Do Robots Increase Wealth Dispersion?*

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Abstract

We demonstrate that increased automation has a significant negative impact on distribution of wealth. Households who are more exposed to industrial robots at work accumulate less wealth and experience greater downward mobility in the wealth distribution. The negative wealth effects of robots are not merely a consequence of differences in earned incomes or differential saving rates. We provide evidence that the adverse effects of rapid robotization on individual workers' human capital, and thereby, on their financial risk taking and investment behavior represent an additional important mechanism. Overall, the portfolio channel amplifies the inequality-enhancing effects of increased automation.

JEL classification: D31, J24, E21, D1, G11.

Keywords: Portfolio choice, wealth inequality, financial wealth, robots, automation, labor income uncertainty.

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1 Introduction

In recent years we have witnessed an accelerated progress in digital technologies and significant advances in robotics and other related technologies. According to the International Federation of Robotics (IFR), the worldwide industrial robot stock has almost tripled in the past decade, and is projected to grow at a similar (or even a faster) rate over the next ten years.[1] The extent and rapidity of the progress in automation, including the major leaps in artificial intelligence capabilities, raises several questions with important implications for individuals.[2] What are the consequences of rapid adoption of robots for wages and employment prospects of individual workers? Does its impact extend beyond the labor market to other dimensions of economic and financial behavior of individuals? Who are the winners and losers of increased automation?

In this paper we empirically explore these questions with a particular focus on the effects of automation on household wealth accumulation, and on potential mechanisms through which pervasive automation contributes to changes in the distribution of wealth, and the implications of these effects for the evolution of wealth inequality.

We operationalize increased importance of automation by focusing on an industry-level measure of robot use. Specifically, we consider adoption of industrial robots, which are defined as reprogrammable and fully autonomous machines that are capable of being adapted to perform different tasks (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; IFR, 2017). We combine this industry-level measure of automation with an extensive individual-level panel dataset that contains detailed wealth records and highly accurate information on the demographics and labor market outcomes of approximately 300,000 individuals between 1999 and 2007.

[1] See also Acemoglu and Restrepo (2020) and the references therein.

[2] There is a burgeoning literature that focuses on the economic consequences of rapid automation, with a particular emphasis on its effects on the labor market. The recent evidence suggests that, despite their positive impact on productivity (Graetz and Michaels, 2018), automation and advances in production methods negatively affect wages and employment opportunities of individual workers (Acemoglu and Restrepo, 2020; Autor and Salomons, 2018), and further correlate with increases in labor income risk and wage inequality (Kogan, Papanikolaou, Schmidt, and Song, 2018).

We provide evidence that increased automation has a significant negative impact on distribution of wealth. Specifically, increased exposure to robots at work significantly lowers the percentile wealth rank of individuals within their birth cohort-year distributions and further increases the probability of downward mobility in the wealth distribution over the sample period. The magnitude of these effects is also meaningful in economic terms. To give an idea of the magnitude of robotization effects, we find that a one-standard deviation exogenous rise in the robot density between 1999 and 2007, which corresponds to an increase of 3.27 robots per thousand workers in a given industry, reduces the rank of individuals in the wealth distribution by 4.1 percentiles. This effect is present, controlling for a wide range of observable household characteristics, industry-level changes and trends, as well as for region specific macro conditions and shocks.

The implication of the negative wealth effects is mirrored in Figure 1 that provides some striking (though informal) evidence on the relationship between increased use of robots and evolution of wealth inequality. We see that the rise in wealth inequality, as measured by the interquartile range of household net wealth, monotonically increases in the changes in robot density across industries, which suggests that rapid automation is likely to play a role in increased wealth dispersion.

To understand the mechanism underlying these results, we consider three distinct wealth accumulation factors that have been shown to contribute to the observed cross-sectional and time-series features of wealth distribution. In a recent paper, Benhabib, Bisin, and Luo (2019) document that skewed and persistent distribution of earnings, differences in saving rates, and heterogeneous returns to capital are all necessary and important to account for high concentration of wealth. Accordingly, we first investigate whether the impact of robots on household wealth operates through its direct effects on earnings of individuals. Indeed, prior literature documents negative impact of automation on wages and employment prospects. For example, Acemoglu and Restrepo (2020) show that increased use of industrial robots across U.S. commuting zones contributes to lower aggregate wages and employment. Even though we find significant negative wage and employment effects of automation, our analysis reveals that differences in earned incomes alone do not explain the variation in levels and dynamics of household wealth. Second, we examine the potential role of heterogeneity in saving behavior across households to explain the variation in household wealth. We document that increased automation still exhibits negative significant effects on household wealth even when we control for differences in initial active or total saving rates of households, suggesting that differential savings do not provide a full explanation for our findings.

