom income quartile in 1990. Our estimates suggest that children with parents who had a high-robot-exposure occupation in a high-robot-exposure industry are significantly less likely to reach the fourth quartile than children whose parents had a low-robot-exposure occupation in a low-robot-exposure industry. Hence, for these parent–child pairs, we observe less upward mobility in earnings.

Third, we analyze a wide range of alternative outcomes when children are in adulthood. These include both measures of direct spillover effects on earnings and non-pecuniary outcomes. Looking at earnings, unemployment risk, and the probabilities of being out of the labor force or going into early retirement, we find that in high-exposure industries, children with parents in high-exposure occupations do relatively worse than children with parents in less exposed occupations.

Our results, based on various specifications, suggest that automation and technology shocks dampen intergenerational mobility. These results indicate a new channel through which technological innovations impact intergenerational mobility. This implies that changes in exposure to new technologies and shocks to robot usage have longer-lasting effects than previously acknowledged. The challenge from a policy perspective is how the long-term effects of structural changes, such as technological change, can be addressed. A long-run perspective that includes transmissions across generations can be important to obtain a more accurate estimate of how structural changes influence individuals.

For future research, comparing results with other types of countries would be interesting. Is the fact that Sweden has been at the forefront of the adoption of new technologies one explanation for our results? Are transmissions different in less advanced countries? Another issue is the type of technological advancement. The focus of this paper has been on the adoption of robots and occupational exposure to robots and software. Would the results be different if one analyzes other types of technological shocks? Future data will, for instance, be able to address how innovations in AI technologies are related to the transmission of labor market outcomes over generations. For now, we note that our new results for Sweden indicate long-lasting effects of shocks to robot usage and exposure to automation on intergenerational mobility in earnings.

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Tables and figures

Table 1: Summary statistics for parent–child sample

Panel A: Children 2014–17	Mean	St. dev.	Min. value	Max. value
Age	38.2	3.5	31.0	45.0
Female	0.5	0.5	0.0	1.0
Earnings	3,436.5	2,295.1	0.0	212,534.7
Earnings rank	57.8	27.0	1.0	100.0
OccExposure:				
Software	42.6	19.7	13.9	88.6
Robots	40.1	20.6	15.8	89.1
I(OccExposure):				
Software	38.4	48.6	0	100
Robots	43.7	49.6	0	100
Panel B: Parents 1990				
Age	41.5	6.1	25.0	65.0
Female	0.5	0.5	0.0	1.0
Earnings	2,413.1	1,275.6	500.7	261,191.2
Earnings rank	50.1	28.8	1.0	100.0
OccExposure:				
Software	45.6	19.6	13.9	88.6
Robots	48.1	22.0	15.8	89.1
I(OccExposure):				
Software	38.3	48.6	0	100
Robots	54.9	49.8	0	100

Notes: This table shows descriptive statistics on the parent–child sample used in the analysis. The sample consists of all available observations on parents and children and contains 994,531 parents and 1,518,080 children. I(OccExposure) takes the value one if the underlying occupational robot or software exposure measure, OccExposure, is above the median and zero otherwise. The exposure measures are created by Webb (2020) and discussed in Section 3.2.

Table 2: Robot and software occupational exposure in the Swedish economy

	1990	2001	2017
I(OccExposure):			
Software	39.5	33.8	30.4
Robots	60.0	54.9	52.1
OccExposure:			
Software	46.6	44.2	42.7
Robots	49.3	46.8	45.2
Observations	3,950,367	4,615,852	4,737,951

Notes: This table shows descriptive statistics on occupational exposure to robots and software for the years 1990, 2001, and 2017. For each year, the sample includes all workers in Sweden with an occupation that can be mapped to the occupational exposure measures created by Webb (2020). I(OccExposure) takes the value one if the underlying occupational robot or software exposure measure, OccExposure, is above the median and zero otherwise.

Table 3: Basic results on intergenerational mobility

	Child outcome					
	Log Earnings	Rank	Robot	Software	Rank	Rank
	(1)	(2)	(3)	(4)	(5)	(6)
Parent outcome						
Log Earnings	0.187***					
	(0.004)					
Rank		0.143***				
		(0.003)				
Robot OccExposure			0.205***		-0.141***	
			(0.004)		(0.004)	
Software OccExposure				0.065***		-0.060***
				(0.002)		(0.004)
Constant	6.663***	51.314***	34.076***	46.068***	65.589***	62.890***
	(0.103)	(2.665)	(1.810)	(1.1758)	(2.553)	(2.521)
Observations	1,293,683	1,362,605	1,223,386	1,223,386	1,362,605	1,362,605
R-squared	0.059	0.088	0.132	0.155	0.087	0.077

Notes: This table reports the results from estimating different versions of Equation (1). Rank refers to percentile earnings rank. Robot OccExposure and Software OccExposure refer to the robot and software occupational exposure measures created by Webb (2020) and discussed in Section 3.2. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Occupational exposure and intergenerational mobility

