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Long–Run Effects of Technological Change: The Impact of Automation on Intergenerational Mobility*

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ABSTRACT

This paper examines how automation shapes intergenerational income mobility. Using Swedish register data on parents and children from 1985 to 2019, we study how parental exposure to robots at the occupational and industry level during the 1990s affected children's outcomes up to thirty years later. To address selection, we match parents on detailed worker, firm, and family characteristics and complement this with firm-level variation based on robot and broader automation imports. We also employ two IV strategies that leverage exogenous variation in automation adoption: one based on foreign industry-level robot adoption, and another exploiting differences in managerial education at the firm level. Our results show that parental exposure to robotization and automation reduces children's income and upward mobility, and leads to worse long-run labor market and educational outcomes. These effects are concentrated among low-income families. Evidence suggests that parental labor market shocks and financial strain are key mechanisms. Taken together, the findings indicate that technological change can reduce intergenerational mobility and contribute to long-run inequality.

Keywords: Intergenerational Mobility; Robots; Automation; Inequality
JEL Codes: 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 (2011) and Cholli and Durlauf (2022) for two literature surveys on intergenerational mobility). The vast majority of papers in this field 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, residential segregation and school quality. These determinants also include the impact of macroeconomic conditions and shocks to the economy, such as economic downturns, trade liberalizations, firm closures, and natural resource booms. However, less attention has been given to how automation and the increased use of industrial robots, which are among the most important structural changes affecting labor markets in recent decades, have shaped intergenerational mobility. Understanding the intergenerational consequences of automation is important for designing policies that support families who may be disproportionately affected by technological change.

It is well established that recent technological advancements have reshaped labor markets and the organization of work and production. A key insight is that the rise of automation has been skill-biased, with robots replacing routine-intensive occupations contributing to increased wage inequality and job polarization.[2] Although new technologies can displace workers performing routine job tasks (the replacement effect), they may also increase the demand for non-routine workers through a productivity effect. Most empirical papers on automation have focused mainly on the direct effects

[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 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 (2024).

on firms and workers.[3]

In this paper, we take an intergenerational perspective and study the long–run effects of automation across generations, going beyond its direct effects. We base our analysis on comprehensive and detailed individual-level register data for Sweden from 1985 to 2019, merged with data on robot exposure at the occupational level and robot adoption at the industry level. This allows us to study how parental robot exposure in the 1990s shaped their children's outcomes up to thirty years later, while explicitly accounting for the compounding role of occupation and industry in transmitting the effects of automation. Combined with Sweden's long-standing position at the forefront of technological adoption, this makes Sweden an ideal setting for examining how automation influences intergenerational mobility.[4]

Data on industry-level robot exposure come from the International Federation of Robotics (IFR), which we use to classify parents as working in high- or low–robot-adopting industries in the 1990s. At the occupational level, we rely on the measure developed by Webb (2020) to distinguish between parents in high- and low–robot-exposed occupations. This measure is based on the textual overlap between patent descriptions of new technologies related to robots and job descriptions. In our setting, industry-level robot adoption captures workers' broad exposure to technological change, while occupational exposure reflects how the specific tasks they perform can be replaced or complemented by automation. Hence, parents in the same type of occupation may differ in their actual exposure to automation depending on whether they worked in an industry that adopted robots or not. By combining these measures on industry and occupational robot exposure, we are able to identify which parents were affected by automation and which were not, and to distinguish those likely to have experienced negative impacts from those who may have benefited. Accounting for the compounding role of industry and occupation is crucial for understanding long-term effects on families

[3]See e.g., Bessen, Goos, Salomons, and van den Berge (2020); Aghion, Antonin, Bunel, and Jaravel (2020); Hirvonen, Stenhammar, and Tuhkuri (2022); Acemoglu, Koster, and Ozgen (2024); Battisti, Dustmann, and Schönberg (2023).

[4]Sweden had one of the highest ratings from the EU's Digital Economy and Society Index in 2022. From a global perspective, Sweden ranks among the most digitally advanced countries and is placed fourth in the 2024 Network Readiness Index published by the Portulans Institute. According to recent statistics from the International Federation of Robotics, Sweden is among the ten most robot-intensive countries in the world and is one of the leading countries in Europe in terms of the number of installed robots per 10,000 workers (International Federation of Robotics, 2024).

and their children's opportunities.[5]

To compare intergenerational mobility between children whose parents were affected by robots and those whose parents were not, we must rule out that any observed differences between the children in adulthood reflect other underlying factors unrelated to automation. To address this, we use a matching procedure to ensure that parents' characteristics are balanced across high- and low–robot-adopting industries. The matching is carried out within groups of high- and low–robot-exposed occupations using a rich set of individual, firm, and family characteristics. Besides accounting for observable characteristics in the analysis, we show that the matching also achieves balance in cognitive ability, a typically unobserved characteristic that affects income mobility. This strengthens our empirical strategy by ensuring that differences in key parental characteristics do not drive the estimates of intergenerational income mobility.

A remaining challenge with our empirical strategy is that industry robot adoption can be correlated with domestic industry demand shocks. To address this problem, we follow the approach taken by Autor, Dorn, and Hanson (2013), Acemoglu and Restrepo (2019) and Dauth, Findeisen, Suedekum, and Woessner (2021) (among others), and instrument industry robot penetration in Sweden with mean robot penetration in the same industries in comparable countries using an instrumental variable (IV) specification.

To complement the industry-level analysis, we also exploit variation in automation adoption at the firm level. Using data on firms' imports of robots and broader automation technologies, we compare parents who were employed in firms that differed in their automation adoption. We estimate models with both industry and firm fixed effects to account for unobserved heterogeneity. To address endogeneity in firm-level adoption, we use an IV strategy based on differences in CEO education, exploiting evidence that human capital and management quality are closely linked to the adoption of new technologies and organizational practices.

Our results demonstrate that accounting for the compounding role of industry and occupations is crucial for understanding long-term effects on families and their children's opportunities. In the

[5] In addition, Hervé (2023) shows that both industry and occupation shape workers' opportunities because mobility across industries depends not only on labor demand, but also on how easily workers can transfer their skills.

main analysis, we study income mobility using rank–rank regressions and find a general reduction in income mobility among children whose parents worked in industries with high levels of robot adoption. However, when accounting for exposure at the occupational level, we find that the decline in mobility is driven by parents in occupations highly exposed to robots. In contrast, we find no significant effects on children's mobility when parents worked in low-exposed occupations, which supports the interpretation that our estimates capture the impact of automation.

These patterns are mirrored in our firm-level analysis. Children of parents employed in firms with higher adoption of automation technologies also exhibit lower income mobility, and the effect is again concentrated among parents in highly exposed occupations. Using IV-regressions that instrument firm automation adoption with CEO education yields estimates that point in the same direction, reinforcing the interpretation that the results capture the consequences of parental exposure to automation rather than unobserved industry or firm shocks.

An important question is whether the estimated reduction in income mobility reflects better or worse outcomes for children. For instance, if the parents most affected by automation are located above the average in the parental income distribution, lower mobility may simply reflect persistence at a high level. Conversely, if the affected parents are concentrated below the average, lower mobility is more likely to reflect reduced upward mobility and weaker labor market outcomes for their children. To assess which interpretation applies in our setting, we examine upward mobility among children whose parents were in the bottom quartile of the income distribution, and whether the effect of parental exposure to automation on children's labor market careers vary across the parental income distribution.

For upward mobility, we estimate that children of parents in high-robot-exposed occupations are substantially less likely to reach the top quartile if their parent worked in a high-robot-adopting industry rather than in a low-adopting one. For children whose parents had low-robot-exposed occupations, industry-level robot adoption does not affect upward mobility. These results indicate that lower mobility in our setting reflects diminished upward prospects for children from less advantaged backgrounds.

Beyond income mobility, we analyze how automation exposure translates into broader labor market outcomes and inequality for the next generation. Our results reveal that robot adoption affects children differently depending on their parents' position in the earnings distribution. In low-income families, parental robot exposure is associated with adverse labor market and educational outcomes for children, including lower earnings and earnings rank, higher unemployment risk, lower high-school grades, and reduced university attendance. In high-income families, none of these effects are present. Taken together, these distributional results suggest that automation may have contributed to rising inequality through an intergenerational transmission channel.

Several mechanisms may explain how parents' exposure to robots affects their children in the long run. One possibility is that automation-related labor market disruptions lead to financial strain, negatively impacting children's development, academic performance, and future prospects. Consistent with this interpretation, we show that exposed parents in the lower part of the income distribution experience earnings losses, a higher risk of leaving the labor force, and increased reliance on social benefits and sick leave. None of these effects appear among parents at the top of the income distribution.

Another mechanism operates through occupational and industry persistence within families, where children often enter the same fields as their parents. When automation reduces labor demand in the parents' occupation or industry, this may either trap children in declining segments of the labor market or weaken intergenerational persistence if parents steer them toward less exposed jobs. We show that both occupational and industry persistence are present across generations. However, these channels cannot account for the observed heterogeneity in children's outcomes across the parental income distribution. Instead, our results indicate that parents' adverse labor market experiences and the resulting financial strain appear to be the primary channels through which automation affects intergenerational mobility. Families facing the largest income losses also exhibit the strongest deterioration in children's long-run outcomes, consistent with a mechanism operating through reduced parental resources and increased instability.

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 the labor market consequences of automation and robot investments. Based on these strands of literature, the contribution of our paper is twofold.

First, a growing literature examines the determinants of intergenerational mobility. Chetty, Hendren, Kline, and Saez (2014) and Chetty and Hendren (2018) show that spatial differences in U.S. mobility correlate with factors such as residential segregation, income inequality, school quality, social capital, and family environment. Parental job loss has been linked to poorer school performance (Rege, Telle, and Votruba, 2011; Stevens and Schaller, 2011) and worse adult outcomes for children (Oreopoulos, Page, and Stevens, 2008). Other studies investigate how macroeconomic shocks shape mobility: economic downturns tend to reduce earnings mobility (Feigenbaum, 2015; Nybom and Stuhler, 2021), while greater trade openness (Ahsan and Chatterjee, 2017) and the Norwegian oil boom (Bütikofer, Dalla-Zuanna, and Salvanes, 2025) increased intergenerational income mobility.

Structural technological transformations, including automation, job polarization, and regional industry decline, have also been studied, typically focusing on spatial patterns of intergenerational mobility in the U.S. (Aziz, 2024; Berger and Engzell, 2022; Guo, 2022; García-Peñalosa, Petit, and Van Ypersele, 2023; Seltzer, 2024). This strand of the literature generally finds lower upward mobility in regions more exposed to structural changes but improved educational mobility, particularly for children from low-income families. Positive effects of technological transformations are also found by Arntz, Lipowski, Neidhöfer, and Zierahn-Weilage (2025), who show that the increased use of computer-controlled tools in Germany has had positive effects on equality of opportunity, improving wages and employment prospects for children with low-income parents.

We contribute to this literature by shifting the focus from regional exposure to automation toward individual exposure transmitted through parents' occupation and industry. By doing so, we can show how parental exposure to robots maps into children's long-run income mobility and labor market careers. Our results suggest that automation not only transforms regional labor markets but also reshapes intergenerational mobility by reallocating opportunities across families rather than places. As such, our study provides novel evidence on the combined impact of occupational exposure to automation and the rising use of robots on intergenerational mobility.

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] 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 et al. (2021) find no evidence that robots cause overall job losses but rather affect aggregate employment composition. While industrial robots negatively impact employment in the manufacturing sector, there is a positive and significant spillover effect as employment in the non-manufacturing sectors increases. The evidence on how individual workers are affected by robot adoption is mixed, with Acemoglu and Restrepo (2020), Acemoglu, Lelarge, and Restrepo (2020), Dauth et al. (2021), Barth, Røed, Schøne, and Umblijs (2025) and Umblijs and Østbakken (2025) finding negative effects on production, blue-, 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 on automation and how it affects intergenerational income mobility. Our analysis covers a multitude of outcomes and reveals that the impact of automation on intergenerational mobility is not uniform across occupations but varies with the specific tasks associated with parents' jobs. This finding is consistent with the predictions of the task-based approach and highlights how occupation-specific exposure to automation interacts with industry-level robot adoption in shaping long-run opportunities for the next generation.

[6] See, for instance, Autor et al. (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018a, 2019, 2020); Benzell, Kotlikoff, LaGarda, and Sachs (2015). Evidence for Sweden is presented in Gardberg, Heyman, Norbäck, and Persson (2020) and Edin, Evans, Graetz, Hernnäs, and Michaels (2023).

2 Data and empirical strategy

To examine how automation affects intergenerational mobility, we compare income mobility among children whose parents were exposed to varying degrees of robotization. This requires addressing several empirical challenges. First, we must link and analyze detailed data on both parents and their adult children. Second, we need to distinguish between parents who were exposed to robots and those who were not. Third, we must account for the fact that robot-exposed parents may differ systematically from non-exposed parents in both observable and unobservable characteristics, which could bias our results.

To address these challenges, we draw on rich individual-level data covering a thirty-year period. These data allow us to analyze parents and their children when both generations are in their late 30s, incorporating information on parental exposure to robots at the industry and occupational levels. In addition, we use firm-level import data on robots and automation technologies discussed in more detail in Section 4.2. To address the non-random nature of parental robot exposure, we compare the mobility of children whose parents share similar observable characteristics and work in similar occupations but are employed in industries or firms with different levels of automation. Finally, this set-up allows us to examine intergenerational mobility in contexts where parents may have either benefited from or been adversely affected by robot adoption. Before presenting our empirical strategy, we begin by describing the data in more detail.

2.1 Longitudinal individual-level data

We use several administrative registers from Statistics Sweden. The core source is the Longitudinal Integration Database for Health Insurance and Labor Market Studies (LISA), which provides annual data on employment, earnings, occupations, and demographics for all Swedish residents aged 16 and older from 1990 to 2019.

We complement this with data from the Swedish Population and Housing Census (1985 and

1990), which report parents' earnings and occupations.[7] Occupations are classified according to the Nordic Standard Occupational Classification, translated into the Swedish system (SSYK) and harmonized with the international ISCO classification.[8]

We link parents and children using the Swedish Multigenerational Register, which covers all individuals born in 1932 or later who have resided in Sweden since 1961. We focus on parents who, in 1990, were employed, earned at least 50,000 SEK annually (corresponding to about 4,450 USD in 2025), and had children aged 7–15.[9] The final dataset includes 565,297 parents and 795,119 children. Parents' earnings are averaged over 1985–1990, while children's earnings are averaged over 2015–2019 to reduce transitory variation. We compute percentile ranks for both generations, by sample for parents and by birth cohort for children.