In fact, our analysis indicates that adverse effects of robotization on individual workers' human capital, and thereby, on their financial risk taking behavior and investment choices appear to be an important channel. In particular, we first document that rapid adoption of robots leads individuals to face significantly higher background labor income risk, which is measured by job-loss risk of individuals.[3] We then show that households who are more exposed to robots at work, and hence, face increased uninsurable risk in their human capital, significantly decrease the share of their risky assets and are more likely to exit from the stock market (Cocco, Gomes, and Maenhout, 2005). Specifically, ceteris paribus, a one-standard-deviation exogenous rise in the robot density in their industry of employment leads to an 15% increase in the exit probability of households from the stock market. As these individuals fully rebalance their financial portfolio away from the stock market, they also forgo substantial equity returns up to 4.3% on a year (Calvet, Campbell, and Sodini, 2007), which corresponds to approximately a cumulative return loss of 40% during the observation period. As a result, these households experience a substantial drop in the growth of their financial wealth and accumulate less financial wealth relative to their income. Overall, the portfolio channel appears to amplify the inequality-enhancing effects of increased automation.

[3]This result is further strengthened by Kogan et al. (2018) who find that automation, or more generally, advances in production methods, are associated with substantial increases in the labor income risk of individual workers.

To quantify the relative importance of these alternative mechanisms through which increased automation affects distribution of wealth, similar to Heckman, Pinto, and Savelyev (2013), and Fagereng, Mogstad, and Ronning (2020), we employ a causal mediation analysis (Pinto, Dippel, Gold, and Heblich, 2019). The mediation analysis allows to disentangle the average causal effect of a treatment on an outcome variable running through an observed intermediate outcome and through other mechanisms (Imai, Keele, and Yamamoto, 2010; Heckman and Pinto, 2015). Our results suggest that realized income growth as a mediator can explain approximately one-third of the total effect of robots on household wealth accumulation, implying that other mechanisms such as the portfolio channel are also at play, and they are also important wealth accumulation factors.

A natural question is whether there are any asymmetries in the distribution of negative wealth effects of automation across individuals. While skill upgrading of jobs as a result of emerging new technologies could favor some people, it can leave behind others, notably, those individuals with lower human capital or skills (Brynjolfsson and McAfee, 2012; Autor, 2015; Sachs, Benzell, and LaGarda, 2015; Berg, Buffie, and Zanna, 2018). For example, Acemoglu and Restrepo (2018c) show that middle-aged workers who perform blue-collar tasks are more likely to be replaced by robots relative to older workers with specialized knowledge in non-production services. Similarly, according to the estimates of the U.S. Council of Economic Advisers, more than 80 percent of jobs paying less than 20 USD per hour in the U.S. would be negatively affected by automation, whereas this number accounts for 4 percent of jobs making above 40 USD per hour.[4] Hence, it is conceivable to argue that automation and advances in production methods have asymmetric effects on the economic and financial behavior of individuals, depending on the required skill-level or type of their occupation.

When we study the distributional effects of automation, we observe that the negative wealth effects of automation is significantly more pronounced for low-skill individuals (i.e.,

[4]See the report on "Artificial Intelligence, Automation, and the Economy" by White House's Council of Economic Advisers, December 2016. The report is available at https://obamawhitehouse.archives.gov/blog/2016/12/20/artificial-intelligence-automation-and-economy.

proxied by lower-educational attainment). Similarly, the reduced financial risk taking and portfolio channel are only operative for the low-skill individuals, presumably because robots are more likely to render the skills of low-educated workers obsolete, and hence, these individuals face a higher idiosyncratic labor income risk. Overall, our findings suggest that rapid automation can widen, the already large and persistent, wealth gap between high- and low-skill individuals, and further caution against the potential distributional challenges created by increased use of robots.

In our empirical analysis, the panel dimension and detailed nature of our dataset allow us to explicitly account for a wide range of relevant individual characteristics and further to isolate the effects of robots from various other industry-level changes and region specific macro shocks. Still, a threat to our identification is posed by the presence of unobserved industry shocks. We overcome this endogeneity issue using two alternative identification strategies.

First, in our base analysis, following a similar identification strategy as in Autor, Dorn, and Hanson (2013), Bloom, Draca, and Van Reenen (2016), and Acemoglu and Restrepo (2020), we instrument for changes in robot density in the Swedish industries, that is the country of interest in our analysis, using the contemporaneous median changes in robot density across eleven other Western European countries. Our identification strategy proceeds from the notion that the adoption of robots in the (non-Swedish) European countries represents the advances in global technological frontier (Acemoglu and Restrepo, 2020). Hence, our instrumental variable (IV) strategy enables us to identify the exogenous variation in the adoption of robots in the Swedish industries induced by improvements in the technological frontier of robotics in the corresponding industries. Since Sweden is a small open economy and we focus on the European countries when defining the technological frontier, we assess the plausibility of the exclusion restriction in detail, and provide evidence that corroborates the validity of the instrument.