	Occupational exposure			
	Robot	Robot	Software	Software
	(1)	(2)	(3)	(4)
Rank	0.113***	0.0863***	0.129***	0.0840***
	(0.003)	(0.0045)	(0.002)	(0.0042)
I(OccExposure)	-4.238***		-4.046***	
	(0.200)		(0.220)	
I(OccExposure) × Rank	0.011***		0.034***	
	(0.003)		(0.003)	
OccExposure		-0.1294***		-0.1210***
		(0.0051)		(0.0063)
OccExposure × Rank		0.0006***		0.0013***
		(0.0001)		(0.0001)
Constant	54.474***	58.5235***	52.452***	56.7214***
	(2.659)	(2.6775)	(2.626)	(2.5913)
Observations	1,362,605	1,362,605	1,362,605	1,362,605
R-squared	0.092	0.0935	0.089	0.0897

Notes: This table reports the results from estimating Equation (2) using children's earnings rank as the dependent variable. Rank refers to the percentile earnings rank of the parent. I(OccExposure) takes the value one if the underlying robot or software exposure measure, OccExposure, is above the median and zero otherwise. The robot and software exposure measures were created by Webb (2020) and are discussed in Section 3.2. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Exposure to robots at the occupational and industry level and intergenerational mobility

	OLS (1)	IV (2)	OLS (3)	IV (4)
Rank	0.138***	0.133***	0.109***	0.105***
	(0.003)	(0.003)	(0.004)	(0.004)
I(Δrobots)	-2.369***	-3.810***	-0.993***	-1.450***
	(0.304)	(0.471)	(0.349)	(0.555)
I(Δrobots) $\times$ Rank	0.027***	0.057***	0.020***	0.038***
	(0.004)	(0.007)	(0.005)	(0.008)
I(OccExposure)			-3.869***	-3.714***
			(0.213)	(0.221)
I(OccExposure) $\times$ Rank			0.007**	0.005
			(0.003)	(0.004)
I(OccExposure) $\times$ I(Δrobots)			-2.802***	-3.822***
			(0.370)	(0.474)
I(OccExposure) $\times$ I(Δrobots) $\times$ Rank			0.024***	0.032***
			(0.006)	(0.008)
Constant	51.518***	51.769***	54.554***	54.667***
	(2.669)	(2.669)	(2.665)	(2.663)
Observations	1,362,605	1,362,605	1,362,605	1,362,605
R-squared	0.088	0.088	0.092	0.092
Kleibergen–Paap		28.82		13.76

Notes: This table reports the results from estimating Equations (4) and (5) using children's earnings rank as the dependent variable. Rank refers to the percentile earnings rank of the parent. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Rank–rank differences

		Industry robot adoption		
		Low	High	High minus low
Occupational Exposure	Low	0.105	0.143	0.038
	High	0.110	0.180	0.07
	High minus low	0.005	0.037	0.032

Notes: This table reports the parent-child rank–rank correlations calculated using the estimates from Column 4 in Table 5. The value for low occupational exposure–low industry adoption is the estimate for Rank. The value for low occupational exposure–high industry adoption is the sum of the estimates for Rank and I(Δrobots) $\times$ Rank. The value for low occupational exposure–high industry adoption is the sum of the estimates for Rank and I(OccExposure) $\times$ Rank. The value for high occupational exposure–high industry exposure is the sum of the estimates for Rank, I(Δrobots) $\times$ Rank, I(OccExposure) $\times$ Rank and I(OccExposure) $\times$ I(Δrobots) $\times$ Rank. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: The 1990s financial crisis

	Unemployment 1991–94		Δrobots
	No	Yes	1996–2015
	(1)	(2)	(3)
Rank	0.102***	0.077***	0.113***
	(0.004)	(0.007)	(0.005)
I(Δrobots)	-1.783***	-1.681**	2.912**
	(0.685)	(0.734)	(1.484)
I(Δrobots) x Rank	0.040***	0.046***	-0.019
	(0.009)	(0.014)	(0.019)
I(OccExposure)	-3.648***	-3.727***	-3.796***
	(0.235)	(0.337)	(0.278)
I(OccExposure) x Rank	0.004	0.012*	0.009**
	(0.004)	(0.007)	(0.004)
I(OccExposure) x I(Δrobots)	-4.090***	-2.925***	-4.248***
	(0.578)	(0.780)	(1.114)
I(OccExposure) x I(Δrobots) x Rank	0.038***	-0.002	0.036***
	(0.009)	(0.015)	(0.014)
Constant	54.445***	66.344***	54.311***
	(2.804)	(6.942)	(2.665)
Observations	1,118,108	242,708	1,362,605
R-squared	0.092	0.084	0.092
Kleibergen-Paap	9.914	50.38	5.509

Notes: This table reports the IV results from estimating Equation (5) using children's earnings rank as the dependent variable. Rank refers to the percentile earnings rank of the parent. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i is above the median change in the period 1993 to 2015 in Columns 1 and 2 and in the period 1996 to 2015 in Column 3, and zero otherwise. Column 1 restricts the sample to children–parent pairs where the parent was not unemployed during 1991–1994, while Column 2 restricts the sample to those where the parent was unemployed at some point during the same period. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Upward mobility

	p(75) (1)	p(75) (2)	p(75) (3)	p(50) (4)	p(50) (5)	p(50) (6)
I(Δrobots)		0.010	0.007		0.014**	0.011
		(0.006)	(0.011)		(0.006)	(0.011)
I(OccExposure)	-0.080***	-0.078***	-0.077***	-0.057***	-0.054***	-0.053***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
I(OccExposure) $\times$ I(Δrobots)		-0.020***	-0.032***		-0.028***	-0.040***
		(0.006)	(0.007)		(0.006)	(0.008)
Constant	0.435***	0.434***	0.433***	0.585***	0.584***	0.583***
	(0.074)	(0.074)	(0.074)	(0.101)	(0.101)	(0.101)
Observations	354,148	354,148	354,148	354,148	354,148	354,148
R-squared	0.092	0.092	0.092	0.085	0.085	0.085
Model	OLS	OLS	IV	OLS	OLS	IV
Kleibergen–Paap			34.02			34.02