2.2 Industry and occupational data on robot exposure

Because LISA does not contain direct measures of individual exposure to robots, we combine industry-level data on robot penetration from the International Federation of Robotics (IFR) with occupational-level data on robot exposure from Webb (2020).

Industry exposure. The IFR reports the operational stock of industrial robots by industry, country, and application for over 20 countries, including Sweden.[10] We define robot penetration as the operational stock of robots per employee, following the IFR definition of a robot as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes." The IFR's 2-digit ISIC Rev.4 classification is matched to Swedish data (NACE Rev.1.1). Figure 1 shows the development of the operational stock of robots per thousand workers in eight Western European countries from 1994 to 2021. All countries except Norway and the U.K. experienced a significant increase in robot penetration during the period, with the largest increase observed in

[7] The census response rate was 98.8% in 1985 and 97.5% in 1990.

[8] We thank Adrian Adermon for sharing the crosswalk between the systems. Detailed ISCO documentation is available at: `http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm`.

[9] The sample excludes parents older than 51 in 1990 to avoid retirement-related effects during the 1990s.

[10] See International Federation of Robotics (2024) for details. IFR data are widely used in studies such as Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Dauth et al. (2021), and Acemoglu and Restrepo (2022).

Germany, followed by Italy and Sweden. For Sweden, an almost linear increase is evident from approximately one robot per thousand workers in 1994 to nearly four robots in 2021.

To understand which parents in our sample that have been affected by increased automation, we calculate the change in the operational stock of robots in each industry i from 1994 to 2004 (a period during which none of the parents in our sample had reached the general retirement age of 65). This change is measured relative to the total employment in industry i in the year 1990 ($L_{i,1990}$):

$$\Delta robots_i = \left(\frac{robots_{i,2004} - robots_{i,1994}}{L_{i,1990}}\right) \tag{1}$$

Figure 2 shows large variation across 19 Swedish industries, with the biggest increases in automotive and rubber/plastics manufacturing, and some industries showing small or negative changes. We then, based on Equation 1, classify industries as high or low robot-adopting depending on whether their robot penetration exceeded the median p(50):

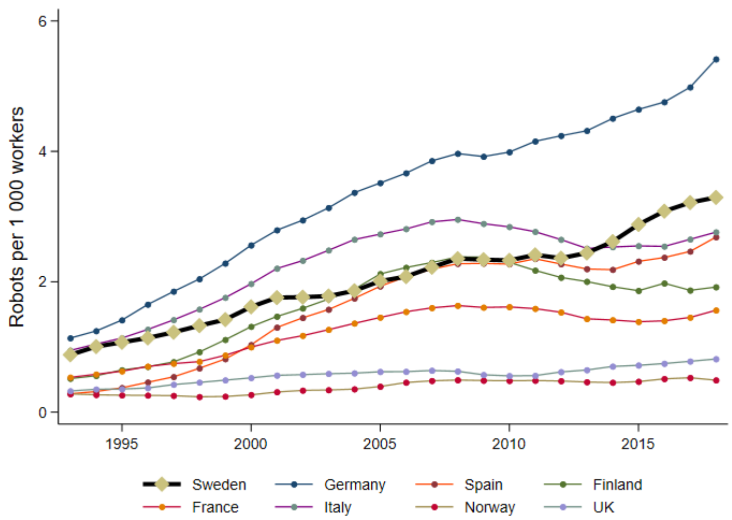
$$I(\Delta robots_i) = \begin{cases} 0, & \text{if } \Delta robots_i \leq p(50) \\ 1, & \text{if } \Delta robots_i > p(50) \end{cases} \tag{2}$$

allowing us to compare the mobility of children whose parents worked in industries with high levels of robot adoption to those whose parents were employed in industries with low levels of robot adoption.[11]

Occupational exposure. In addition to leveraging variation in robot penetration across industries, we allow the impact of automation to vary at the occupational level. This allows us to analyze parents working in similar robot-exposed occupations but in industries with varying levels of robot penetration. To capture variation in exposure within occupations, we use the robot exposure measure from Webb (2020), which quantifies how similar occupational tasks are to those described

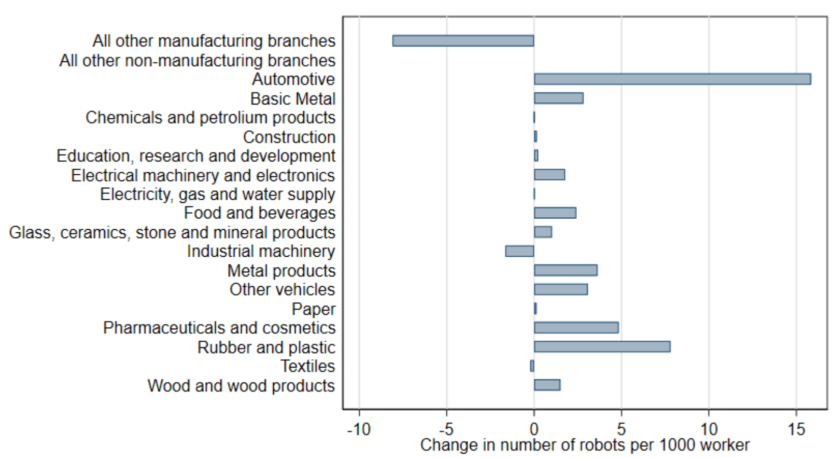
[11] Hence, our empirical strategy utilizes the change in post-1994 installations rather than the initial stock.

Figure 1: 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 1994 to 2021. Data on the operational stock of robots originate from the IFR. Employment data come from OECD and are based on 1993.

Figure 2: Industry variation in robot adoption



Notes: The figure displays the 1994 to 2004 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 measured in 1990 and come from Statistics Sweden.

in robot-related patents.[12] This measure, based on U.S. O*NET data, is translated to Swedish occupational codes (SSYK96) through ISCO88 using established crosswalks. When multiple U.S. occupations map to one Swedish occupation, we take the average exposure score. To assess how occupations are affected by robot technologies, the method identifies the tasks robots can perform and calculates to which extent each occupation involves performing similar tasks. The final measure is expressed as score percentiles, with an occupation's overall score being the average of its task-specific scores.[13] In total, we link exposure percentiles for 90 Swedish occupations.

For the entire Swedish economy, Figure 3, Panel A, shows that employment fell in high-exposure occupations and rose in low-exposure ones between 1990 and 2013, consistent with automation displacing routine jobs. In addition, Panel B displays that exposure is highest at the bottom of the earnings distribution, flat through the middle, and lowest at the top, and Panel C shows that the share of workers in high-robot adopting industries is an increasing function of occupational robot exposure.[14] When analyzing robot exposure in our sample of parents, we compute their average occupational exposure in 1985 and 1990.[15]

To assess the impact of automation on intergenerational income mobility, we compare children's mobility depending on whether their parents were exposed to robots or not. Directly comparing parents across occupations with different robot exposure, however, may also capture other differences unrelated to automation. As shown in Figure A1 in the Online Appendix, occupational exposure to robots is negatively correlated with several parental characteristics such as the share of females, university education, average earnings, and age.

To address this, we classify parents into two groups based on their occupational robot exposure:

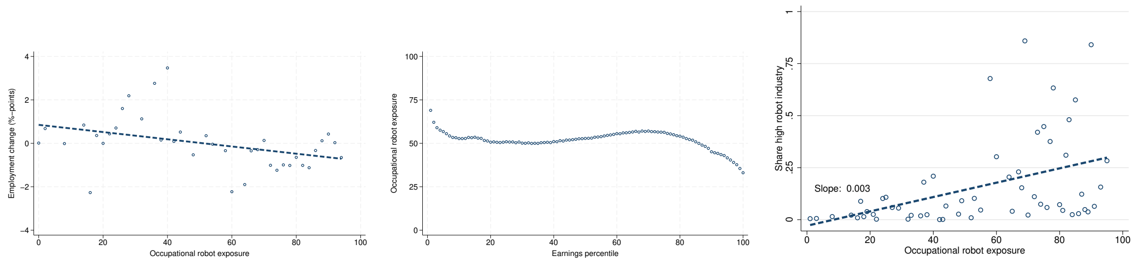
[12] We are grateful to Michael Webb for providing this measure.

[13] The three most exposed occupations are construction equipment operating engineers, industrial truck operators, and elevator installers and repairers (all with a percentile score of 98 or higher); the three least exposed occupations are art/entertainment artists, priests, and mail carriers for postal service (all with a percentile score equal to one).

[14] In our sample of parents, Table A1 in the Online Appendix shows that more than 77% of the parents in high robot-adopting industries are in highly robot-exposed occupations.

[15] If a parent is observed only in 1990, that year's exposure value is used (17% of cases).

Figure 3: Occupational robot exposure



(A) Employment change **(B)** Earnings distribution **(C)** Share high-robot industries

Notes: Panel A displays employment changes between 1990 and 2013 in Sweden by occupational robot exposure (measure defined by Webb (2020)). Panel B displays the average occupational robot exposure across the labor earnings distribution. Panel C displays the correlation between the share of workers in high robot adopting industries and occupational robot exposure. The sample consists of all individuals with positive labor earnings and an occupation that can be linked to the occupational robot exposure measure defined by Webb (2020).

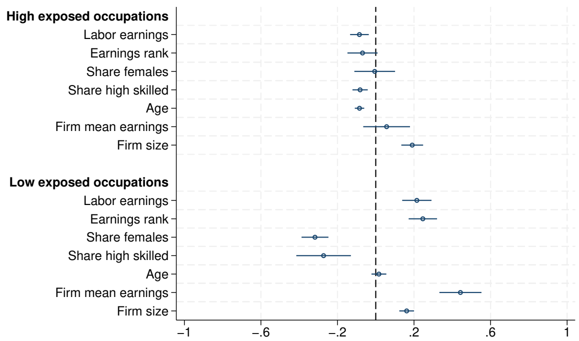
$$I(OccExposure_o^p) = \begin{cases} 0, & \text{if } OccExposure_o^p \leq 50 \\ 1, & \text{if } OccExposure_o^p > 50 \end{cases}$$

where $OccExposure_o^p$ is the parent's occupational robot exposure percentile. This distinction makes it possible to compare children with parents in comparable robot-exposed occupations as well as to analyze how children's mobility differs depending on whether their parents worked in occupations where robots likely replaced or complemented labor.

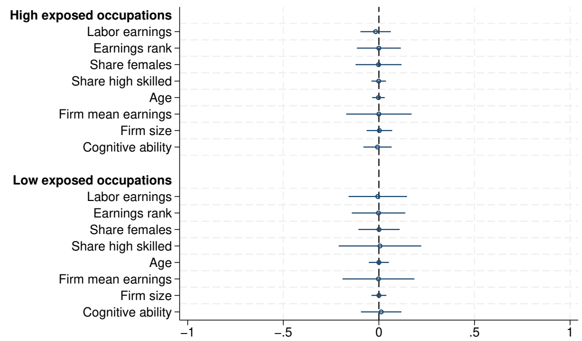
2.3 Balancing the sample

A key assumption for our empirical strategy is that parents in similarly robot-exposed occupations are as good as randomly sorted between industries with varying degrees of robot penetration. However, Figure 4, Panel A, reveals a systematic disparity between parents in high- and low-robot industries within occupations with similar robot exposures. Specifically, within occupations heavily impacted by robots, i.e., when $OccExposure_o^p > 50$, we notice that average labor earnings tend to be lower in more robotized industries, as well as the share of high-skilled and the average age. In addition, workers in high robot adopting industries tend to be employed in larger firms with higher

Figure 4: Differences in characteristics between high- and low-robot-adoption industries



(A) Panel A: Initial sample



(B) Panel B: Balanced sample

Notes: The figures display the average differences in worker characteristics between parents employed in high- and low-robot-adoption industries by robot-exposure occupations. All variables are standardized with a mean zero and a one standard deviation. Panel A shows the difference in the initial sample, while Panel B shows the difference in the balanced sample.

average earnings, factors that may correlate with automation.[16] This pattern of disparity extends to parents in occupations less affected by robots, i.e., when $OccExposure_o^p \leq 50$, which is also marked by significant differences across industries with varying levels of robot adoption.

To address these imbalances, we employ the following matching procedure within the groups of high- and low-robot-exposed occupations: For every parent in a high-robot industry, we identify a counterpart in a low-robot industry that matches in terms of (i) occupational robot exposure (above or below 50th percentile of the occupational exposure distribution $OccExposure_o^p$), (ii) labor earnings (same percentile), (iii) age (less than 30 years, 30–34, 35–39, 40–44, 45–51), working in the same business sector, (iv) educational attainment, (v) gender, (vi) working in a firm of similar size (using quartiles of the number of employees), and (vii) with similar firm-level earnings (using quartiles of the firm average earnings distribution). This reduces the number of parents from 565,297 in the initial sample to 166,758 in the balanced sample (see Table A1 in the Online

[16]Differences in firm size and mean labor earnings may bias our results if they capture systematic variation in productivity or worker composition. More productive firms typically pay higher wages (see, e.g., Card, Devicienti, and Maida (2014)), and firm-level heterogeneity is a key determinant of both wage and productivity differences. Larger firms also tend to offer higher wages (Brown and Medoff, 1989), exhibit greater productivity (Syverson, 2011), invest more in human capital (Barron, Black, and Loewenstein, 1987), and are typically more innovative and R&D intensive (Cohen and Klepper, 1996). These factors can influence parents' labor market careers and, in turn, their children's outcomes.

Appendix). The balanced sample includes 83,379 parents in high-robot-exposed industries and 83,379 parents in low-robot-exposed industries, with an equal sample size in the occupational robot exposure groups. While the matching reduces the overall sample size, the number of parents in highly exposed industries is only reduced by 4.2%.

Table 1 presents summary statistics for the matched sample of parents and their children. A key feature of our data is that parents and children are, on average, 40 and 38 years old, respectively. This alignment in age helps to mitigate life-cycle bias, which arises when parents and children are observed at different points in their earnings trajectories. In addition, since the relationship between current and lifetime earnings varies over the life cycle, measuring income around midlife provides a more accurate approximation of permanent income and, consequently, of intergenerational income mobility.[17]

Moreover, Figure 4, Panel B, shows that our matching procedure balances average characteristics between parents employed in high- and low-robot-adopting industries, within both the high- and low-exposed occupational groups. This further ensures comparability between groups and reduces potential confounding from differences in key worker characteristics when analyzing intergenerational income mobility.