Second, we use an alternative identification strategy, that follows the spirit of a difference-in-difference (DiD) type identification, which allows us to control for potential industry confounds. Specifically, we employ a novel approach and exploit the heterogeneity in the intersectoral transferability of human capital (acquired through formal education) of individuals working in the same industry. Reassuringly, the estimates from the DiD design are similar to those from the IV regressions, which suggests that the negative wealth effects of robots are not an artefact of any unobserved industry factors and trends.

Our paper complements a small but growing literature which analyzes the economic consequences of increased automation.[5] For example, Acemoglu and Restrepo (2020) find that penetration of industrial robots across U.S. local labor markets reduces aggregate employment and wages, while, in an international sample, Graetz and Michaels (2018) document positive productivity effects of automation, which, however, reduce employment of low-skill workers. We contribute to this literature along several dimensions. We provide the first direct evidence that negative effects of robotization extend beyond the labor market to the dynamics of wealth accumulation, explore the potential underlying mechanisms, and further show its implications for wealth inequality. Second, our micro-data evidence on the negative wage and employment effects parallels and complements the findings of these studies in a different country and time period.

Our work also links to the empirical literature on the importance of uninsurable background risk in the demand for risky assets (Fagereng, Guiso, and Pistaferri, 2017; Betermier, Jansson, Parlour, and Walden, 2012). Specifically, we identify an additional source of idiosyncratic labor income risk, which is likely to become more important in the future, and document its effects on the portfolio choice and financial wealth accumulation of individuals.

Finally, our findings on the relative importance of different wealth accumulation factors also relate to the literature that focuses on the mechanisms that generate the observed patterns in the distribution of wealth (Benhabib, Bisin, and Zhu, 2011; Gabaix, Lasry, Li-

[5]See, e.g., Bessen, Goos, Salomons, and Van den Berge (2019); Acemoglu and Restrepo (2018a); Martinez (2019); Dauth, Findeisen, Südekum, and Woessner (2017); Aghion, Jones, and Jones (2017); Arntz, Gregory, and Zierahn (2016); Freeman (2015); Benzell, Kotlikoff, LaGarda, and Sachs (2015); Hémous and Olsen (2018); Sachs and Kotlikoff (2012).

ons, and Moll, 2016; Hubmer, Krusell, and Smith, 2016). Recent empirical evidence finds that there is considerable heterogeneity in returns to wealth across the population, which emerges as an important channel to explain the variation in household wealth (Bach, Calvet, and Sodini, 2020; Fagereng, Guiso, Malacrino, and Pistaferri, 2020; Campbell, Ramadorai, and Ranish, 2019). For example, Bach et al. (2020) document that households in the top of the wealth distribution earn significantly higher returns on their financial wealth compared to the median household, which, as the authors argue, are primarily compensations for their exposure to higher levels of systematic risk.

The remainder of the paper proceeds as follows. Section 2 introduces the data sources, and informs about the construction of the main variables of interest in our empirical analysis. In Section 3, we discuss the econometric challenges in the analysis, and explain how we tackle them. In Section 4, we present the results of the wealth analysis, and and further report the results of a sensitivity analysis where we use a complementary empirical strategy. Section 5 further discusses and explores mechanisms. Section 6 reports our findings on the distributional effects of robots. Finally, Section 7 concludes the paper.

2 Data and Variable Definitions

In the analysis of the effects of automation on economic behavior and wealth accumulation of households, we make use of information from several sources. In what follows, we describe our data sources, provide detailed information on our main variables of interest, and present descriptive statistics for the sample.

To measure the degree of automation, we acquire time-series data on the stock of industrial robots disaggregated at the industry level from the International Federation of Robotics (IFR).[6] The IFR collects annual information on the total stock of robots and new robot instal-

[6]Industrial robots are defined as reprogrammable and fully autonomous machines that are capable of being adapted to perform different tasks (i.e., being multipurpose) (IFR, 2017). According to the definitions of the IFR (2017), reprogrammable means that "*robots are designed so that programmed motions or auxiliary functions can be changed without physical alteration*", and multipurpose refers to the "*capability of being*

lations, detailed at the 2-digit industry level, for approximately 50 countries since 1993 by surveying the robot producers and suppliers around the world (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; IFR, 2017).[7] For Sweden, on which we focus our empirical investigation, we observe the total stock of robots for 14 industries on a yearly basis for the time period between 1993 and 2016. These industries include agriculture, forestry, fishing; mining and quarrying; manufacturing; utilities; construction; and education, research, and development. For the manufacturing industry, we have a more detailed breakdown of industries approximately at the 3-digit level, which includes along others food and beverages; textiles; wood and furniture; basic metal and metal products; electrical and electronics; and automative industries.[8] In Table I, we provide information on the use of industrial robots and number of workers for the Swedish industries during our sample period.