Notes: This table reports the results from estimating different versions of Equation (6) focusing on the sample of parents in the top quartile of the earnings distribution. The dependent variable is an indicator variable equal to one if the child is in the top 25 percent in 2014–17 (Columns 1–3), or in the top 50 percent in 2014–17 (Columns 4–6). I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure is created by Webb (2020) and discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Additional outcomes

Panel A	Unem	Out	Early retired	Sick	Social ben
	(1)	(2)	(3)	(4)	(5)
I(Δrobots)	0.006*	-0.000	-0.001	-0.001	0.005***
	(0.004)	(0.003)	(0.001)	(0.005)	(0.002)
I(OccExposure)	0.024***	0.008***	0.001***	0.037***	0.016***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
I(OccExposure) × I(Δrobots)	0.018***	0.014***	0.002***	0.006**	0.009***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Constant	0.105***	0.168***	0.019	0.140***	0.033**
	(0.028)	(0.029)	(0.013)	(0.040)	(0.014)
Observations	1,362,605	1,362,605	1,362,605	1,362,605	1,362,605
R-squared	0.007	0.003	0.001	0.059	0.006
Kleibergen-Paap	28.62	28.62	28.62	28.62	28.62
Panel B	**Married**	**Single**	**Log earnings**	**Rank**	**Uni**
	(1)	(2)	(3)	(4)	(5)
I(Δrobots)	-0.005	0.003	-0.000	0.375	0.002
	(0.006)	(0.002)	(0.024)	(0.480)	(0.012)
I(OccExposure)	-0.058***	0.009***	-0.173***	-5.001***	-0.155***
	(0.002)	(0.001)	(0.010)	(0.177)	(0.007)
I(OccExposure) × I(Δrobots)	-0.009**	0.006***	-0.124***	-2.157***	0.005
	(0.004)	(0.002)	(0.020)	(0.315)	(0.009)
Constant	0.540***	0.103***	8.218***	62.051***	0.326***
	(0.054)	(0.021)	(0.215)	(2.571)	(0.046)
Observations	1,362,605	1,362,605	1,362,605	1,362,605	1,355,406
R-squared	0.025	0.013	0.010	0.084	0.086
Kleibergen-Paap	28.62	28.62	28.62	28.62	28.72

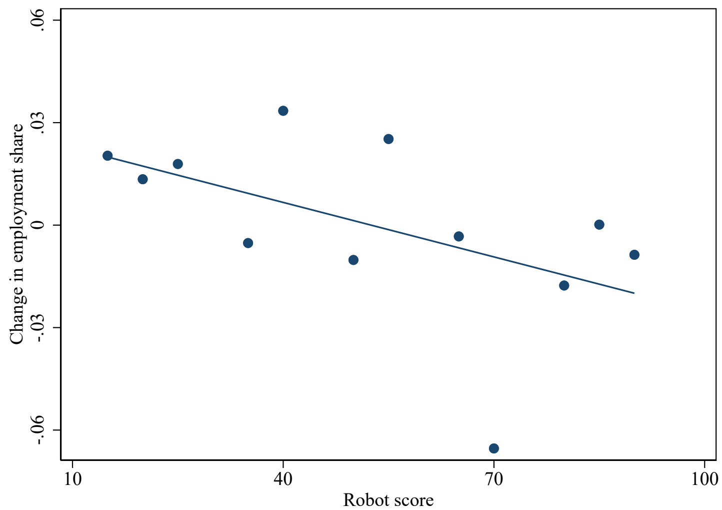
Notes: This table reports the IV results from estimating Equation (7). The dependent variables in the different columns (displayed on the top row in each panel) are defined in Section 5.4. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Exposure to robots at the occupational and industry levels and intergenerational mobility by daughters and sons

	Log earnings		Rank			
	Sons	Daughters	Sons	Daughters	Sons	Daughters
	(1)	(2)	(3)	(4)	(5)	(6)
Rank					0.097***	0.114***
					(0.006)	(0.003)
I(Δrobots)	0.023	-0.026	0.484	0.239	-1.631**	-1.283**
	(0.030)	(0.030)	(0.570)	(0.497)	(0.727)	(0.568)
I(Δrobots) × Rank					0.046***	0.029***
					(0.010)	(0.009)
I(OccExposure)	-0.161***	-0.185***	-4.399***	-5.637***	-3.685***	-3.750***
	(0.013)	(0.010)	(0.209)	(0.186)	(0.283)	(0.222)
I(OccExposure) × Rank					0.016***	-0.007**
					(0.005)	(0.004)
I(OccExposure) × I(Δrobots)	-0.150***	-0.096***	-2.937***	-1.330***	-4.905***	-2.671***
	(0.024)	(0.024)	(0.376)	(0.349)	(0.631)	(0.556)
I(OccExposure) × I(Δrobots) × Rank					0.036***	0.029***
					(0.011)	(0.009)
Constant	8.264***	7.907***	60.226***	49.616***	53.912***	41.130***
	(0.270)	(0.294)	(3.639)	(3.151)	(3.605)	(3.321)
Observations	700,185	662,420	700,185	662,420	700,185	662,420
R-squared	0.006	0.007	0.015	0.022	0.023	0.031
Kleibergen–Paap					13.74	13.77