Despite the implementation of a matching procedure, we cannot dismiss the possibility that unobserved characteristics not related to automation may influence our results. One such unobservable characteristic is cognitive ability, which may bias our results if parents in high- and low-exposed occupations are systematically sorted by ability into industries with different degrees of robotization. For instance, workers with a more sophisticated understanding of the labor market may anticipate that their occupation will face less exposure to robotics in certain industries and, consequently, self-select into those sectors. To address this concern, we examine parents' abilities as quantified by cognitive scores from the Swedish enlistment test. This test evaluates an individual's ability to perform various mental tasks indicative of learning and problem-solving capabilities. The cognitive test scores are good measures of worker ability, are closely related to labor market success (Lindqvist

[17]See Haider and Solon (2006), Böhlmark and Lindquist (2006), and Nybom and Stuhler (2016).

Table 1: Summary statistics for the parent–child sample

	Mean	SD	Min	Max
Panel A: Parents				
Female	27.68	44.74	0.00	100.00
Age	39.72	5.32	25	51
University (%)	5.36	22.53	0	100
Labor earnings (TSEK)	403.44	166.37	50.06	3,646.47
OccExposure	64.02	21.78	1.00	95.25
I(OccExposure)(%)	76.58	42.35	0	100
Δrobots (%)	2.27	4.47	-8.10	15.85
I(Δrobots) (%)	50.00	50.00	0	100
Panel B: Children				
	Mean	**SD**	**Min**	**Max**
Female	48.50	49.98	0	100
Age	38.01	2.60	32	44
University (%)	33.09	46.81	0	100
Labor earnings (TSEK)	346.68	217.34	0	18,665.09

Notes: The sample consists of 166,758 parents, 212,899 children and 233,504 child-parent observations.

and Vestman, 2011; Baghai, Silva, Thell, and Vig, 2021), and are available for 62,329 fathers in our sample.

Figure 4, Panel B, plots the average difference in cognitive ability between parents employed in industries with high and low levels of robot exposure within similar occupational categories. Encouragingly, the average abilities are comparably distributed among parents across industries with different levels of robot exposure within the same occupational categories.

2.4 Estimating income mobility

The starting point for our empirical analysis is a so-called rank–rank regression model that relates children's earnings ranks to those of their parents:

$$Rank^c = \pi + \beta Rank^p + X'\theta + \epsilon^c \tag{3}$$

In our setting, $Rank^c$ is the average earnings percentile rank for child c during the 2015–2019 period, and $Rank^p$ is the corresponding average earnings percentile rank of her parent p 1985 and 1990. The coefficient β is the rank parameter that varies from minus one to one, where a higher value means a tighter link in the earnings position of parents and children as adults, indicating less mobility and a lower value means a higher degree of mobility between parents and children.[18] Since our sample includes all possible father–child and mother–child dyads, the interpretation of β differs from models that focus solely on the father–son pair, combine fathers' and mothers' incomes, or include separate regressors for each parent. The pooled estimate captures the average rank–rank gradient between parental rank and the child's adult rank, where each type of parent–child dyad contributes in proportion to its prevalence in the sample.

The vector X includes separate controls for children and parents and contains age fixed effects and an indicator for being female. It also includes fixed effects for the number of children in the family (family size) and indicator variables for whether the parent has a university education, is married, or was born outside Sweden, as well as regional fixed effects. On the firm side, the model includes controls for average earnings, the share of high-skilled workers and females, and the number of employees (firm size) in the firm in which the parent is employed. All parental controls are measured in 1990. Finally, ϵ^c denotes the error term and we apply clustering based on the father's and mother's industries of employment.

To identify the impact of automation on income mobility we compare parents with similar occupational robot exposure but who work in industries with different degrees of robot adoption. Therefore, we extend the basic rank–rank model to account for parental industry exposure to robots $I(\Delta robots_i^p)$:

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

[18]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; second, it allows the relationship in earnings over generations to be nonlinear. 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 this model, the coefficient β_1 is the rank–rank correlation for parents working in low–robot–adopting industries. β_2 is the difference in children's average percentile rank if the parents worked in an industry with high rather than low levels of robot penetration. The coefficient of the interaction term, β_3, captures the difference in income mobility when parents worked in industries with high versus low levels of robot penetration. A positive (negative) β_3 means that children's income mobility is lower (higher) if parents are employed in industries that more heavily adopt robots, indicating a stronger (weaker) persistence of earnings rank across generations. In the model, parental earnings rank is included to characterize the association between parents' and children's positions in the earnings distribution, while the identifying variation comes from differences in parents' exposure to automation rather than from differences in parental rank.

To account for parents' occupational exposure to robots, we either estimate Equation (4) separately for parents in high- or low-exposed ones or use a fully flexible model:

$$\begin{aligned}
Rank^c = \alpha + \beta_1 Rank^p + \beta_2 I(\Delta robots_i^p) + \beta_3 Rank^p \times I(\Delta robots_i^p) + \beta_4 I(OccExposure_o^p) \\
+\beta_5 I(OccExposure_o^p) \times I(\Delta robots_i^p) + \beta_6 Rank^p \times I(OccExposure_o^p) \\
+\beta_7 Rank^p \times I(OccExposure_o^p) \times I(\Delta robots_i^p) + X'\theta + \epsilon^c \qquad (5)
\end{aligned}$$

to estimate the rank–rank correlations for all combinations of high/low occupational and industry robot exposure and their differences. For parents in low-exposed occupations, β_3 captures the differences in mobility when parents worked in industries with high versus low levels of robot penetration. The same industry difference for parents in high-exposed occupations is given by $\beta_3 + \beta_7$. Consequently, β_7 estimates whether the impact of automation on intergenerational income mobility is stronger when both the parent's occupation and industry are technologically vulnerable.[19]

Finally, when estimating Equations (4) and (5), a concern is that industry robot penetration can be correlated with domestic industry demand shocks. To address this potential endogeneity

[19] The rank–rank correlation for when parents worked in a low-exposed occupation and industry is given by β_1, in a low-exposed occupation in high-robot industry by $\beta_1 + \beta_3$, in a high-exposed occupation in low-robot industry by $\beta_1 + \beta_6$, and for high-exposed occupation in high-robot industry by $\beta_1 + \beta_3 + \beta_6 + \beta_7$.

problem, we follow the approach taken by Autor et al. (2013), Acemoglu and Restrepo (2019), and Dauth et al. (2021) (among others) and instrument industry robot installations in Sweden with mean robot installations in the same industries in comparable countries using IV regressions.[20] The validity of the instrument requires two conditions to be met. First, robot adoption in Swedish industries must be sufficiently correlated with robot adoption in the same industries abroad. This is the relevance condition, which can be tested using the first-stage Kleibergen–Paap F-statistic. Second, conditional on the covariates in the model, the instrument must affect the outcome only through the endogenous variable of interest. This is the exclusion restriction. In our setting, this implies that foreign industry-level robot adoption can influence children's outcomes only through its correlation with domestic robot adoption across industries. Although the exclusion restriction cannot be tested directly and must be assumed, it is plausible in our case, as global diffusion of robots is largely driven by technological supply factors rather than by Swedish demand or labor-market shocks.[21]

We complement the rank–rank analysis of relative mobility with evidence on children's upward mobility and absolute outcomes. While the rank–rank specification captures overall intergenerational mobility, upward mobility focuses on opportunities for children from low-income families. Specifically, we estimate the probability that children of parents in the bottom quartile of the parental earnings distribution reach the top quartile of the child income distribution. This extension is important because changes in relative mobility can have different implications depending on where families and children start. A decline in mobility is positive for already advantaged groups but potentially problematic if it reflects diminished upward prospects for low-income families. For the absolute outcomes, we analyze a wide range of outcomes that reflect both labor market status and educational outcomes. These complementary approaches help us understand if automation affects both the relative transmission of economic status and the absolute well-being of the next

[20] We use the same set of countries as 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.

[21] In addition, if automation has heterogeneous effects on parents, the so-called monotonicity conditions must hold for the IV-estimate to be interpreted as LATE. Monotonicity requires that the instrument must have the same directional effect on all parents, though the magnitude can be different.

generation.

For both the upward mobility and absolute outcomes, we estimate the following model:

$$Y^c = \alpha + \beta I(\Delta robots_i^p) + X'\theta + \epsilon_i \tag{6}$$

where Y^c is the average outcome Y for child c during the 2015–2019 period. Equation (6) is estimated for the whole sample and separately by the two occupational robot exposure groups (high and low). To test whether the impact of robotization varies across the two occupational robot exposure groups, we run the following model:

$$\begin{aligned} Y^c = \alpha + \beta_1 I(OccExposure_o^p) + \beta_2 I(\Delta robots_i^p) + \\ \beta_3 I(OccExposure_o^p) \times I(\Delta robots_i^p) + X'\theta + \epsilon^c \end{aligned} \tag{7}$$

where the focus is on the estimate of the coefficient β_3 that reveals whether the impact of robotization is stronger when both the parent's job and industry are technologically vulnerable.

3 Results

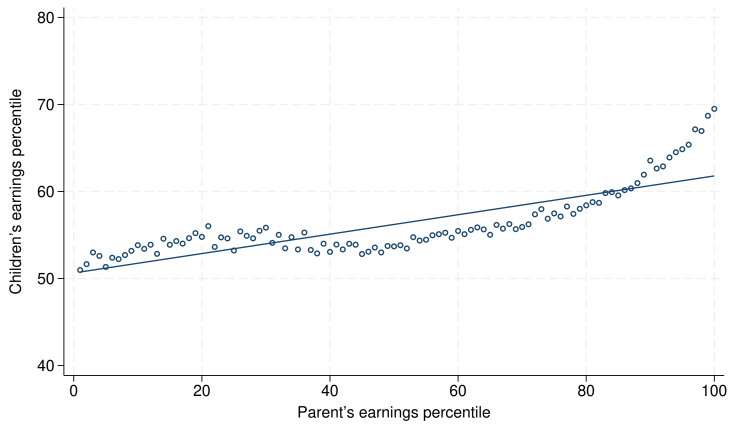
We begin this section by examining the general patterns of intergenerational mobility, followed by an analysis of how parental occupational exposure to robots correlates with children earnings. Subsequently, we focus on the impact of automation on intergenerational income mobility.

3.1 Basic intergenerational mobility

Figure 5 plots the relationship between the average earnings rank of children and their parents in their respective earnings distribution, demonstrating a positive and nearly linear correlation until the top decile of the parental earnings distribution. By estimating this relationship using Equation (3), Column 1 in Table 2 shows that the estimated rank–rank correlation equals 0.12. This means that, on average, a 10-percentage-point increase in a parent's earnings rank corresponds to a 1.2-

percentage-point increase in the child's earnings rank. For comparison, the intergenerational income elasticity is presented in Column 2 and equals 0.14.[22]

Figure 5: Earnings rank correlation



Notes: The figure displays the average earnings rank for children from 2015 to 2019 by parents' mean earnings rank in 1985 and 1990.

Next, we consider how children's earnings rank relates to the robot exposure measure created by Webb (2020). Columns 3 and 4 in Table 2 show a negative association between parents' occupational robot exposure and children's earnings rank later in life. In Column 3, parental robot exposure is measured as a continuous variable, whereas Column 4 is based on the indicator variable $I(OccExposure_o^p)$, which takes the value of one if the underlying exposure measure $OccExposure_o^p$ is above the median and zero otherwise. Quantitatively, the estimate in Column 3 indicates that a 10-percentage-point increase in parents' robot exposure rank is associated, on average, with almost a one percentage-point lower earnings rank for their children.

Before addressing how parental exposure to robots has affected earnings mobility for children, we end this section by displaying results that compare basic rank–rank estimates between parents with high- or low-robot-exposed occupations. The estimates in Column 5 show that children whose

[22]As we include fathers, mothers, sons, and daughters in our analysis, 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) show that intergenerational mobility is even stronger when the extended family is considered.

Table 2: Basic results

	Child outcome					
	Rank	Log Earnings	Rank	Rank	Rank	Rank
	(1)	(2)	(3)	(4)	(5)	(6)
Rank	0.118***				0.098***	0.100***
	(0.005)				(0.005)	(0.008)
Log Earnings		0.135***				
		(0.005)				
OccExposure			-0.093***			-0.091***
			(0.004)			(0.007)
I(OccExposure)				-3.567***	-5.111***	
				(0.189)	(0.397)	
OccExposure × Rank						0.000***
						(0.000)
I(OccExposure) × Rank					0.038***	
					(0.006)	
R^2	0.01	0.01	0.11	0.10	0.11	0.11
Observations	233,504	221,721	233,504	233,504	233,504	233,504

Notes: This table reports results from estimating different versions of specification (3). Rank refers to percentile earnings rank. I(OccExposure) takes the value one if the underlying robot exposure measure, OccExposure, is above the median and zero otherwise. The models in Columns 3–6 control for age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1

parents worked in high-robot-exposed occupations have an earnings rank on average 5.1 percentage points lower than that of children whose parents worked in low-exposed occupations. Furthermore, the rank–rank correlation is approximately 39 percent higher if the parent was in a high-exposed occupation rather than a low-exposed occupation (0.038 divided by 0.098), suggesting that exposure to robots is associated with lower income mobility. The results are robust when using a continuous measure of robot exposure, as shown in Column 6.

3.2 Robot exposure and intergenerational mobility

Next, we examine whether technological change has influenced intergenerational mobility by exploiting variation in industry-level robot adoption among parents working in similarly robot-exposed occupations.

Table 3, Column 1, presents the ordinary least squares (OLS) results using specification (4) for the whole sample of parents and children. The estimate on $I(\Delta robots_i^p)$ shows that the children's income rank in adulthood is, on average, 1.5 lower if the parent worked in an industry with a large positive change in the number of robots per employee. Furthermore, the estimated coefficient for $Rank^p$ reveals that the correlation between the child's and the parent's earnings rank is 0.122 if the parent worked in an industry with relatively low levels of robot penetration. However, the rank–rank correlation is 18 percent higher if the parent was employed in an industry with a high level of robot penetration, as captured by the interaction term $I(\Delta robots_i^p) \times Rank^p$ (0.022 divided by 0.122).

When estimating separate models by parental occupational exposure, the results in Columns 2 and 3 show that the lower intergenerational mobility in high-robot industries (Column 1) stems primarily from parents in highly exposed occupations. For these parents, the rank–rank correlation is approximately 25 percent higher if the parent was employed in an industry with a high level of robot investment instead of in an industry with a low level of robot adoption (Column 2). No statistically significant difference between industries exists for parents in low-exposed occupations, as shown in Column 3, underscoring that automation has heterogeneous effects across occupations.