Following Acemoglu and Restrepo (2020), we merge the industry-level robot data with the number of workers in each corresponding industry, which we collect from the *EU KLEMS* dataset (Jäger, 2016). We then compute the robot density per thousand workers for each industry in a given year as follows:

$$Robot\_Density_{jt} = \frac{\text{No of Robots}_{jt}}{\text{No of Workers}_{jt}} \tag{1}$$

As presented in Table I, the automative industry has the highest robot density with 27.86 robots per thousand workers, which is followed by basic metal and metal products industry with 11.35 robots per thousand workers as of 1999.

We next merge the processed data on stock of robots with the household-level LINDA

adapted to a different application with physical alterations".

[7]The IFR also provides information on the application of robots (e.g., handling, dispensing, processing), though, there is no industry breakdown for this particular information, and it is only available at the country level. According to the information provided by the IFR, as of 1999, the application areas of industrial robots in the Swedish industries that we consider in our analysis are as follows: 63% of industrial robots are used in handling and machine tending; 22% are in welding and soldering; 7% are in assembling and disassembling; 2.3% are in dispensing, and 2% are in processing.

[8]The IFR also reports the number of robots that are not classified into any industry. To minimize potential misclassification and measurement errors, we do not consider those values that fall into the "Unspecified" category when computing the robot exposure variable.

dataset, which is provided by Statistics Sweden.[9] LINDA consists of an annual cross-sectional sample of around 300,000 individuals, or approximately 3% of the entire Swedish population, and their family members. The data contain highly accurate information on financial (e.g., detailed decomposition of household wealth at the individual-security level) and demographic characteristics (e.g., age, marital status, level and orientation of education) of each sampled individual as well as very detailed information on their labor market outcomes such as earnings, employment status, and industry of employment (i.e., detailed at the five-digit SNI code) for the period from 1999 to 2007.

When constructing the working sample, we adopt a conservative strategy in order to minimize potential misclassification and measurement errors. First, we only focus on working-age households between the ages of 22 and 60 during the sample period (Autor et al., 2013). Second, we exclude from the sample households who are classified as student, housemaker, self-employed, unemployed or retired, focussing only on the employed individuals in the initial period. Next, we restrict our attention only to those households who are employed in industries, which are directly affected by adoption of industrial robots and for which the IFR provides information on the number of robot stock.[10] According to the employment counts from the *EU KLEMS* database, the number of employees in the industries which we consider in our analysis represents 55.5% of the workers in the market economy and 35% of the workers in all industries in Sweden. When constructing the final sample, we require households to be employed in certain industries only in the initial period, that is, we allow for the sampled households to switch industries or become unemployed or move to a differ-

[9]It is important to note that the IFR and Statistics Sweden use different industry classifications. For example, LINDA dataset provides information for households' industry of occupation as detailed as at the 5-digit level. We follow a similar matching procedure as in Graetz and Michaels (2018). We provide further details about the matching procedure in Table O.A.1 in the Online Appendix.

[10]We exclude from the sample households who are employed in industries such as information and communication; community social and personal services; and other service activities. Alternatively, we could have set the value for stock of robots for those industries to zero, and include the households from those industries in the empirical analysis. We opt out for that approach, as we want to minimize the measurement error in household's exposure to robots, which is the key variable of interest in our empirical analysis. In robustness analysis, we verify our findings using the full set of industries (rather than focussing only on those that are directly affected by increased automation).

ent location in the following years. Finally, out of this conservatively constructed sample, we eliminate households with any missing information on labor market outcomes, financial and real assets or demographics. Overall, our final sample comprises $30,375$ households in any given year between 1999 and 2007. Descriptive statistics on the financial and demographic characteristics of the households are presented in Panel A of Table II.

The key variable of interest in our analysis is the household's exposure to increased use of robots, which we define at the industry level as follows:

$$\Delta Robot\_Density_j^{99\to07} = \frac{\text{No of Robots}_j^{07}}{\text{No of Workers}_j^{95}} - \frac{\text{No of Robots}_j^{99}}{\text{No of Workers}_j^{95}} \tag{2}$$

In our empirical analysis, we focus on the effect of long-differences in exposure to robots on various dimensions of household economic behavior, hence, we consider the changes in robot density in a given industry between 1999 and 2007. Note that we use the number of workers in 1995 (rather than the contemporaneous values) as our baseline employment level when constructing our variable to limit the potential simultaneity bias among employment and adoption of robots, mainly because current employment levels may be affected by the anticipation of increased automation (Acemoglu and Restrepo, 2020).[11] Panel B of Table II provides some detailed information on our key variable. We observe an increase in the number of robots per thousand workers between 1999 and 2007 with a mean (standard deviation) value of 2.69 (3.27) with the rubber, plastic and chemical product industry experiencing the largest growth (i.e., 11.5 robots per thousand workers) during the observation period.