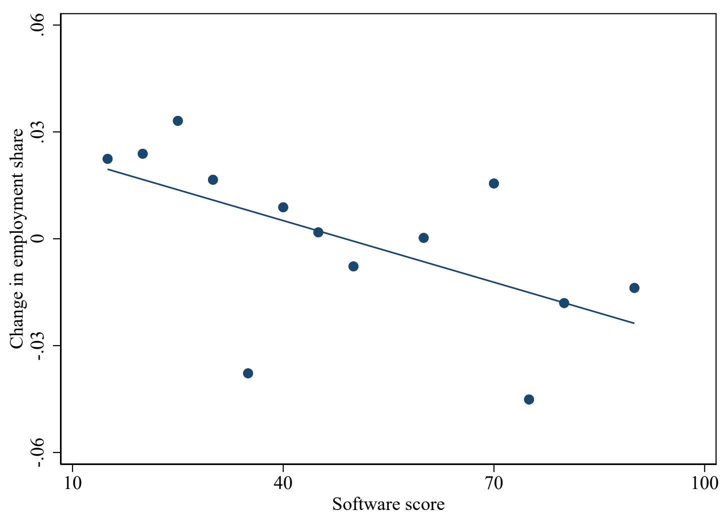
Notes: This table reports the IV-results from estimating Equations (5) and (7) separately for sons and daughters. Rank refers to the percentile earnings rank of the parent. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Employment change by occupational robot exposure



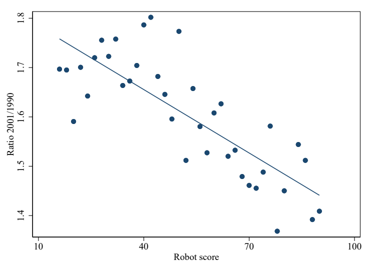
Notes: The figure displays the difference in employment share between 1990 and 2017 in Sweden by the robot exposure score created by Webb (2020).

Figure 2: Employment change by occupational software exposure

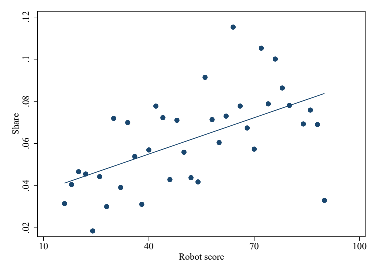


Notes: The figure displays the difference in employment shares between 1990 and 2017 in Sweden by the software exposure score created by Webb (2020).

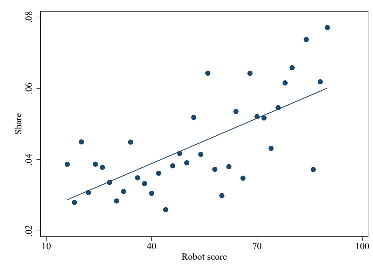
Figure 3: Occupational exposure and parental outcome