For the OLS results shown in Columns 1–3, $\Delta robots_i^p$ is measured as the change in robot adoption (operational stocks) in Sweden between 1994 and 2004. To address endogeneity concerns (discussed in Section 2.4), Columns 4–6 present the IV results, where we instrument Swedish robot adoption with the average robot adoption in comparable countries. The results based on IV are very similar to the OLS results. Columns 4–6 show evidence of lower income mobility for children with parents who worked in an industry with high levels of robot adoption, again originating from parents with a high-robot-exposed occupation.

Next, we estimate the fully flexible specification (5) to directly test the difference in intergenerational mobility between high- and low-exposed occupations in high- versus low-exposed industries. The results based on OLS are presented in Column 7, and the corresponding IV estimates are shown in Column 8. The main variable of interest in these specifications is the estimated coefficient for $I(OccExposure_o^p) \times I(\Delta robots_i^p) \times Rank^p$. This triple interaction term captures whether intergenerational mobility is affected by both occupational and industry exposure. Effectively, it compares if industry robot adoption has a different effect on children's income mobility when parents worked in high- or low-exposed occupations. This is indeed the case in Columns 7–8, showing that parents' occupational exposure plays a key role in the intergenerational effects.

In sum, the results in Table 3 suggest that automation has long-run effects across generations, where parental exposure lowers their children's income mobility in adulthood. In Section B of the Online Appendix, we show that the dampening effect on income mobility is present among both sons and daughters.

Table 3: Income mobility: Rank–rank regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank	0.122***	0.117***	0.112***	0.117***	0.113***	0.108***	0.098***	0.095***
	(0.004)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)	(0.006)	(0.006)
I(Δrobots)	-1.526***	-2.344***	0.594	-2.231***	-2.795***	0.080	0.844	0.298
	(0.370)	(0.432)	(0.564)	(0.418)	(0.496)	(0.621)	(0.570)	(0.630)
I(Δrobots) $\times$ Rank	0.022***	0.030***	-0.001	0.032***	0.036***	0.006	-0.000	0.007
	(0.005)	(0.007)	(0.008)	(0.006)	(0.008)	(0.009)	(0.008)	(0.009)
I(OccExposure)							-3.513***	-3.544***
							(0.526)	(0.562)
I(OccExposure)$\times$Rank							0.023***	0.023***
							(0.008)	(0.008)
I(OccExposure) $\times$ I(Δrobots)							-3.213***	-3.150***
							(0.733)	(0.827)
I(OccExposure) $\times$ I(Δrobots)							0.030***	0.031***
x Rank							(0.011)	(0.012)
Occ. exposure	All	High	Low	All	High	Low	All	All
Model	OLS	OLS	OLS	IV	IV	IV	OLS	IV
F-stat.				483	383	727		183
Observations	233,504	179,407	54,097	233,504	179,407	54,097	233,504	233,504

Notes: This table reports the OLS and IV estimates from Equations (4) and (5), using children's earnings rank as the dependent variable. Rank refers to the parental percentile earnings rank. I(OccExposure) equals one if the underlying robot exposure measure is above the median and zero otherwise. I(Δrobots) equals one if the change in robot adoption per employee in industry i over the 1994–2004 period is above the median change and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. F-stat is the Kleibergen–Paap rk Wald F-statistic. Standard errors are clustered at the father's and mother's industries of employment level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.3 Robot exposure and upward mobility

An important question is whether the reduction in income mobility reflects better or worse outcomes for children. To assess this, we examine upward mobility among children of parents in the bottom earnings quartile and study how the effects of parental exposure to automation vary across the parental income distribution. To this end, we estimate Equations (6) and (7) where the dependent variable is equal to one if the child has an earnings rank above the 75th earnings percentile in the 2015–2019 period, and zero otherwise.

Table 4 presents the results for upward mobility for all children in Column 1, whereas separate estimates by parents' occupational robot exposure (high and low) are presented in Columns 2 and 3. Column 1 shows that children whose parents worked in industries with a large increase of robots are 1.7 percentage points less likely to reach the top quartile of the income distribution compared with children whose parents worked in low robot adopting industries. Hence, for these parent–child pairs, we observe less upward mobility in earnings. Importantly, and in line with the rank-rank results, we note that this effect originates from parents in highly exposed occupations (Column 2). No statistically significant effect of robot adoption on upward mobility is found for children of parents with occupations with low levels of robot exposure (Column 3). In the joint specification (Column 4), the coefficient on the interaction term $I(OccExposure_o^p) \times I(\Delta robots_i^p)$ indicates a statistically significant difference in the impact of robot adoption on upward mobility between children of parents in high- and low-exposed occupations.

Quantitatively, the estimate in Column 2 implies that a child whose parent held a high-robot-exposed occupation in an industry with a relatively large increase in robot adoption is, on average, 2.4 percentage points (roughly 14.5 percent, –0.024/0.166) less likely to reach the top quartile of the income distribution as an adult compared with a child whose parent worked in a low-robot-adoption industry.

Table 4: Upward mobility

	p(75)	p(75)	p(75)	p(75)
	(1)	(2)	(3)	(4)
I(Δrobots)	-0.017***	-0.024***	0.001	0.011
	(0.006)	(0.007)	(0.010)	(0.010)
I(OccExposure)				-0.045***
				(0.009)
I(OccExposure) $\times$ I(Δrobots)				-0.037***
				(0.012)
Constant	0.162***	0.166***	0.129	0.222***
	(0.052)	(0.059)	(0.114)	(0.054)
Occ. exposure	All	High	Low	All
Observations	37,075	26,620	10,455	37,075

Notes: This table reports IV estimates from Equations (6) and (7), for the sample of parents in the bottom quartile of the earnings distribution. The dependent variable is an indicator variable equal to one if the child belongs to the top quartile of the 2015–2019 mean income distribution, and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for parental earnings rank, family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

4 Robustness

To ensure the robustness of our main results, we conduct an extensive set of robustness checks. First, we estimate a series of alternative specifications that address potential concerns with the main model. Second, we run a placebo test using occupational exposure to artificial intelligence (AI) to assess whether our measure of occupational exposure to robots can be attributed to automation or is the result of underlying variations not directly related to automation. Finally, we show that using firm-level robot adoption gives quantitatively the same results as using industry-level robot adoption.

4.1 Alternative specifications

In Table 3, we run several robustness specifications, displayed in Table 5, where IV estimates from the fully flexible Equation (5) are presented. For comparison, the main IV results from Table 3 are displayed in Column 1. Identical robustness checks for the upward mobility results in Table 4 are shown in Table A2 in the Online Appendix.

As discussed in Section 2.4, we follow Autor et al. (2013), Acemoglu and Restrepo (2019), and Dauth et al. (2021) (among others) and instrument industry robot installations in Sweden with the mean robot installations in the same industries in comparable countries. Econometrically, one alternative approach is to use one instrument for each country instead of the mean. Column 2 in Table 5 demonstrates that the results are robust (basically identical) when specifying the IV regression in this alternative way.

Column 3 displays the results obtained when we control for the initial stock of robots at the industry level. Accounting for the initial stock of robots does not influence how the change in robots affects income mobility, confirming that our specification captures the effect of the increase in robot penetration rather than pre-existing industry differences.

Another important issue to consider is whether our results are biased by technologies other than robots that were implemented during the period we study. To address this question, we follow Bessen, Goos, Salomons, and Van den Berge (2025) and Acemoglu et al. (2024) and control for industry variation in investments in software. We are also able to control for the parent's occupational exposure to software.[23] Column 4 shows that adding these controls has no impact on how intergenerational mobility is affected by occupational exposure to robots and differential exposure to robots at the industry level. This result increases our confidence that our model captures the impact of robot adoption.

Next, we allow for an alternative time window for industry robot adoption. Our default period is 1994–2004, ensuring that parents are of working age. Column 5 uses robot penetration from 1994 to 2015, and the results again show lower income mobility among children whose parents were more

[23]Industry-level data on software usage originate from the EUKLEMS database (based on the "Euklems and INTANProd database, 2023" release; see Bontadini, Corrado, Haskel, Iommi, and Jona-Lasinio (2023) for details). We use computer software and database capital stock as our measure of software adoption. Similar to the IFR data, we use a crosswalk from the EUKLEMS data to NACE Rev. 1.1. The final measure is the industry change in software capital in terms of initial employment over the 1997–2004 period, which is as similar as possible to our $\Delta robots_i$ variable. The EUKLEMS data starts in 1997, as opposed to the IFR data, which starts in 1994. The occupational exposure to software is based on Webb (2020). The industry software and occupational software variables are both created in the same way as the corresponding robot variables.

exposed to robots at both the industry and occupational levels, although the estimated effects are somewhat larger when the longer period is used.

Our main analysis is based on all available observations on children and parents; thus, for a child with both parents in the sample, two parent-child observations will be included in the regressions. To account for "treatment dos", we restrict the sample to children with two parents in the sample. We are then able to estimate the combined effect of the two parents' occupational exposure to robots. The estimated triple interaction term (0.122) is now larger than in the main specification in Column 1 (0.031), but it is less precisely estimated. This suggests that the intergenerational effects of automation may be even stronger when considering both parents jointly.

Next, we investigate how differences in parents' educational attainment influence the relationship between cross-industry variation in robot adoption and income mobility. In Column 7, we substitute our indicator for high occupational exposure to robots with a dummy variable representing low education levels among parents.[24] While the results remain qualitatively similar, the standard errors are larger. One conclusion from this is that education is too a crude measure to fully capture the impact of robot exposure as compared to our occupational-specific measure of robot exposure.

In Column 8, we re-estimate Equation (4) using occupational exposure to AI, based on measures from Felten, Raj, and Seamans (2021), instead of exposure to robots. Since AI technologies, such as machine learning, only emerged later than the period we study, we do not expect differences in hypothetical AI exposure among parents to be systematically related to robot adoption or intergenerational mobility. As such, this serves as a placebo test: if our estimates were driven by unrelated factors rather than robot adoption itself, we would expect AI exposure to produce similar patterns. The results show that the triple-interaction term is close to zero, both statistically and economically. This null result strengthens our confidence in the main results.[25]

[24] Low education is defined as having less than two years of university education.

[25] We also fail to estimate significant differences in rank–rank correlations across high- and low-robot industries using the Felten, Raj, and Seamans (2023) measure of large language models.

Table 5: Income mobility: Robustness

	Main	**Separate IVs**	**Robots 1994**	**Software exp.**	**Robots 1995–2015**	**Dose**	**Low educ.**	**AI**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank	0.095***	0.096***	0.095***	0.094***	0.096***	0.235***	0.143***	0.104***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.027)	(0.019)	(0.006)
I(Δrobots)	0.298	0.587	0.256	0.388	1.033	4.965**	-0.406	-2.086***
	(0.630)	(0.553)	(0.634)	(0.639)	(0.896)	(2.154)	(2.949)	(0.572)
I(Δrobots) $\times$ Rank	0.007	0.004	0.007	0.007	0.005	-0.079*	0.008	0.021***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.014)	(0.041)	(0.032)	(0.009)
I(OccExposure)	-3.544***	-3.503***	-3.549***	-3.233***	-2.800***	-0.470	-2.864*	3.424***
	(0.562)	(0.539)	(0.562)	(0.575)	(0.654)	(1.903)	(1.684)	(0.483)
I(OccExposure) $\times$ Rank	0.023***	0.023***	0.023***	0.024***	0.014	-0.056	-0.023	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.038)	(0.019)	(0.007)
I(OccExposure)$\times$I(Δrobots)	-3.150***	-3.232***	-3.160***	-3.184***	-5.163***	-8.249***	-2.011	1.528**
	(0.827)	(0.737)	(0.825)	(0.826)	(1.144)	(2.843)	(2.974)	(0.776)
I(OccExposure)$\times$I(Δrobots) $\times$ Rank	0.031***	0.031***	0.030**	0.030**	0.053***	0.122**	0.028	-0.006
	(0.012)	(0.011)	(0.012)	(0.012)	(0.017)	(0.056)	(0.033)	(0.011)
Occ. exposure	All	All	All	All	All	All	All	All
Observations	233,504	233,504	233,504	233,504	233,504	20,605	233,504	233,504

Notes: This table reports IV estimates from Equation (5), using children's earnings rank as the dependent variable. Rank refers to the parental percentile earnings rank. I(OccExposure) equals one if the underlying robot exposure measure is above the median and zero otherwise. I(Δrobots) equals to one if the change in robot adoption per employee in industry i over the 1994–2004 period is above the median change and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

Another issue to consider is whether the Swedish economic crisis in the early 1990s affects our results regarding the impact of automation on intergenerational mobility in earnings. In Section C in the Online Appendix, we show that our results are not driven by parents having a history of unemployment during the 1990s crisis in Sweden.

Finally, our measure of robot penetration leverages variation across industries. An alternative approach, which is often employed in studies measuring robot adoption based on IFR data, involves analyzing variation across local labor markets; see, e.g., Acemoglu and Restrepo (2019) and Dauth et al. (2021).[26] In Section D in the Online Appendix, we show that results based on a shift-share approach that uses variation across local labor markets mask considerable within-regional heterogeneity in comparison to our empirical strategy.

As noted above, we also conduct identical robustness checks for upward mobility. These results, presented in Table A2 in the Online Appendix, confirm that the adverse effects of automation extend to children's upward mobility.

4.2 Firm-level adoption

A recent literature focuses on firm-level robot adoption to account for firm heterogeneity using trade data on imports of robots, see, e.g., Barth et al. (2025), Bonfiglioli and Gancia (2024) and Acemoglu et al. (2024). A few papers also analyze imports of general automation technologies (Acemoglu and Restrepo, 2022; Domini, Grazzi, Moschella, and Treibich, 2021). We complement our industry-level IFR analysis with firm-level measures of robot and automation adoption based on detailed trade data from the Swedish Trade Data Statistics. These data record firm-level trade transactions at the country–product level and are reported at the 8-digit level according to the Harmonized System (HS).

Firm-level trade data make it possible to analyze within-industry heterogeneity in technology adoption and to examine how broader measures of automation, beyond industrial robots, relate to

[26]The local labor market approach is similar to the strategy used in several papers on the effects of import competition and technology (Autor et al., 2013; Autor, Dorn, and Hanson, 2015; Autor, Dorn, Hanson, and Song, 2014).

intergenerational mobility. However, these data also have important limitations, particularly in a Swedish context. One reason is that one of the world's largest robot manufacturers, ABB, produces for the European market in Västerås, Sweden. As a result, many robot purchases by firms in Sweden are domestically sourced and therefore not captured in import data. In addition, firms frequently acquire automation equipment through European suppliers and intermediaries, and such intra-EU transactions were not recorded during our sample period if their value was below 172,500 euros. Consequently, the trade data are likely to understate the true extent of automation adoption among firms in Sweden.