As our main variable of interest is defined at the industry level, we control for numerous industry characteristics in our analysis to isolate the effects of exposure to robots from other industry-wide changes and trends. First, we construct a control variable for exposure

[11] Even though the time-series data on the number of industrial employees in the *EU KLEMS* database are available from 1993 onwards for Sweden, we use 1995 as our base employment year mainly because of the data availability for other developed European countries. In later stages of the paper, we use the exposure to robots from various developed countries as an instrument for that of in Sweden to address the potential endogeneity issue.

to imports from China at the industry level. Previous literature shows that increased imports from China (and other low-wage countries) have a negative effect on the employment, wages, and labor-force participation (Autor et al., 2013; Bloom et al., 2016). To address this issue, following Autor et al. (2013), we construct a variable that captures the changes in the exposure to Chinese imports per thousand workers between 1999 and 2007 as follows:

$$\Delta Chinese\_Import_j^{99\to07} = \frac{\Delta Imports_j^{99\to07}}{\text{No of Workers}_j^{95}} \tag{3}$$

where $\Delta Imports_j^{99\to07}$ is the changes in imports from China (measured in Swedish Kroner in thousands) in industry j between 1999 and 2007. We normalize this variable by the employment levels (in thousands) in industry j from 1995. Similarly, international trade competition, other than import exposure to China, may also affect economic and financial outcomes of Swedish households and proliferation of robots in both Swedish and European industries. To address this issue, we also account for contemporaneous median changes in import exposure to eleven developed Western European countries that we use to construct the excluded instrument described in Section 3. The import data are collected from Statistics Sweden, and information on employment levels again comes from the *EU KLEMS* database. Next, following Acemoglu and Restrepo (2020), we control for whether a given industry is declining in terms of change in the nationwide employment levels between 1993 and 1998. Fourth, we introduce control variables for changes in profitability in Swedish industries between 1999 and 2007 and labor intensity in 1999 (that is proxied by labor-to-capital ratio of a given industry). For example, an industry with declining profitability may exhibit lower income growth, and at the same time, higher automation growth to increase profits. Similarly, more labor intense and potentially more profitable industries (such as luxury goods or high-end fashion) may also offer higher income growth and less potential for adoption of robots. As we discuss in the following section, robotization appears to be distinct from other contemporaneous industry trends. Lastly, we introduce control variables for changes in the capital intensity, and ICT capital in our regressions, respectively. We obtain information on the capital stock (i.e., net capital stock volume in millions) for each industry from the OECD's STAN database, and calculate the percentage change in the capital stock between 1999 and 2007. The change in the ICT capital is calculated analogous to the change in the capital intensity variable. The information on industry-level ICT capital is collected from the *EU KLEMS* database. In Panel D of Table II, we provide descriptive statistics for the industry controls.

3 Empirical Specification

In our empirical analysis, we investigate the long-term relationship between changes in exposure to robots and changes in economic outcomes of individuals, accounting for a wide range of household characteristics, industry trends, and local economic conditions through regional fixed effects. Our base model takes the following form:

$$\Delta Y_{ijk}^{99\to07} = \alpha \cdot \Delta Robot\_Density_j^{99\to07} + \beta \cdot \Delta HH\_Controls_i^{99\to07} + \gamma \cdot \Delta IND\_Controls_j^{99\to07} + \delta_k + \epsilon_{ijk} \tag{4}$$

where $\Delta Y_{ijk}^{99\to07}$ represents the long-differences (that we refer to changes between 1999 and 2007) in the economic and financial outcomes of interest for household i who works in industry j and lives in municipality k in 1999.

Our dataset provides detailed and accurate information on numerous household demographic and financial characteristics, which are represented by vector $\Delta HH\_Controls_i^{99\to07}$. In our regressions, we control for changes in educational attainment measured by different indicator variables (i.e., having attended/completed high school or college), changes in marital status of the household head, separate variables for changes in number of adults and number of children in the household, and deciles of household disposable income and net wealth defined at the initial time period that is 1999.

In addition to household characteristics, we account for several relevant industry controls (i.e., $\Delta IND\_Controls_j^{99\to 07}$) so as to isolate the effect of automation from other industry level trends. The vector $\Delta IND\_Controls_j^{99\to 07}$ includes changes in exposure to Chinese imports and international trade competition between 1999 and 2007; changes in profitability in Swedish industries between 1999 and 2007; labor intensity of a given industry in 1999; percentage changes in capital intensity and ICT capital; and change in the nationwide industry level employment between 1993 and 1998, all of which are described in the previous section. Lastly, we control for regional fixed effects, defined at the municipality level and denoted by δ_k, to account for potential differences in regional economic conditions. In Sweden, there is a total of 290 municipalities, which are responsible for various tasks such as social services or physical planning. Hence, the municipality fixed effects account for latent regional characteristics and capture the direct effects of the location of households. In our main specifications, we also control for initial robot density (measured in our base year of 1995) of an industry, which allows us to focus on the variation coming from differences in changes in robot density across industries within a municipality.