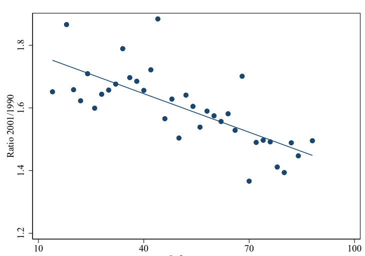
(A) Labor earnings



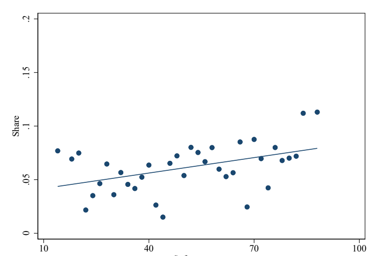
(B) Unemployment



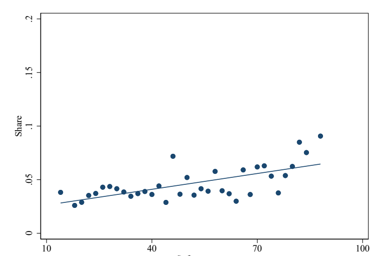
(C) Out of labor force



(D) Labor earnings



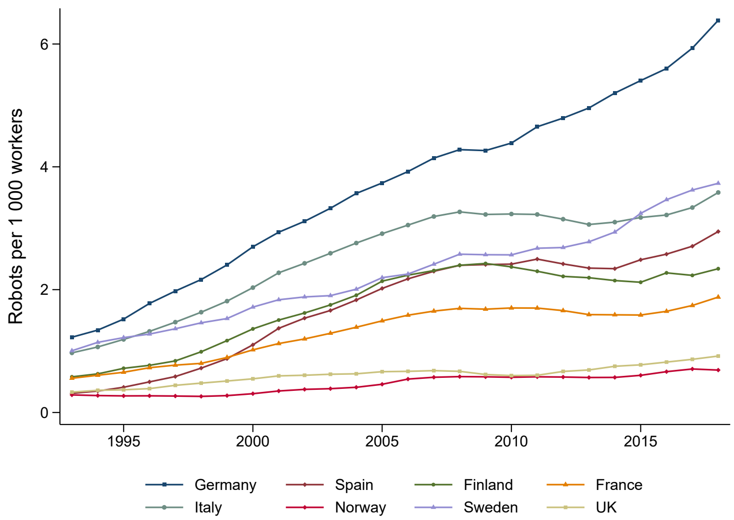
(E) Unemployment



(F) Out of labor force

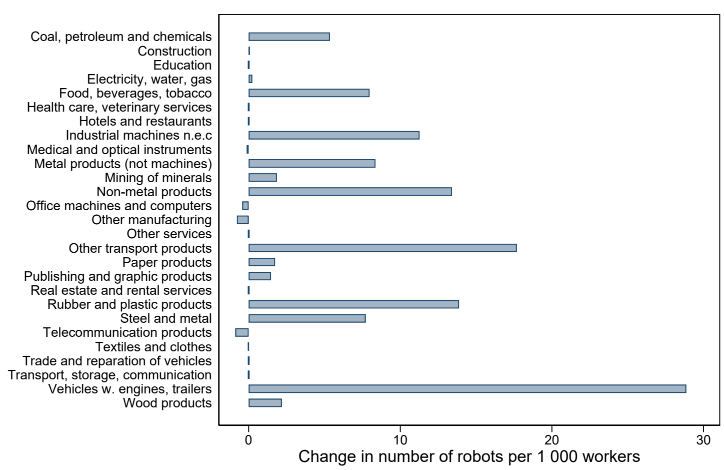
Notes: The figure shows the correlation between parents' occupational exposure to robots and software and various labor market outcomes in 2001. "Labor earnings" is the ratio of earnings between 2001 and 1990, "Unemployment" is defined as receiving unemployment benefits in 2001, and "Out of labor force" is defined as no employment, no wage income, and no unemployment days in 2001.

Figure 4: Cross-country variation in robot adoption



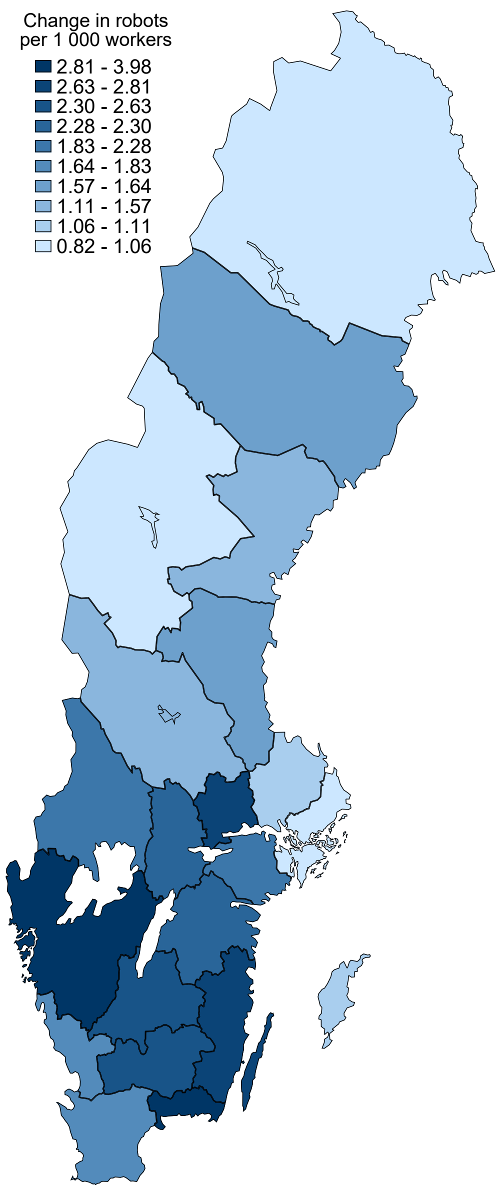
Notes: The figure displays the development of the operational stock of robots per 1,000 employees in eight Western European countries from 1993 to 2018. Data on the operational stock of robots originate from the IFR. Employment data come from OECD and are based on 1993.

Figure 5: Industry variation in robot adoption



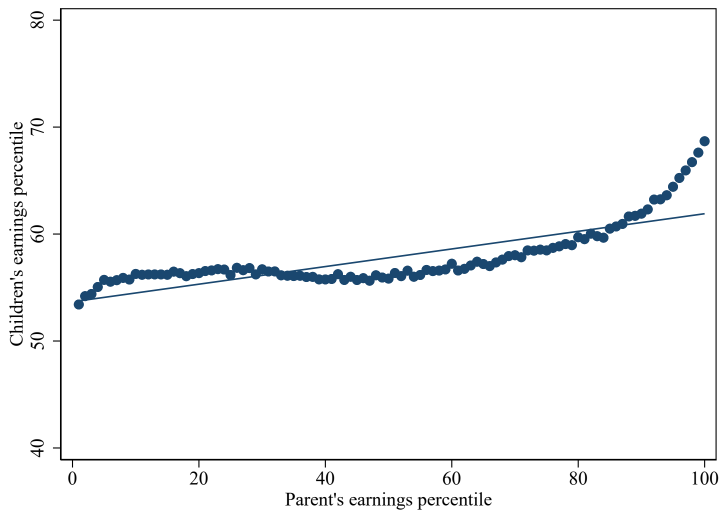
Notes: The figure displays the 1993 to 2018 change in the operational stock of robots per 1,000 employees for different industries. Data on the operational stock of robots originate from the IFR. Employment data come from Statistics Sweden and are based on 1990.