Our measure of firm-level robot imports is identical to the definition in the above-mentioned papers, namely, the HS code 84795000. This code refers to the import of industrial robots. To move beyond narrowly defined imports of robots, we construct a broader measure of imports of automation technologies following the product classifications in Acemoglu and Restrepo (2022) and Domini et al. (2021). This measure captures HS codes associated with a variety of different automation-related capital goods.[27] Details, including the full list of HS codes, are presented in Table A3 in the Online Appendix.

Based on firms' imports of robots and general automation-related technologies, we construct an indicator variable equal to one if a firm recorded any imports of robots or automation technologies in 1997 (the first year for which we have import data), and zero otherwise. To map parents to firms with import activity, we restrict the sample to parents who were employed by the same firm in 1997 as they were in 1990, ensuring that firm-level exposure is measured for the correct employer. This implies a much smaller sample of parents, and therefore, we base this analysis on our unmatched sample of parents and children.

Empirical set-up. Based on our firm-level import measures, we estimate rank–rank models analogous to Equations (4) and (5), replacing the industry-level IFR variable $I(\Delta\text{robots})$ with our

[27] The classification covers the following ten categories: (1) industrial robots, (2) dedicated machinery, (3) numerically controlled machines, (4) automatic welding equipment, (5) textile automation, (6) automatic conveyors, (7) automatic regulating instruments, (8) automatic measurement devices, (9) 3D printing equipment, and (10) auxiliary automation systems.

firm-level import variable F(Δrobots).

We include either industry fixed effects or firm fixed effects to capture unobserved heterogeneity. Industry fixed effects specifications identify variation across firms within the same industry. The firm fixed effects model exploits the fact that multiple workers are employed in each firm. The fixed effects, therefore, absorb all level differences across firms, including the main effect of robot adoption. As a consequence, the rank–rank coefficient is identified from within-firm variation. In turn, the interaction between parental rank and firm-level robot exposure is identified from systematic differences in the within-firm rank–rank gradient across firms with high versus low robot adoption. The latter approach accounts for all factors that are common to all workers within a firm, such as management quality, productivity, and HR practices, when estimating children's income mobility.

Furthermore, to address potential endogeneity in firms' automation adoption, we implement an IV approach that exploits differences in managerial absorptive capacity. The instrument we exploit is whether the CEO holds a civil engineering degree.[28]

This choice is motivated by the idea that firms require internal knowledge to evaluate and implement new technologies, as emphasized in the absorptive-capacity framework of Cohen and Levinthal (1990). A civil engineering education provides technical skills and prior knowledge that are directly relevant for assessing and adopting automation technologies such as industrial robots. More broadly, the empirical literature shows that human capital and management quality are closely linked to the adoption of new technologies and organizational practices. For instance, Caroli and Van Reenen (2001) document that skills and organizational change are complements in the adoption of new work practices, and Bloom and Van Reenen (2007) show that better-managed firms are more likely to use advanced management practices and production technologies.

The validity of this instrument relies on two key conditions: relevance and exclusion. Regarding relevance, the Kleibergen–Paap F-statistic provides a test of whether firms led by civil engineering

[28] We define the CEO as the individual within each firm with the highest annual labor income. If multiple individuals share the top income, the oldest is selected. This approach follows Statistics Sweden's method for identifying operational firm leaders in administrative microdata.

CEOs are empirically more likely to adopt robots and automation technologies, thereby ensuring a strong first stage. Regarding exclusion, conditional on our rich set of controls and fixed effects, CEO education is assumed to affect children's outcomes only through the firm's automation decisions and not through any direct channels.

The firm-level IV complements our industry-level instrument based on international robot diffusion. Whereas the IFR-based IV approach captures sectoral shifts in technology intensity, the CEO-education IV approach uses firm variation in managerial capacity to adopt robots and automation technologies.

Firm-level robotization. Results on firm import are presented in Table 6. Panel A presents OLS estimates with industry fixed effects (Columns 1–4) and firm fixed effects (Columns 5–8). The results mirror those based on IFR-industry exposure: income mobility is significantly lower for children whose parents were employed in firms importing robots, and the effect is concentrated among parents in high-exposed occupations. The estimated triple-interaction term is positive and statistically significant in both models and is more than twice as large as the corresponding IFR-based estimate in Table 3.

Panel B uses the CEO-education IV strategy. However, the Kleibergen–Paap F-statistic shows that the instrument is very weak, which substantially inflates the estimates. Even so, the pattern persists, with children of parents in high-exposure occupations showing larger effects and those of parents in low-exposure occupations showing smaller ones.

Firm-level automation. Panel A of Table 7 presents the OLS estimates for the broader measure of automation. Similar to the results for robot adoption, we find lower income mobility among children whose parents held high-exposure occupations and were employed by firms that imported automation technologies. The interaction term $F(automation) \times Rank^p$ is positive and statistically significant for children of highly exposed parents in the specifications with industry fixed effects (Columns 1–4), and the pattern remains robust when firm fixed effects are included (Columns 5–8).

Panel B reports the IV estimates using CEO education as an instrument for firm-level automation adoption. The first stage is notably stronger than in the corresponding robot-import specifications, as indicated by the Kleibergen–Paap F-statistics. In the second stage, the coefficients increase in magnitude relative to the OLS estimates in Panel A. The estimated triple-interaction term remains positive and statistically significant across both the industry and firm fixed-effects specifications.

Overall, the firm-level results (either based on robots or broadly captured via automation imports) are consistent with those obtained using IFR industry-level exposure and the direction and significance of the coefficients remain stable across all specifications. They all point to muted income mobility for children if their parents worked in high-exposed occupations, while no impact is found if parents had a low-exposed occupation. These patterns indicate that our main results are not artifacts of industrial aggregation or firm heterogeneity.

Table 6: Firm-level robotization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS		Industry FE				Firm FE		
F(robots) × Rank	0.055**	0.081***	0.008	0.007	0.055**	0.070***	0.015	0.010
	(0.022)	(0.019)	(0.036)	(0.037)	(0.027)	(0.023)	(0.043)	(0.040)
F(robots) × Rank				0.079**				0.071*
× I(OccExposure)				(0.037)				(0.039)
Occ. exposure	All	High	Low	All	All	High	Low	All
Observations	371,068	146,691	224,377	371,068	371,068	146,691	224,377	371,068
Panel B: IV		Industry FE				Firm FE		
F(robots) × Rank	1.524	1.018	-0.073	-0.026	0.381	0.892	-0.219	-0.309
	(31.461)	(0.630)	(0.550)	(0.579)	(0.379)	(0.781)	(0.881)	(0.869)
F(robots) × Rank				1.048				1.045
× I(OccExposure)				(1.844)				(1.140)
Occ. exposure	All	High	Low	All	All	High	Low	All
F-stat.	0.00	0.19	0.58	0.013	2.1	1.2	2.1	0.23
Observations	371,068	146,691	224,377	371,068	358,722	138,968	215,912	358,722

Notes: This table reports OLS and IV estimates from Equations (4) and (5), using firm-level robot adoption instead of industry-level adoption. The dependent variable is children's earnings rank. Rank refers to the parental percentile earnings rank. I(OccExposure) equals one if the parent's underlying occupational robot exposure measure is above the median and zero otherwise. F(robots) equals one if the firm the parent is employed in imported robots in 1997 and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. F-stat is the Kleibergen–Paap rk Wald F-statistic. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Firm-level automation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS		Industry FE				Firm FE		
F(automation) × Rank	0.018***	0.030***	0.003	0.003	0.015**	0.027***	0.002	0.004
	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)
F(automation) × Rank				0.030***				0.022**
× I(OccExposure)				(0.009)				(0.010)
Occ. exposure	All	High	Low	All	All	High	Low	All
Observations	371,068	146,691	224,377	371,068	371,068	146,691	224,377	371,068
Panel B: IV		Industry FE				Firm FE		
F(automation) × Rank	0.044**	0.092***	-0.006	-0.004	0.030	0.086***	-0.014	-0.009
	(0.019)	(0.027)	(0.033)	(0.032)	(0.027)	(0.032)	(0.054)	(0.049)
F(automation) × Rank				0.100**				0.098*
× I(OccExposure)				(0.042)				(0.056)
Occ. exposure	All	High	Low	All	All	High	Low	All
F-stat.	7.2	8.5	4.5	2.6	16	21	7.7	2.7
Observations	371,068	146,691	224,377	371,068	358,722	138,968	215,912	358,722

Notes: This table reports OLS and IV estimates from Equations (4) and (5), using firm-level automation adoption instead of industry-level adoption. The dependent variable is children's earnings rank. Rank refers to the parental percentile earnings rank. I(OccExposure) equals one if the parent's underlying occupational robot exposure measure is above the median and zero otherwise. F(automation) equals one if the firm the parent is employed in imported automation technologies in 1997 and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. F-stat is the Kleibergen–Paap rk Wald F-statistic. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

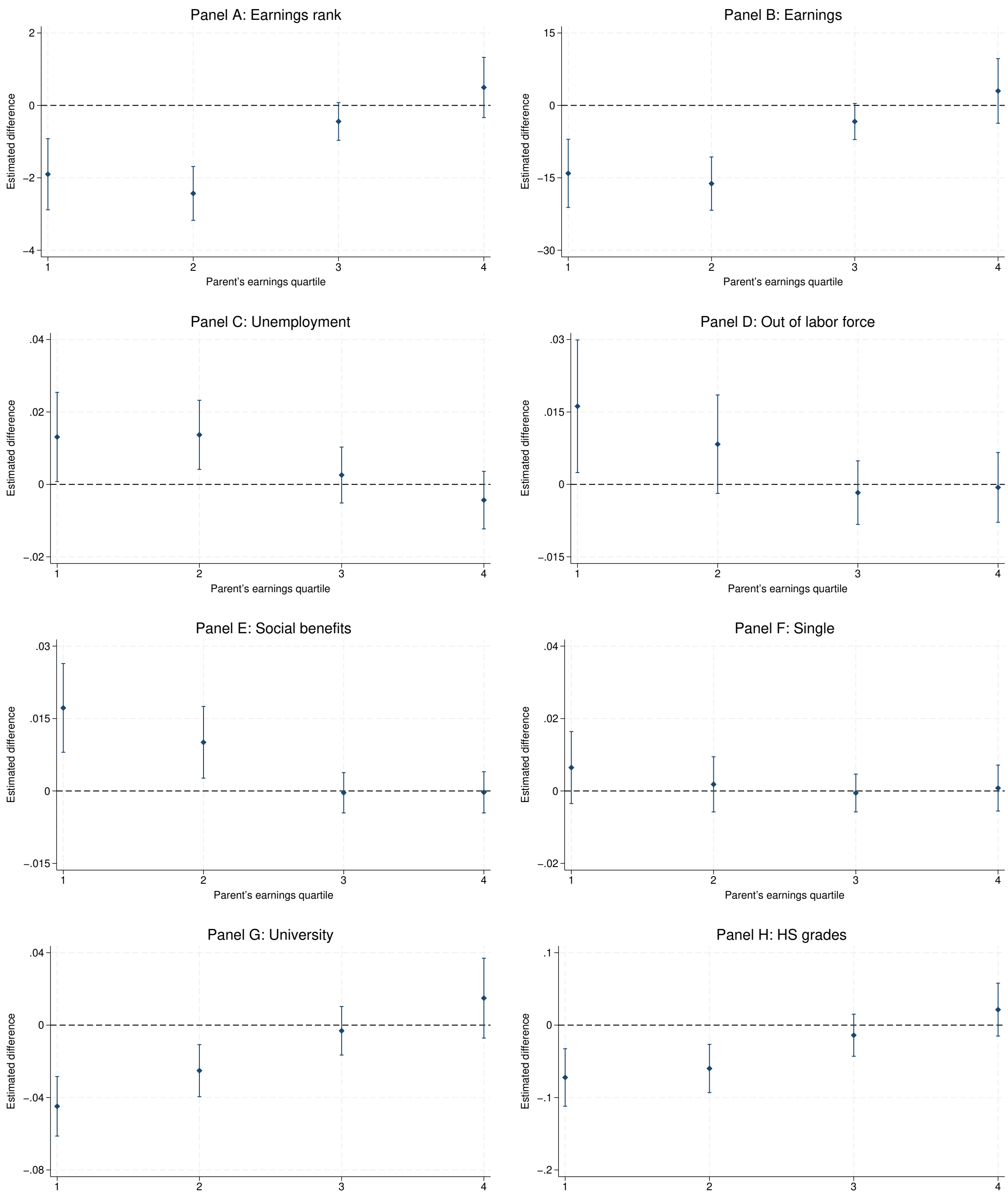
5 Distributional effects

We have thus far shown that parents' exposure to robots affects their children's earnings mobility, and that these effects stem specifically from parents in highly robot-exposed occupations. However, are other outcomes of these children also affected by parental exposure to new technologies? In this section, we extend our analysis and examine a wide range of outcomes. We first look at earnings and earnings rank, which capture children's general labor market status, and then analyze whether they are more likely to be unemployed, out of the labor force, or have received social security benefits. We also analyze the family-related outcome of whether a person is living in a single household, as well as differences in higher education attainment and high-school grades.[29] Studying these outcomes could elucidate additional long-lasting career effects of automation on intergenerational mobility. Our primary focus here is on distributional effects, i.e., whether these effects differ systematically across the parental income distribution. Documenting distributional effects helps clarify whether automation may have contributed to rising inequality through an intergenerational transmission channel. Section E in the Online Appendix provides an analysis of the average effect across the whole income distribution.

Figure 6 presents estimates of β_1 from Equation (6) across the parental income distribution, revealing how children's outcomes differ when parents in highly robot-exposed occupations work in industries with high rather than low robot adoption. Panel A shows that children whose parents were in the bottom half of the income distribution experience an average decline of about two percentile ranks in adult earnings if their parents worked in high robot industries. In contrast, the estimates for children of higher income parents are close to zero and not statistically significant. Panel B reveals a similar pattern for earnings, with negative effects concentrated among children from lower income families.

[29] A person is defined as unemployed if she has at least one day of unemployment compensation in at least one year during the 2015–2019 period. A person is defined as being out of the labor force if she in at least one year during the period 2015–2019 has no employment, wage income, or unemployment days. The variable social benefits is a dummy variable that takes the value of one if a person or someone in the family received social security benefits at any point between 2015 and 2019 and zero otherwise. Higher education is defined as at least two years of university studies. High-school grades refer to final grades.