Even though we include a rich set of industry controls in our regressions, there may be still some unobserved factors and trends that are correlated with growth in robot density and economic outcomes of households working in that industry. This would pose a threat to our identification. For example, a rapid increase in unionization in some of the Swedish industries could both lead to an increased adoption of robots and higher wages and improved job security in those industries, which would yield a positive correlation without implying a causal link between the two.[12]

To pin down the causal effects of increased exposure to robots on economic outcomes of households, in our base analysis, we use an instrumental variable (IV) approach that is estimated in a 2SLS fashion. Following a similar identification strategy as in Autor et al. (2013), Bloom et al. (2016), and Acemoglu and Restrepo (2020), we instrument for changes

[12]Note that if any unobserved industry shocks are positively correlated with the degree of automation and employment and other economic outcomes in that industry, OLS regressions would underestimate the true effect of automation on household economic behavior. In other words, the OLS coefficients on the exposure to robots variable would be downward biased.

in robot density between 1999 and 2007 in the Swedish industries using the contemporaneous median changes in robot density across eleven other developed Western European countries.[13] Building on the same ideas as in Acemoglu and Restrepo (2020), we use adoption of robots in the (non-Swedish) European countries to capture the advances in global technological frontier, which is assumed to be positively correlated with the robot density growth in Sweden but uncorrelated with the error term in the equations of interest. Indeed, the first-stage regressions, presented in Table O.A.2, show a positive and statistically highly significant effect (p-value<0.01) of the excluded instrument on the endogenous robot exposure variable. In addition, we observe that the F-statistics for the first-stage regressions are far greater than 10, which indicates that the excluded instrument is strongly correlated with the endogenous robot exposure variable and thus do not suffer from a weak instrument problem.

Since Sweden is a small open economy and we focus on the European countries when defining the technological frontier of robotics, one can worry about the validity of the exclusion restriction. For example, changes in robot adoption in the European countries may be correlated with some negative shocks to Swedish industries, which could contaminate our identification strategy. We tackle this concern in a number of ways. First, in all regressions, we allow for a rich set of differential industry factors and trends, including contemporaneous changes in exposure to imports from China and European countries, percentage changes in the capital intensity and IT capital, changes in the profitability, early trends in employment growth, labor intensity, and initial automation density in the Swedish industries, which would partially mitigate concern of omitted time-varying factors. Second, as shown in Figure O.A.I, we document that the correlations between adoption of robots in the European countries and other industry-level trends in Sweden such as changes in exposure to imports from China and European countries, percentage changes in the capital intensity and

[13]The eleven other developed countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Portugal, and the United Kingdom. Note that industry breakdown of robot stock for Austria, Belgium, Netherlands, and Portugal is not available prior to 2004. Hence, for these countries, we use the robot density in 2007 in the corresponding industries.

IT capital, and changes in the profitability are relatively weak (ranging from 0.06 to 0.2), which suggests that robotization is distinct from other contemporaneous industry trends. Importantly, we also observe a positive association between early trends in industry-level employment growth (i.e., between 1993-98) and adoption of robots both in the Swedish and European industries during the sample period. This implies that there appears to be no significant industry pre-trends such as declining labor demand, and confounding industry pre-trends are not likely to drive our results. Third, it is important to note that, even though Sweden is a member of the European Union (EU) since 1995, it is not a part of the European Monetary Union. Sweden has its own currency, a floating exchange rate regime, and an independent monetary policy, which makes Sweden less prone to EU-wide common shocks. Consistent with this argument, Söderström (2008) shows that, despite the common component in the Swedish and Euro area business cycles, the Sweden-specific shocks represent a significantly more important source of Swedish business cycle fluctuations than foreign (i.e., European) shocks, and country-specific shocks account for most of the variability in the Swedish economy. Fourth, when defining the technological frontier of robotics, we could have considered a non-European country such as the U.S. or Japan, which would be potentially less susceptible to unobserved industry shocks. However, this is not feasible for various reasons. For example, U.S. is lagging behind the European countries (as well as Sweden) in terms of robot adoption, hence, U.S. industries would not represent an appropriate frontier in technological advances for the Swedish industries. Similarly, the robot stock data for Japan provided by the IFR were subject to significant reclassification; therefore, we are not able to use industry-level robot adoption data for Japan in our analysis. Finally, to further assess the plausibility of the exclusion restriction, we compute the gross value-added beta of the Swedish industries with respect to the European and U.S. industries, respectively.[14]

[14]To compute industry betas, we obtain annual data on industry value-added for Sweden, eleven developed Western European countries as well as for the U.S. from the EU KLEMS database for the period between 1970 and 2015. The industry betas are calculated as the slope coefficients from rolling regressions of value-added growth of the Swedish industries on the value-added growth of the U.S. and European countries using 25 years of data up to t, respectively.