Figure 6: Regional variation in robot adoption



Notes: The figure displays the 1993 to 2018 change in the operational stock of robots per 1,000 employees in all Swedish regions. Data on the operational stock of robots originate from the IFR. Employment data come from Statistics Sweden and are based on 1990.

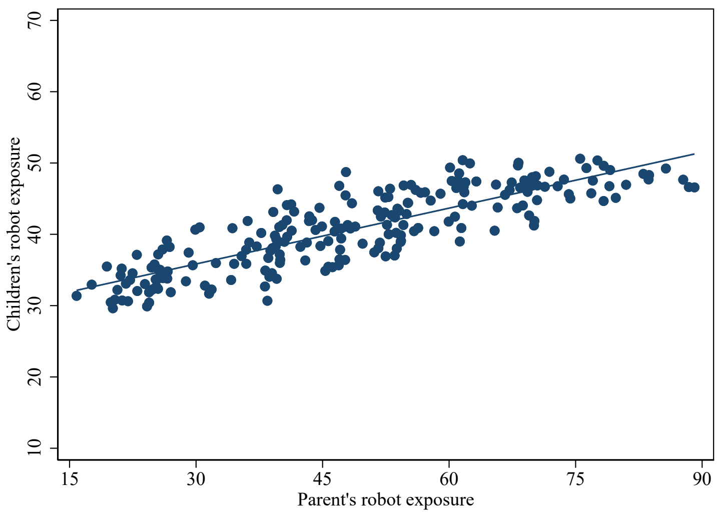
Figure 7: Earnings rank correlation



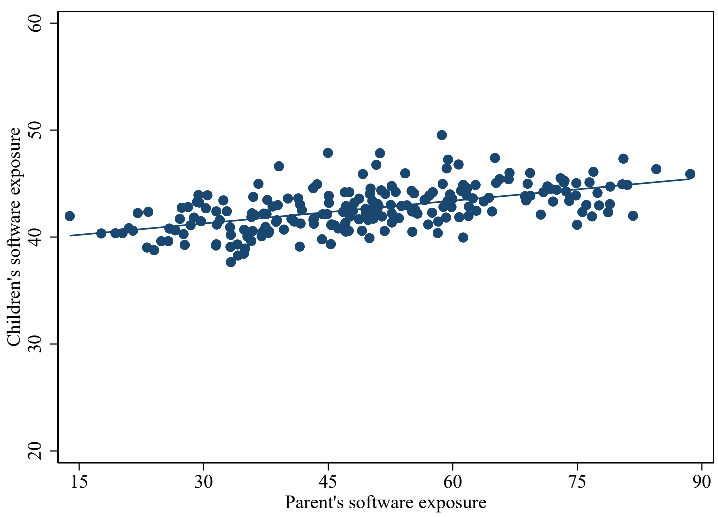
Notes: The figure displays the mean earnings rank for children in 2014-17 by parents' earnings rank in 1990.