Figure 6: Distributional effects



Notes: The figures show IV estimates of β_1 with 95% confidence intervals across different points of the parental earnings distribution, based on Equation (6). The distribution is constructed from parents' average earnings in 1985 and 1990. The sample includes children whose parents worked in highly robot-exposed occupations.

The pattern that children from lower income families fare worse on the labor market than children from higher income families extends beyond labor earnings. Panels C, D and E show similar patterns in unemployment rates, the probability of being out of the labor force, and receiving social benefits, respectively. For the likelihood of living in a single household, all estimates remain statistically insignificant (Panel F).

Finally, Panels G and H show a negative impact of robot adoption on university attainment and high-school grades for children to high-exposed parents in the lower part of the income distribution.

The main message from this section is that parental exposure to automation and heterogeneous adoption of robots across industries exert negative long-term effects on children from low-income families. Our findings reveal adverse labor market outcomes, including increased risks of unemployment, reduced earnings, lower education, and reliance on social benefits. These results complement our previous findings on how automation influences intergenerational mobility in earnings. Furthermore, the concentration of negative effects among children of parents in the lower income quartiles suggests that robotization exacerbates income inequality.

6 Mechanisms

Why does parental exposure to automation dampen mobility and worsen children's outcomes? There are at least two mechanisms through which parents' exposure to robots may affect their children. The first operates through parents' own adverse labor market experiences, which can generate financial strain. For instance, if automation leads to unemployment or weaker earnings growth, it may reduce parents' ability to provide adequate resources for their children, thereby hindering their development, academic performance, and future opportunities.

Another mechanism stems from career persistence within families, whereby children follow their parents into similar occupations and industries. It is well known that children often choose careers similar to those of their parents (see, e.g., Blau, Duncan, and Tyree (1978) for early evidence and Almgren, Kramer, and Sigurdsson (2025) for Swedish evidence). However, automation and robotization have reduced the labor demand for certain occupations, potentially affecting the likelihood of children following in their parents' footsteps.[30] This implies that a decrease in labor demand for parents' occupations can, in addition to having a direct negative impact on the parents, also affect their children indirectly. Ex ante, the direction of such indirect effects is theoretically ambiguous. On the one hand, children who want to follow in their parents' footsteps may find themselves in declining occupations with poor career opportunities. On the other hand, parental exposure to automation could also undermine persistence if parents try to steer their children away from robot-exposed occupations, thereby accelerating beneficial occupational mobility across generations, as children adapt to new technologies and move into less exposed occupations.

6.1 Parental labor market experiences

To examine whether adverse labor market experiences among parents could serve as a potential mechanism, we analyze direct effects of robotization on parents in high-exposed occupations and whether these effects follow the same pattern across the income distribution as shown for children in Section 5. We do this by studying changes in their labor earnings between 1991 and 2004, and whether they experienced unemployment, were out of the labor force, took sick leave, or received social benefits during the same period.

In terms of earnings, Figure 7 shows a similar pattern for parents in high-exposed occupations as we saw for their children in Figure 6. Specifically, low-income parents in high-robot industries experience significantly lower earnings growth than their counterparts in the same occupations in low-robot industries (Panel A). In contrast, high-income parents in the top quartile experience a positive change if they worked in a high-robot adopting industry.

While we see no significant differences in unemployment rates in Panel B, Panels C and D reveal that parents in the lowest earnings quartiles are more likely to be out of the labor force or receive social benefits if they are in high-robot industries. This disparity diminishes and becomes

[30] Edin et al. (2023) show that workers in declining occupations lose out in terms of lower earnings (conditional on employment), reduced years of employment, and increased time spent in unemployment. On the other hand, workers in non-declining occupations are better off due to a direct effect on automation-driving occupations and an indirect effect from an income increase.

statistically insignificant higher up in the parental income distribution.

Finally, Panel E shows a similar pattern for sick leave where parents in the lower part of the income distribution are significantly more likely to have taken sick leave if they worked in high-robot industries rather than in low-robot industries. No statistically significant differences are observed in the upper half of the distribution.[31]

The results in Figure 7, showing adverse impacts on parents with lower incomes, align with the finding that children from low-income families are disproportionately affected when their parents faced high exposure to robotics, as detailed in Figure 6. Taken together, these results suggest that financial strain and reduced parental resources may serve as an important transmission channel from parental robot exposure to children's future labor market outcomes.

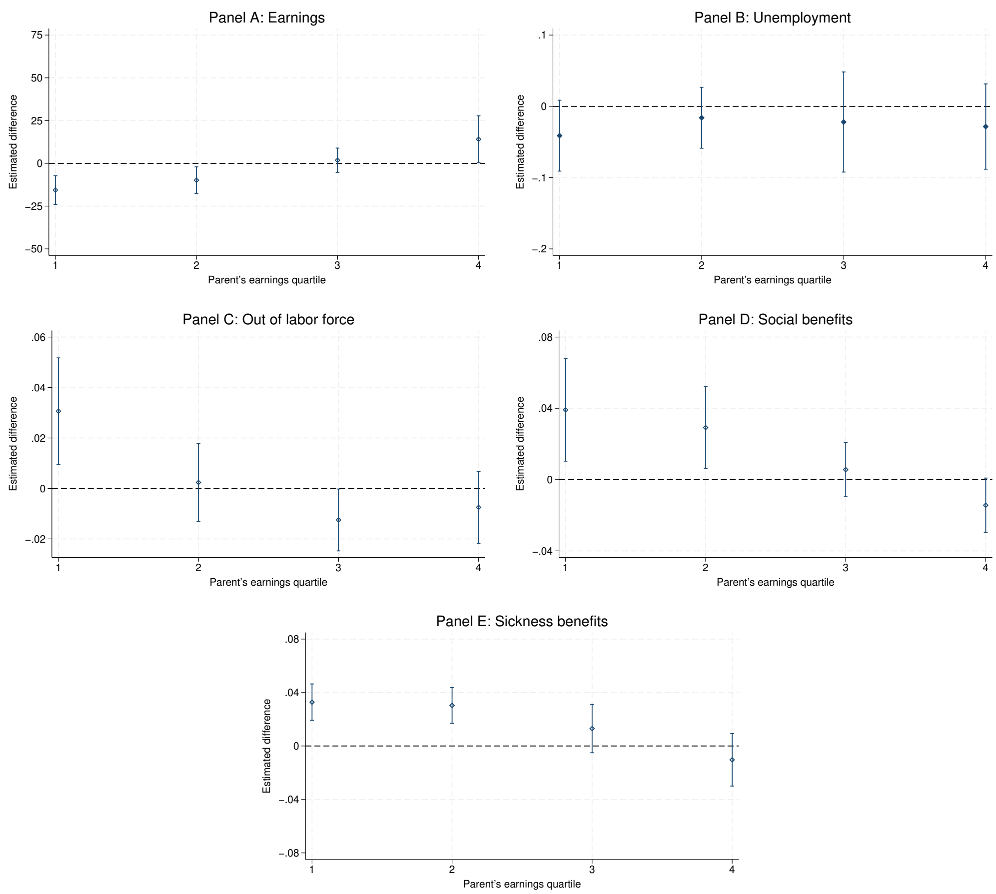
6.2 Occupational and industry persistence

We now turn to the second mechanism: occupational and industry persistence across generations. In this analysis, we examine whether children work in occupations and industries with similar levels of robot exposure as their parents. Specifically, we estimate Equation (6) to test whether the occupational and industry choices of children vary depending on whether their parents were employed in high- or low-robot-adopting industries, and whether the effects across the parental income distribution mirror those in Figure 6, where adverse labor market outcomes for children are shown to be concentrated in the lower part of the distribution. If career persistence is the primary mechanism, we would expect the distributional pattern of children's occupational and industry choices to closely match the distributional pattern of their labor market outcomes.

As a first step, Table 8 reports estimates of whether children of parents in high-robot-adopting industries are more likely to have a highly robot-exposed occupation than children of parents in low-robot-adopting industries. Comparing Columns 2 and 3 shows that independent of whether the parent had a high or low-exposed occupation, children to parents in high-robot industries are more likely to have a high exposed occupation themselves. That the impact of industry robot

[31] These results are consistent with Umblijs and Østbakken (2025), who show that robotization in Norway affects workers' sick leave.

Figure 7: Distributional effects: Parents



Notes: The figures show IV estimates of β_1 with 95% confidence intervals across the parental earnings distribution, based on Equation (6). The distribution is constructed from parents' average earnings in 1985 and 1990. The sample includes parents working in highly robot-exposed occupations.

Table 8: **Children's probability to have a high-exposed occupation**

	(1)	(2)	(3)	(4)
I(Δrobots)	0.016***	0.019***	0.013***	0.008
	(0.004)	(0.005)	(0.005)	(0.005)
I(OccExposure)				0.082***
				(0.005)
I(OccExposure) $\times$ I(Δrobots)				0.011
				(0.007)
Constant	0.609***	0.579***	0.449***	0.505***
	(0.045)	(0.050)	(0.119)	(0.047)
Occ. exposure	All	High	Low	All
Observations	233,504	179,407	54,097	233,504

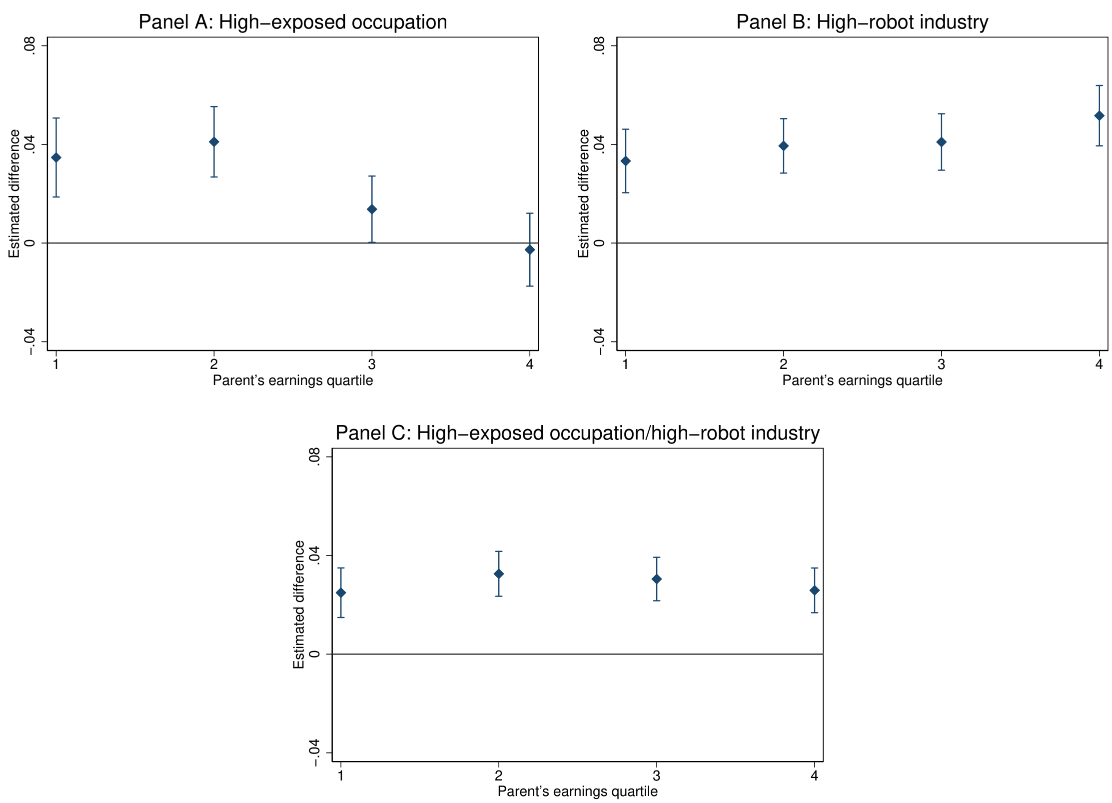
Notes: This table reports IV estimates from Equations (6) and (7). The dependent variable equals one if the child is in a high robot-exposed occupation, and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for parental earnings rank, family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

adoption does not vary by parental occupational exposure is confirmed in Column 4 and indicates that occupational persistence alone cannot fully explain our main findings where the compounding effect of occupation and industry is important.

We next zoom in on the group of children whose parents held highly exposed occupations to examine whether occupational and industry persistence varies across the parental income distribution. Figure 8, Panel A, shows that in the lower part of the parental income distribution, children whose parents worked in a high-robot-adopting industry are more likely to have a highly exposed occupation themselves compared with those whose parents worked in a low-robot-adopting industry. In the upper part of the distribution, the relationship between occupational persistence and parental industry is weaker and statistically insignificant. The overall pattern in Panel A is consistent with the distributional effects shown in Figure 6.

In Panel B, we observe a somewhat different pattern when examining industry persistence. In contrast to the results on occupational persistence in Panel A, all children, regardless of their parents' position in the income distribution, are more likely to work in a high-robot-adopting industry if their parents did so as well. This uniform pattern across the income distribution does not match the concentration of adverse child outcomes among low-income families documented in Figure 6. A similar uniform pattern across the parental income distribution appears in Panel C, where we analyze whether parents' industry affiliation affects the probability that children hold a highly exposed occupation within a high-robot-adopting industry, that is, being highly exposed to automation.

Figure 8: Occupational and industry dependence



Notes: The figures show IV estimates of β_1 with corresponding 95% confidence intervals across the parental earnings distribution based on Equation (6). The sample includes parents in highly robot-exposed occupations. Panel A uses a dependent variable equal to one if the child works in a highly exposed occupation, and zero otherwise. Panel B uses a dependent variable equal to one if the child is employed in a high–robot-adopting industry, and zero otherwise. Panel C uses a dependent variable equal to one if the child works in a highly exposed occupation within a high–robot-adopting industry, and zero otherwise.

Finally, we examine the importance of occupational similarity between parents and children for our main rank-rank results in Table 3. We do this by looking at income mobility for sub-samples where the parents and children have the same or different occupational exposure status. The results are presented in Table A4 in the Online Appendix and show that the effects of parental exposure to automation appear only in the "not same" occupation sub-samples, while the estimates in the "same" occupation sub-samples are small and statistically insignificant. This pattern suggests that the intergenerational effects are not driven by children directly entering their parents' occupations, but arise instead through channels unrelated to occupational persistence.