Interestingly, we see that changes in labor productivity in the Swedish industries are on average significantly less sensitive to labor productivity growth in the corresponding European industries than that of the U.S. industries, which provides further evidence in support of the exclusion restriction.

Overall, our IV strategy will identify the exogenous variation in robot adoption in the Swedish industries that is induced by advances in the technological frontier of robotics, and allows us to isolate the effect of an exogenous increase in robot density on the economic outcomes of households.

Note that we also verify our findings from the IV regressions using an alternative identification strategy, that follows the spirit of a difference-in-difference type identification, presented and described fully in Section 4.2. Specifically, we focus on within industry variation and exploit the heterogeneity in the intersectoral transferability of human capital (acquired through formal education) of individuals working in the same industry, which circumvents potential concerns in interpretation that could arise from unobserved industry factors and trends.

Finally, recall that Equation 4 is defined and estimated in first differences, and hence, is equivalent to fixed effects regressions. The first-differencing addresses the concerns arising from unobserved household characteristics that may otherwise contaminate estimation of the true effect of automation on household wealth and other economic outcomes. Also, we correct standard errors for potential spatial correlation across households within municipality-industry level by clustering at the municipality-industry level. We obtain similar results when we account for possible serial correlation and heteroskedasticity within an industry.

4 The Effects of Robots on Household Wealth

This section first presents and discusses the household wealth analysis, and further reports the results of a sensitivity analysis where we use a complementary empirical strategy.

4.1 Robots and Distribution of Wealth

We first analyze the effects of automation on distribution of wealth. Our main variable of interest is household net wealth, which we compute, as standard in the literature, by subtracting the household debt (i.e., mortgage loans and consumer debt) from total gross wealth that is the sum of all financial (i.e., direct and indirect stocks, bonds, cash) and real assets (i.e., value of primary residence, and other real estate holdings).

We measure the percentile rank of a household within the birth cohort-year distribution of net wealth, and use it as our preferred specification (Black, Devereux, Lundborg, and Majlesi, 2020; Chetty, Hendren, Kline, and Saez, 2014).[15] This wealth measure, by definition, accounts for life-cycle differences across households (Black et al., 2020). Also, it can be defined for zero or negative values of net wealth, which is, for example, not feasible with a log transformation.[16] Finally, when measuring the percentile rank of sampled households within their birth cohort distribution, we no longer restrict our attention to the households in the final sample but rather consider all sampled households in the LINDA dataset with non-missing wealth information.

First, we consider the net wealth percentile rank of a household at the end of the observation period as our dependent variable, and ask whether increased use of robots in an industry affects the relative position of households in the wealth distribution. Columns (1) and (2) of Table III present the estimation results. The regression estimates imply a nega-

[15] We define 12 birth cohorts, with each birth cohort consisting of five-year intervals between the years 1923 and 1983.

[16] Use of percentile wealth rank of households (rather than wealth growth or wealth levels) as the preferred specification is primarily motivated by our focus on (the evolution of) wealth inequality. In additional tests, presented in Section 5.2, we also consider the effects of robotization on growth in financial wealth and (financial) wealth-to-income ratio, respectively.

tive and statistically highly significant effect of exposure to robots on the rank of households in the wealth distribution (t-stat. = -10.14). To give an idea of the magnitude of automation effects, a one-standard-deviation increase in the robot density in an industry reduces on average the rank of individuals in the wealth distribution by 4.1 percentiles. To put this into context, we contrast it with the effect of changes in exposure to Chinese import on the wealth rank of households (Autor et al., 2013; Bloom et al., 2016). We observe that the effect of robots is more than twice as large as that of the changes in exposure to Chinese import, hence, the magnitude of the automation effects is quite considerable.

The percentile rank variable focuses on the net asset holdings of households and reflects the position of households in the wealth distribution relative to their peers. However, it is silent on the changes within the distribution of wealth over time (Quadrini, 2000). To address this issue, we next focus on the wealth mobility of households over the sample period using two different measures. First, we define an indicator variable that is equal to 1 if a household falls into a lower wealth percentile rank within the birth cohort distribution in 2007 relative to her initial position in 1999, and zero otherwise. Second, we focus on the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. Note that these measures enable us to assess the intracohort mobility of households over time, and thus, provides insights about the potential effects of robots on the household wealth dynamics (net of any life-cycle effects).