Figure 8: Robot rank correlation and software rank correlation

Panel A

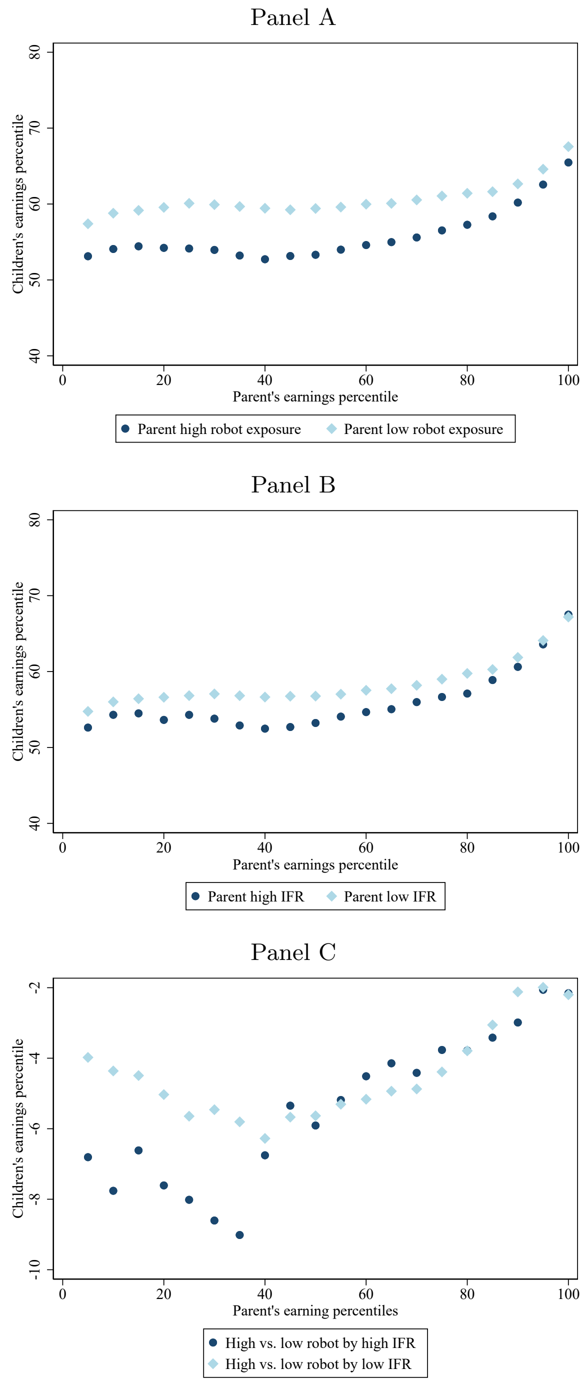


Panel B



Note: Panel A displays the correlation between parents' occupational robot rank in 1990 and children's average occupational robot rank in 2014-17. Panel B displays the correlation between parents' occupational software rank in 1990 and children's average occupational software rank in 2014-17. The robot and software rank was created by Webb (2020); see Section 3.2 for more details.

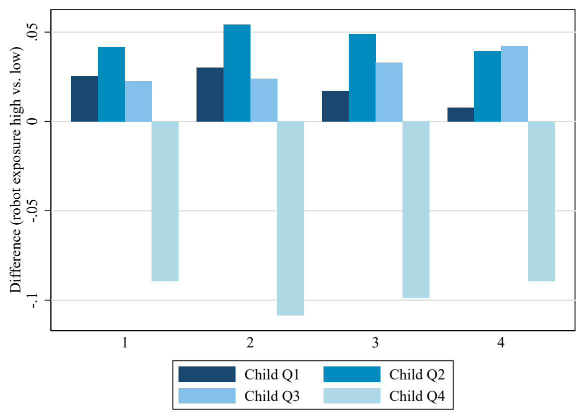
Figure 9: Robot rank correlation by occupational robot exposure



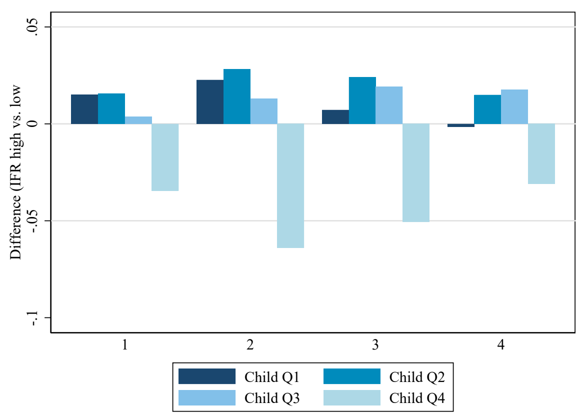
Notes: Panel A displays the robot rank correlation between parents and children when parents had a high- or low-robot-exposure occupation. Panel B displays the robot rank correlation between parents and children when parents worked in high- and low-robot-exposure industry regions. Panel C combines Panels A and B.

Figure 10: Upward mobility by occupational robot exposure

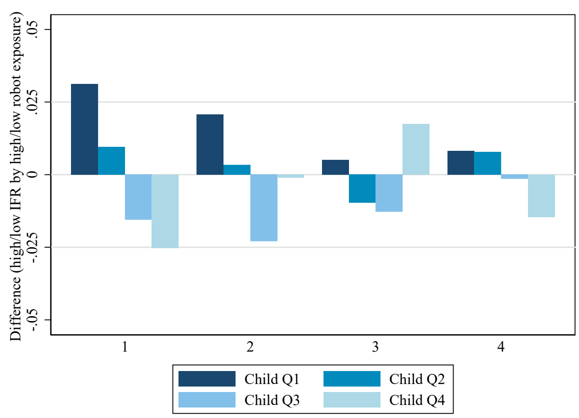
Panel A



Panel B



Panel C



Notes: For each parental earnings quartile (measured on the x-axis), we divide children's earnings into quartiles. Panel A displays the difference in upward mobility when parents had a high- or low-robot-exposure occupation. Panel B displays the difference in upward mobility when parents worked in high- and low-robot-exposure industry regions. Panel C combines Panels A and B.

Internet Appendix

Long-Run Effects of New Technologies: The Impact of Automation and Robots on Intergenerational Mobility

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Table IA1: Treatment dose

	Child outcome				
	Rank	Robot	Software	Rank	Rank
	(1)	(2)	(3)	(4)	(5)
Average parent outcome					
Rank	0.240***				
	(0.003)				
Robot OccExposure		0.310***		-0.200***	
		(0.003)		(0.004)	
Software OccExposure			0.127***		-0.091***
			(0.003)		(0.004)
Constant	52.004***	29.179***	42.589***	71.874***	68.437***
	(3.159)	(1.724)	(2.093)	(3.097)	(3.053)
Observations	722,034	657,174	657,174	722,034	722,034
R-squared	0.104	0.152	0.152	0.099	0.085
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results from estimating different versions of Equation (1) using average family parental outcomes. Rank refers to the percentile earnings rank. Robot and Software OccExposure refer to the occupational robot and software exposure measure created by Webb (2020) and discussed in Section 3.2. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table IA2: Separate country instruments