Taken together, the results in this section point to two channels through which parental robot exposure affects children's outcomes. The distributional evidence shows that adverse outcomes are concentrated among low-income families, suggesting that financial strain plays an important transmission role. At the same time, there is some occupational and industry persistence across generations in high-robot industries. However, the pattern across the parental income distribution does not match the distributional pattern in Figure 6, whereby children of low-income parents are disproportionately affected in terms of labor market outcomes. Overall, the evidence is most consistent with a mechanism in which adverse parental labor market outcomes are central, with occupational persistence operating as a complementary but secondary channel.

7 Conclusion

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 of children's expected future earnings. In this paper, we build on this literature by examining whether recent technological advancements have affected intergenerational earnings mobility.

More specifically, we analyze how parental exposure to robotization and automation is related to intergenerational mobility. The analysis is based on comprehensive and detailed register data for Sweden from 1985 to 2019, merged with data on robot exposure at the occupational level and robot adoption at the industry level, as well as firm-level data on imports of robots and broader automation technologies.

To identify the impact of automation and robot adoption on intergenerational mobility, we run rank-rank regressions, with estimates varying based on parents' industry exposure to robots. We take great measures to account for the selection of parents into industries with different degrees of robot penetration and adopt an IV approach to account for industry shocks unrelated to robotization. We complement the industry-level analysis with firm-level specifications, applying an IV strategy based on CEO education.

Our findings reveal that having a parent who worked in an industry with a significant increase in robot usage lowers a child's income mobility. When considering occupational exposure, we show that this effect is evident for children of parents in highly robot-exposed occupations, but not for those whose parents were in low-exposed occupations. This pattern highlights the compounding role of occupation and industry in shaping how automation affects intergenerational mobility.

To further understand the long-run effects of automation, we complement the main analysis with several extensions. First, 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 show that parents' industry exposure to robots leads to statistically lower upward mobility for children if the parents worked in a highly exposed occupation. No effect is found if parents worked in low-exposed occupations.

Second, we analyze a wide range of alternative outcomes for children in adulthood. Looking at earnings, unemployment risk, and the probability of being out of the labor force or receiving social benefits, we find that industry exposure negatively impacts children whose parents worked in highly exposed occupations. These children also experience adverse effects on educational attainment and high-school performance. Importantly, these negative effects are concentrated among children from low-income families, suggesting that automation may contribute to rising inequality through an intergenerational transmission channel.

Turning to potential mechanisms, we find that occupational and industry persistence exist but do not fully account for why differences in parents' occupational exposure to robots translate into lower income mobility and adverse labor market outcomes for their children. Instead, the evidence is more consistent with adverse parental labor market experiences, particularly among low-income parents, playing an important role, though we acknowledge that other factors may also contribute.

Our results, based on various specifications and an extensive set of robustness checks, suggest that automation and technology shocks dampen intergenerational mobility. These results provide new evidence on how technological change can affect 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-run effects of structural changes, such as technological change, can be addressed. A long-run perspective that includes transmissions across generations can be important for obtaining a more accurate estimate of how structural changes influence individuals.

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Online Appendix

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

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A Auxiliary tables and figures

Table A1: Number of parents by industry and level of occupational robot exposure

Panel A: Initial sample			
		Robot industry	
		Low	High
Occupational exposure	Low	288,622	19,766
		(0.60)	(0.23)
	High	189,624	67,285
		(0.40)	(0.77)
	Total	478,246	87,051
Panel B: Balanced sample			
		Robot industry	
		Low	High
Occupational exposure	Low	19,524	19,524
		(0.23)	(0.23)
	High	63,855	63,855
		(0.77)	(0.77)
	Total	83,379	83,379

Notes: This table displays the number of parents in the unmatched sample and in the final sample after the matching procedure. The shares of workers in high- and low-robot industries for the two occupational exposure groups are displayed in parentheses. A high-robot industry is defined as one where the change in robot adoption per employee over the 1994–2004 period is above the median change; otherwise, it is defined as a low-robot industry. Occupational exposure refers to the robot exposure measures created by Webb (2020) and is split at the median.

Table A2: Upward mobility: Robustness

	Main	**Separate IVs**	**Robots 1994**	**Software exp.**	**Robots 1995–2015**	**Dose**	**Low educ.**	**AI**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Δrobots)	0.011	0.015	0.012	0.014	0.027*	0.077	0.040	-0.017**
	(0.010)	(0.010)	(0.011)	(0.011)	(0.015)	(0.049)	(0.055)	(0.007)
I(OccExposure)	-0.045***	-0.045***	-0.045***	-0.039***	-0.037***	-0.019	-0.168***	0.060***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.010)	(0.038)	(0.036)	(0.060)
I(OccExposure)	-0.037***	-0.036***	-0.036***	-0.037***	-0.060***	-0.074	-0.060	0.017
×I(Δrobots)	(0.012)	(0.011)	(0.012)	(0.012)	(0.017)	(0.057)	(0.056)	(0.012)
Occ. exposure	All	All	All	All	All	All	All	All
Observations	37,075	37,075	37,075	37,075	37,075	1,166	37,075	37,075

Notes: This table reports IV estimates from Equation (7), for the sample of parents in the bottom quartile of the earnings distribution. The dependent variable is an indicator variable equal to one if the child belongs to the top quartile of the 2015–2019 mean income distribution, and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for parental earnings rank, family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: HS 2012 codes for industrial automation

Label	HS codes
1. Industrial robots	847950
2. Dedicated machinery	847989
3. Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221, 846231, 846241, 84629120, 84629920
4. Automatic machine tools	845600–846699, 846820–846899, 851511–851519[a]
5. Automatic welding machines	851521, 851531, 851580, 851590
6. Weaving and knitting machines	844600–844699, 844700–844799
7. Other textile dedicated machinery	844400–844590
8. Automatic conveyors	842831–842839
9. Automatic regulating instruments	903200–903299
10. 3-D printers	847780

[a] Excluding the codes listed under *Numerically controlled machines.*

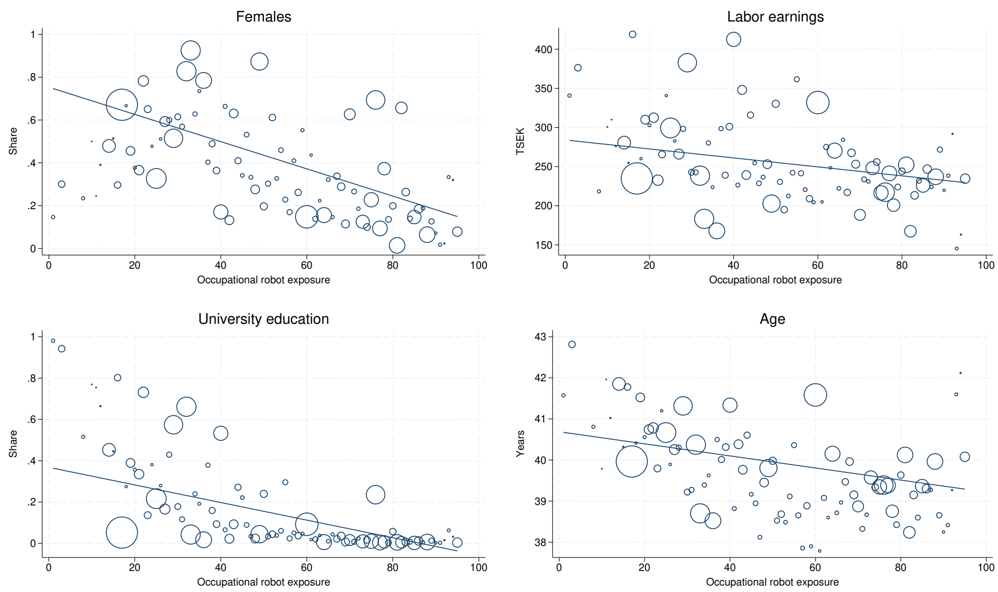
Notes: HS codes follow the concordance used in Acemoglu and Restrepo (2022) and Domini et al. (2021). Source: Domini et al. (2021).

Table A4: Income mobility: Rank–rank regressions by occupational similarity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank	0.125***	0.075***	0.084***	0.108***	0.125***	0.053***	0.083***	0.024**
	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.015)	(0.007)	(0.012)
I(Δrobots)	-1.792***	-1.049**	0.084	-2.730***	-3.715***	1.897*	0.199	2.219**
	(0.500)	(0.449)	(0.590)	(0.674)	(0.783)	(1.017)	(0.593)	(1.057)
I(Δrobots) $\times$ Rank	0.032***	0.013	0.008	0.035***	0.048***	-0.020	0.006	-0.015
	(0.009)	(0.008)	(0.009)	(0.011)	(0.012)	(0.016)	(0.009)	(0.017)
I(OccExposure)							-12.821***	6.823***
							(0.525)	(0.991)
I(OccExposure)$\times$Rank							-0.008	0.105***
							(0.009)	(0.015)
I(OccExposure) $\times$ I(Δrobots)							-1.266*	-6.038***
							(0.751)	(1.397)
I(OccExposure) $\times$ I(Δrobots) $\times$Rank							0.008	0.065***
							(0.013)	(0.022)
Parent's occ. exposure	All	High	Low	All	High	Low	All	All
Child's occ. exposure	Same	Same	Same	Not same	Not same	Not same	Same	Not same
Observations	105,635	68,827	36,808	127,869	110,580	17,289	105,635	127,869

Notes: This table reports IV estimates from Equations (4) and (5) for sub-samples where the parents and children have the same or different occupational exposure status. The dependent variable is children's earnings rank. Rank refers to the parental percentile earnings rank I(OccExposure) equals one if the underlying robot exposure measure is above the median and zero otherwise. I(Δrobots) equals one if the change in robot adoption per employee in industry i over the 1994–2004 period is above the median change and zero otherwise. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Occupational exposure and worker characteristics



Notes: The figures display the correlation between occupational robot exposure and the share of females, labor earnings, educational level, and age in the initial sample. Occupational robot exposure and labor earnings are measured as the average in 1985 and 1990, while educational level and age are measured in 1990.

B Gender differences

While intergenerational mobility in earnings has been extensively researched, most related 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 Mazumdltener (2005) for two seminal papers). A common result in this literature is that women experience higher levels of intergenerational mobility than men. For instance, Jäntti, Bratsberg, Røed, Raaum, Naylor, Österbacka, Björklund, and Eriksson (2006) analyzed and compared intergenerational earnings mobility in the United States, the United Kingdom, and Nordic countries and examined earnings mobility among combinations of fathers, sons, and fathers and daughters. Their results on gender differences suggest higher mobility for daughters than for sons. Brandén, Nybom, and Vosters (2023) analyzed gender differences in how intergenerational income mobility has evolved during recent decades. They reported increased persistence in mobility for women over time, while male mobility has remained stable. This applies to both Sweden and the US, which are the two countries that they studied.

In our setting, 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 B1 presents the results on gender differences. More specifically, the table replicates the IV results from Columns 4-6 and 8 in Table 3 separately for sons and daughters.

Overall, the rank–rank correlation for sons in Column 1 and for daughters in Column 5 are identical the overall results shown in Table 3 (0.032). Columns 2, 3, 6, and 7 present the results by gender, where we differentiate the impact of robot adoption at the industry level by parents with high and low occupational exposure. Again, the results indicate that the effects of working in highly exposed industries originate from highly exposed parents. For these children, irrespective of gender, the rank–rank correlation is significantly higher if the parent was employed in an industry with a high level of robot investment than if the parent was employed in an industry with a low level of such investment. No such relationship is found for parents with low levels of exposure. If we compare the estimates by gender, we again note no significant differences between sons and daughters.

Finally, Columns 4 (sons) and 8 (daughters) display the results of the fully flexible Equation (5) directly comparing intergenerational mobility between high- and low-exposed occupations in high- versus low-exposed industries. The estimated coefficient for $I(OccExposure_o^p) \times I(\Delta robots_i^p) \times Rank^p$ is basically identical for sons and daughters. In sum, the results shown in Table B1 indicate that the long-run negative effect of automation on intergenerational mobility is a general effect that is not different between sons and daughters.

Table B1: Exposure to robots at the occupational and industry level and intergenerational mobility: Sons and daughters

	Sons				Daughters			
	Rank	Rank	Rank	Rank	Rank	Rank	Rank	Rank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank	0.131***	0.134***	0.109***	0.102***	0.102***	0.092***	0.108***	0.087***
	(0.006)	(0.007)	(0.012)	(0.009)	(0.006)	(0.008)	(0.011)	(0.008)
I(Δrobots)	-2.357***	-2.772***	0.088	0.160	-2.115***	-2.812***	0.084	0.367
	(0.528)	(0.636)	(0.833)	(0.831)	(0.481)	(0.573)	(0.738)	(0.750)
I(Δrobots) × Rank	0.032***	0.033***	0.007	0.009	0.032***	0.039***	0.005	0.005
	(0.007)	(0.009)	(0.012)	(0.012)	(0.008)	(0.010)	(0.012)	(0.012)
I(OccExposure)				-3.867***				-3.233***
				(0.741)				(0.611)
I(OccExposure)×Rank				0.034***				0.012
				(0.011)				(0.010)
I(OccExposure) × I(Δrobots)				-3.024***				-3.208***
				(1.086)				(0.926)
I(OccExposure)×I(Δrobots)				0.026*				0.035**
				(0.016)				(0.015)
Occ. exposure	All	High	Low	All	All	High	Low	All
Observations	120,252	92,434	27,818	120,252	113,252	86,973	26,279	113,252

Notes: This table reports IV estimates from Equations (4) and (5) separately for sons and daughters. The dependent variable is children's earnings rank. Rank refers to the parental percentile earnings rank I(OccExposure) equals one if the underlying robot exposure measure is above the median and zero otherwise. I(Δrobots) equals one if the change in robot adoption per employee in industry i over the 1994–2004 period is above the median change and zero otherwise. All models include age fixed effects both children and parents and gender for parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C The financial crisis in the early 1990s

An important issue to consider is whether the Swedish economic crisis in the early 1990s affects our results on the impact of automation on intergenerational mobility in earnings.[C1] 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 was weaker in Swedish municipalities that were more heavily affected by the 1990s.

To test whether unemployment during the financial crisis in the early 1990s affects our results, we divide our sample of parents into those who experienced unemployment during the 1991–1994 period and those who did not. We then run separate regressions for parents in high- and low-exposed occupations. Columns 1–3 in Table C1 in the Online Appendix present the results for parents in high-exposed occupations, and Columns 4–6 show the corresponding results for parents in low-exposed occupations.