	(1)	(2)
Rank	0.137***	0.108***
	(0.003)	(0.004)
I(Δrobots)	-3.110***	-1.242***
	(0.336)	(0.380)
I(Δrobots) x Rank	0.032***	0.020***
	(0.005)	(0.005)
I(OccExposure)		-3.804***
		(0.213)
I(OccExposure) x Rank		0.006*
		(0.003)
I(Δrobots) x I(OccExposure)		-3.356***
		(0.401)
I(Δrobots) x I(OccExposure) x Rank		0.029***
		(0.006)
Constant	51.549***	54.535***
	(2.666)	(2.663)
Observations	1,362,605	1,362,605
R-squared	0.088	0.092
Kleibergen–Paap	2463	1334

Notes: This table reproduces the IV-results in Table 5, Columns 2 and 4, but with separate instruments for each country instead of the average. Children's earnings rank is the dependent variable. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table IA3: Child age heterogeneity

	(1)	(2)
Rank	0.093***	0.112***
	(0.005)	(0.004)
I(Δrobots)	-0.784	-1.842***
	(0.689)	(0.595)
I(Δrobots) x Rank	0.031***	0.042***
	(0.010)	(0.009)
I(OccExposure)	-2.809***	-4.139***
	(0.231)	(0.254)
I(OccExposure) x Rank	0.007	0.003
	(0.005)	(0.004)
I(OccExposure) x I(Δrobots)	-4.125***	-3.675***
	(0.626)	(0.562)
I(OccExposure) x I(Δrobots) x Rank	0.034***	0.032***
	(0.010)	(0.009)
Constant	55.681***	54.385***
	(6.759)	(2.824)
Observations	534,930	827,675
R-squared	0.101	0.090
Kleibergen-Paap	13.22	14.07
Child age in 1990	< 12	>= 12

Notes: This table reports the IV-results from estimating Equation (5) for children younger and older than 12 years of age in 1990 separately. Children's earnings rank is the dependent variable. Rank refers to the percentile earnings rank of the parent. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1

Table IA4: Expected earnings rank

	OLS (1)	OLS (2)	IV (3)	IV (4)
I(Δrobots)	0.018	0.608*	0.530	0.537
	(0.310)	(0.355)	(0.480)	(0.636)
I(OccExposure)	-4.914***	-4.422***	-4.667***	-4.325***
	(0.186)	(0.171)	(0.223)	(0.177)
I(OccExposure) $\times$ I(Δrobots)	-1.062***	-1.828***	-2.069***	-2.783***
	(0.267)	(0.310)	(0.361)	(0.396)
Constant	62.209***	60.558***	62.151***	60.459***
	(2.975)	(4.084)	(2.977)	(4.078)
Observations	819,777	542,828	819,777	542,828
R-squared	0.082	0.091	0.082	0.091
Parent's earnings rank below p-40	No	Yes	No	Yes

Notes: This table reports the results on splitting the sample on whether parents' earnings rank us below or above the 40th percentile and relates to Figure 9. Children's earnings rank is the dependent variable. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table IA5: Additional outcomes by daughters and sons

Panel A–Daughters	Unem	Out	Retired	Sick	Social ben	Married	Single
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Δrobots)	0.003	0.004	-0.001	-0.002	0.005**	0.002	0.000
	(0.005)	(0.004)	(0.001)	(0.007)	(0.002)	(0.007)	(0.003)
I(OccExposure)	0.020***	0.009***	0.002***	0.039***	0.017***	-0.053***	0.009***
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)
I(OccExposure) × I(Δrobots)	0.017***	0.012***	0.003***	0.007	0.008***	-0.009*	0.013***
	(0.004)	(0.004)	(0.001)	(0.004)	(0.002)	(0.006)	(0.003)
Constant	0.075**	0.192***	0.043*	0.277***	-0.005**	0.635***	0.124***
	(0.033)	(0.044)	(0.024)	(0.060)	(0.002)	(0.062)	(0.034)
Observations	662,420	662,420	662,420	662,420	662,420	662,420	662,420
R-squared	0.005	0.004	0.000	0.009	0.006	0.016	0.011
Panel B–Sons	Unem	Out	Retired	Sick	Social ben	Married	Single
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Δrobots)	0.009**	-0.004	-0.001	0.001	0.005**	-0.012*	0.006*
	(0.004)	(0.004)	(0.001)	(0.005)	(0.002)	(0.007)	(0.003)
I(OccExposure)	0.027***	0.007***	0.001***	0.035***	0.016***	-0.063***	0.009***
	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)
I(OccExposure) × I(Δrobots)	0.018***	0.016***	0.002*	0.005	0.009***	-0.008*	0.001
	(0.003)	(0.003)	(0.001)	(0.004)	(0.002)	(0.004)	(0.003)
Constant	0.149***	0.149***	0.000	0.216***	0.071**	0.511***	0.106***
	(0.043)	(0.042)	(0.001)	(0.052)	(0.028)	(0.070)	(0.030)
Observations	700,185	700,185	700,185	700,185	700,185	700,185	700,185
R-squared	0.008	0.003	0.000	0.005	0.007	0.027	0.011

Notes: This table reports the IV results from estimating different versions of Equation (7) for daughters and sons separately. The dependent variables in the different columns (displayed on the top row in each panel) are defined in Section 5.4. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The robot exposure measure was created by Webb (2020) and is discussed in Section 3.2. I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in industry i over the period 1993–2015 is above the median change and zero otherwise. All models include birth year fixed effects and control for female dummies (separately for parents and children). They also include regional and industry fixed effects for the parents. Standard errors are clustered at the industry and regional level. *** p<0.01, ** p<0.05, * p<0.1