Once again, the results reveal that industry robot penetration affects mobility only if parents worked in highly robot-exposed occupations. However, whether highly exposed parents experienced unemployment during the 1990s crisis or not does not matter for the impact of industrial robots on intergenerational mobility. The estimated coefficient for the variable $I(\Delta robots_i^p) \times Rank^p$ is 0.023 in the sample where parents experienced unemployment (Column 1) and 0.039 in the sample where parents did not (Column 2). Combining the two models, the triple-interaction term in Column 3, $I(\Delta robots_i^p) \times Rank^p \times Unemployed^p$, shows that the difference between unemployed and employed parents is statistically insignificant. Turning to low-exposed parents, Columns 4–6 show no statistically significant effects irrespective of unemployment history during the financial crisis; again, these results are in line with the main results shown in Table 3.

The estimates in Table C1 suggest that the negative impact of robot adoption on intergenerational mobility in earnings that originates from industries with a relatively large increase in robot

[C1] Sweden experienced a decrease in GDP for three years in a row, i.e., from 1991 to 1993, and unemployment rose from just below 4 percent in 1991 to nearly 11 percent in 1994.

adoption is not systematically related to parents' unemployment history during the 1990s crisis in Sweden. Instead, automation and investments in robotics seem to have affected intergenerational mobility, irrespective of exposure to the crisis in the early 1990s.

Table C1: Income mobility: 1990s crisis and unemployment

	Unemployed	Employed	Diff.	Unemployed	Employed	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Rank	0.093***	0.114***	0.113***	0.081***	0.104***	0.106***
	(0.011)	(0.007)	(0.007)	(0.017)	(0.009)	(0.009)
I(Δrobot)	-2.263***	-3.005***	-3.020***	-0.881	0.230	0.155
	(0.763)	(0.623)	(0.623)	(1.198)	(0.733)	(0.728)
I(Δrobot)×Rank	0.023	0.039***	0.039***	0.026	0.004	0.004
	(0.015)	(0.009)	(0.009)	(0.021)	(0.010)	(0.010)
Unemployed			-0.524			-1.056
			(0.549)			(0.903)
Rank×Unemployed			-0.019**			-0.027*
			(0.009)			(0.015)
I(Δrobot)×Unemployed			0.726			-0.556
			(0.918)			(1.350)
I(Δrobot)×Rank ×Unemployed			-0.015			0.016
			(0.016)			(0.023)
Occ. exposure	High	High	High	Low	Low	Low
Observations	43,722	135,427	179,149	9,943	44,085	54,028

Notes: This table reports the OLS and IV estimates from Equations (4) and (5), using children's earnings rank as the dependent variable. Rank refers to the parental percentile earnings rank I(OccExposure) equals one if the underlying robot exposure measure is above the median and zero otherwise. I(Δrobots) equals one if the change in robot adoption per employee in industry i over the 1994–2004 period is above the median change and zero otherwise. Columns 1 and 4 restrict the sample to children–parent pairs where the parent was unemployed at some point during the 1991–1994 period, while Columns 2 and 5 restrict the sample to those where the parent was not unemployed during the same period. All models include age fixed effects and gender indicators for both children and parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. *** p<0.01, ** p<0.05, * p<0.1.

D Local labor market effects: A shift-share approach

Our empirical strategy leverages robot penetration across industries. An alternative approach, which is often employed in studies measuring robot adoption based on IFR data, involves analyzing variation across local labor markets (see, e.g., Acemoglu and Restrepo (2019) and Dauth et al. (2021)).[D1]

The idea behind this approach is that industry-level robot penetration has differential effects on local labor markets originating from differences in their employment industry structure. The shift-share approach links robot adoption at the industry level to local labor markets based on their employment industry structure. Hence, the source of identifying variation is at the industry level, whereas outcomes are measured at the level of local labor markets.

In our setting, this shift-share approach estimates the overall average effect on intergenerational mobility using all parents—directly and indirectly, affected—and their children in the local labor market. Such a general approach is relevant in many cases, but it fails to shed light on heterogeneous effects relating to whether parents' job tasks are being complemented or replaced by robot technology. Nevertheless, it is important that we understand how a more general local labor market estimation relates to our more direct approach that uses industry-level data on robots.

We construct the following shift-share variable that measures the predicted change in robot adoption in the local labor market r (defined in terms of 284 Swedish municipalities) over the 1994–2004 period relative to employment in the base year 1990:

$$\Delta robots_r = \sum_{i=1}^{I}(\frac{L_{ir}}{L_r} \times \frac{\Delta robots_i}{L_i}). \tag{D1}$$

Here, $\Delta robots_i$ is the change in robot penetration (operational stocks) in industry i between 1994 and 2004, L_i is the total employment in industry i in 1990, and $\frac{L_{i,r}}{L_r}$ represents industry i's share of the total employment of the local labor market r, measured in 1990. The shift-share variable $\Delta robots_r$ varies across local labor markets and uses by construction initial heterogeneity

[D1] The local labor market approach is similar to the strategy used in several papers on the effects of import competition and technology (Autor et al., 2013, 2015, 2014).

in industry employment across local labor markets to predict local labor market robot penetration. It is important to note that $\Delta robots_r$ does not measure actual regional robot adoption because the shift-share approach allocates industrial variation based on the initial industrial composition of a given local labor market. This is different from our preferred measure of robot exposure at the industry level, $\Delta robots_i$ from Equation (1).

Figure D1 in the Internet Appendix depicts the geographical distribution of the predicted robot adoption ($\Delta robots_r$). The figure highlights that the largest increase is predicted in the middle and southern parts of the country, although there is extensive heterogeneity across Sweden.

To estimate the general local labor market effects of robot penetration, we use our initial, unmatched sample of parents and run specification (3) separately for each municipality in Sweden to recover the estimated municipality-specific rank–rank correlations.[D2] These are then regressed against the robot penetration measure in Equation (D1). Columns 1–2 in Table D1 present results where robot penetration is measured as a continuous variable, whereas the results shown in Columns 3–4 are based on the indicator variable $I(\Delta robot_r)$ (taking the value one for municipalities with an above-median value, zero otherwise). Regardless of whether we use OLS or IV, or a continuous variable or not, we do not find any statistically significant estimates of the effect of robot penetration at the local labor market level on intergenerational mobility. Hence, in contrast to the results shown in Table 3, which utilize more disaggregated data and take into account occupational heterogeneity, the local labor market-level shift-share estimates are all close to zero and lack statistical significance.

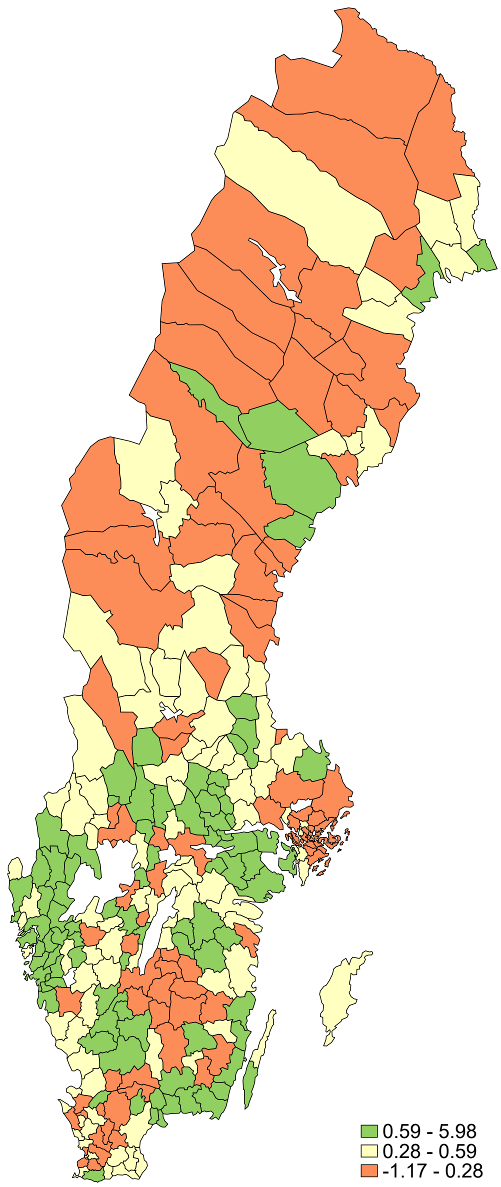
Our evidence that the aggregated local labor market effects are smaller than the more disaggregated effects with industry variation is in line with Dauth et al. (2021). They study the adjustment of local labor markets to robot penetration and find small and, in most cases, insignificant effects at the local labor market level, whereas focusing on adjustments to individual workers suggests considerable worker heterogeneity. One reason for this discrepancy is that analyses at the aggregate level do not distinguish between partial and general equilibrium effects (see discussion in Aghion et al. (2020)). The negative or non–significant labor market effects of robot adoption are in accordance

[D2]The unmatched sample is used to ensure that we have a sufficiently large sample of parents in each municipality when estimating specification (3).

with a partial equilibrium view that implies a decrease in labor demand and a decrease in wages. This may be counteracted in a general equilibrium framework, for instance, as in Acemoglu and Restrepo (2018b), by a lower equilibrium wage, which has a positive impact on subsequent labor demand.

In the context of our focus on intergenerational mobility, we can conclude from this section that results based on variation across local labor markets mask considerable within-regional heterogeneity.

Figure D1: Regional variation in robot adoption



Notes: The figure displays the change from 1994 to 2004 in the operational stock of robots per 1,000 employees across all Swedish regions. Data on robot stocks come from the IFR, and employment data from Statistics Sweden, measured in 1990.

Table D1: Shift share analysis: Local labor market effects

	Rank–rank (1)	Rank–rank (2)	Rank–rank (3)	Rank–rank (4)
Δrobots	-0.004	-0.005		
	(0.004)	(0.005)		
I(Δrobots)			-0.004	0.004
			(0.006)	(0.010)
Model	OLS	IV	OLS	IV
Observations	284	284	284	284

Notes: This table presents results for a shift-share approach where the dependent variable is the estimated rank–rank correlation at the municipality level, and robot penetration is defined at the municipality level. See Section D for details. The control variables are industry-fixed effects, the share of females and parents with university education, and the average parental age in the municipality. Robust standard errors are used. *** p<0.01, ** p<0.05, * p<0.1.

E Average labor market effect

In this section we present the overall average results for the same outcomes analyzed in Section 5 across the whole parental income distribution. The results are presented in Table E1.

Panel A, Column 1 shows that children whose parents worked in industries with a large positive change in robot installations have, on average, a 0.476 lower earnings rank than children of parents in low-robot industries. Running separate regressions for parents in high- and low-exposed occupations, it is clear that the overall effect is driven by children whose parents had a high-robot-exposed occupation in a high-robot industry (Column 2). No significant difference is present among children whose parents were in a low-exposed occupation, as shown in Column 3.

We also run the fully flexible model, Equation (7), to compare the estimates in Columns 2 and 3. The estimate for the interaction term suggests that the average difference is -1.436 earnings rank and is statistically significant (Column 4). Panel B, Column 2, shows that the lower earnings rank for children whose parents had a highly exposed occupation in the high-robot-exposed industry is associated with, on average, SEK 6,124 lower earnings.

The importance of accounting for parents' occupational exposure in understanding how children fare in adulthood is also seen in Panel C when considering unemployment. Overall, children whose parents worked in a high-robot-adapting industry are not more likely to be unemployed in adulthood than children whose parents worked in a low-robot-adopting industry (Column 1). However, we estimate a statistically difference between children with parents in high-robot-exposed occupations and in low-exposed occupations (Column 4)

Table E1: Additional outcomes

Occupational exposure	All (1)	High (2)	Low (3)	Diff. (4)	All (1)	High (2)	Low (3)	Diff. (4)
	Panel A: Earnings rank				**Panel B: Earnings**			
I(Δrobot)	-0.476**	-0.823***	0.347	-1.436***	-3.452**	-6.124***	2.850	-10.086***
	(0.207)	(0.232)	(0.271)	(0.378)	(1.587)	(1.735)	(2.561)	(3.286)
%-difference	-.84	-1.5	.61		-.99	-1.8	.74	
	Panel C: Unemployment				**Panel D: Out of labor force**			
I(Δrobot)	0.002	0.005*	-0.004	-0.013***	0.002	0.003	-0.001	0.006
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
%-difference	1.2	3.1	-3.2		1.5	2.5	-.7	
	Panel E: Social benefits				**Panel F: Single**			
I(Δrobot)	0.003	0.004**	-0.002*	0.007***	0.002	0.001	0.003	-0.001
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
%-difference	7	10	-11		1.9	1.3	4	
	Panel G: University				**Panel H: HS grades**			
I(Δrobot)	-0.002	-0.010*	0.016**	-0.035***	-0.006	-0.021*	0.025**	-0.053***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.011)	(0.012)	(0.016)
%-difference	.34	.3	.44		-.094	-.16	.11	
Observations	233,504	179,407	54,097	233,504	233,504	179,407	54,097	233,504

Notes: This table reports the IV results from estimating Equations (6) and (7). The dependent variables are defined in footnote 29 in Section 5. High exposure refers to above median occupational exposure and low to below median exposure using measure created by Webb (2020). I(Δrobots) is an indicator variable equal to one if the change in robot adoption per employee in the industry i over the 1994–2004 period is above the median change and zero otherwise. All models include age fixed effects both children and parents and gender for parents. They also control for family size, parental university education, marital status, and foreign-born status. In addition, the models include regional fixed effects for parents and firm-level controls measured in 1990: firm size (number of employees), average earnings, and the shares of female and high-skilled workers. Standard errors are clustered at the father's and mother's industries of employment level. %-difference is the estimated effect divided by the mean value when I(Δrobot)=0 in each sample of occupational exposure. *** p<0.01, ** p<0.05, * p<0.1.

The fact 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 (Panel D), and receiving social benefits (Panel E). The former is not statistically significant, but the sign of the point estimate suggests a higher risk of being out of the labor force for children with robot-exposed occupations who worked in high-robot industries. The higher risk of receiving social benefits is statistically significant.

Taken together, all these additional outcomes point to negative labor market effects for children with parents who worked in robot-exposed occupations in high-robot industries. In terms of magnitudes, we see that the negative effect of parental occupational exposure in high-robot industries is especially severe for receiving social benefits and unemployment incidence.

We also consider a family-related outcome, namely, 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 (see, e.g., Pilossoph and Wee (2021) for evidence on the wage premium). Panel F shows no evidence of a changed probability of living in a single household for children whose parents worked in high-robot-exposed industries, regardless of whether they worked in high- or low-exposed occupations.

Finally, we explore the impact on educational outcomes in Panels G and H. Here we find that parental robot industry exposure is associated with lower university attainment and high-school grades if the parent had a high exposed occupation, while we estimate positive effects of robot industry exposure if the parent had a low exposed occupation.