Columns (3) to (6) of Table III present the regression results. We find that households who are more exposed to industrial robots at work also experience greater downward mobility in the 1999-2007 period. For example, the IV estimate in column (3) of 0.008 indicates that a one-standard-deviation exogenous rise in the robot use in an industry leads to a 2.7 percentage points increase in the probability of a household falling in the wealth distribution over the sample period (t-stat. = 4.84). To complement the analysis, we also consider the upward mobility of individuals, that is, the probability of moving to a higher wealth class during the observation period. In tests presented in Table O.A.3 in the Online Appendix, we document significant and negative effects of robots on upward mobility of individuals in the wealth distribution. All in all, the results from the mobility regressions indicate that rapid automation can contribute to a more dispersed wealth distribution.

To address any concerns that our findings may be driven by the differences in the housing investments of households, in a robustness exercise, we verify our results including homeownership of households as an additional covariate in the wealth regressions. The results, tabulated in Table O.A.4, show that the negative impact of robots on household wealth remains almost identical even after accounting for initial homeownership and differences in house prices and other regional economic conditions through municipality fixed effects. Next, one can argue that observed variation in household wealth could be induced by differences in risk preferences of households. Table O.A.5 hence repeats the exercise controlling for initial risk exposure that is measured by the share of financial wealth in risky assets in 1999 (Fagereng et al., 2020). We again find very similar results. Finally, we analyze whether changes in household debt contribute to observed differences in household net wealth. For example, in a recent paper, Barrot, Loualiche, Plosser, and Sauvagnat (2018) show that households who live in regions where manufacturing industries are more exposed to import competition significantly lever up to smooth their consumption. To address this possibility directly, we next regress the log changes in household debt between 1999 and 2007 on the industry-level changes in robot density over the same time period and other household and industry controls. As presented in Table O.A.6, we find no significant effect of increased robotization on household debt, suggesting that automation affects household wealth through its effects on the asset side of household balance sheets. Collectively, wealth analysis yields strong evidence for the negative effects of pervasive automation on distribution of wealth.

4.2 Intersectoral Transferability of Human Capital and Robots

The identification strategy which we use so far in the wealth analysis is standard in the literature and is similar to that of Autor et al. (2013) and Acemoglu and Restrepo (2020). One potential concern with our IV strategy is that any unobserved shocks in the Swedish industries may be correlated with industry shocks in other European countries that we use to construct the excluded instrument. While it is not possible to test the validity of the exclusion restriction explicitly, the evidence and corresponding discussion presented in Section 3 suggest that confounding industry factors are not likely to drive our results. Still, to examine the robustness of our findings, we next consider an alternative identification strategy. Specifically, we focus on within-industry variation by studying the effects of adoption of industrial robots on the wealth changes of individuals working in the same industry.

We estimate an interaction model using first-differences regressions that is also in spirit to a difference-in-differences type identification. To be more precise, we exploit heterogeneity in the intersectoral transferability of human capital (acquired through formal education) of individuals working in the same industry. The importance of general and specific human capital for job mobility and determination of earnings has been focus of a rich theoretical and empirical literature (Becker, 1962; Altonji and Shakotko, 1987; Topel, 1991). For example, Neal (1995) and Parent (2000) provide evidence on the importance of the industry specificity of human capital for the determination of earnings.[17] Motivated by the existing literature, we argue that individuals with more industry-specific human capital are more adversely affected by increased use of robots in their industry, mainly due to higher moving frictions across industries (Artuç, Chaudhuri, and McLaren, 2010; Autor, Dorn, Hanson, and Song, 2014), as compared to their peers with skills that are more portable across jobs in different sectors.

To measure the transferability of human capital empirically, we employ a novel approach

[17] More recent studies by Kambourov and Manovskii (2009) and Gathmann and Schönberg (2010) emphasize the importance of occupational- and task-specificity of human capital, respectively. See also Donangelo (2014) for a similar measure of interindustry labor mobility.

and focus on the orientation and level of formal education of individuals. Our focus on the orientation of education (rather than on occupational experience as in Kambourov and Manovskii (2009) or tasks performed in occupations as in Gathmann and Schönberg (2010)) is motivated by several reasons. First, formal education represents one of most important sources of human capital. Second, it is reasonable to conjecture that choice of educational major, and hence, the intersectoral transferability of human capital is exogenous to the current advances in automation and increased adoption of industrial robots, since educational choices were made many years in the past.

We make use of auxiliary data that provide detailed and high-quality information on the orientation and level of education of all households in our database provided by Statistics Sweden.[18] Considering all sampled individuals aged between 25 and 60, we first compute the distribution of individuals within each educational orientation-level (aggregated into two groups: higher and lower levels of education based on college attendance) over their initial (2-digit) industry of employment. We then construct a Herfindahl-Hirschman index (HHI) of industry-of-employment concentration for each educational group-level separately. A higher (lower) HHI would imply lower (higher) levels of intersectoral transferability of human capital of individuals. We present in Table O.A.7 the top and bottom 10 educational majors by their intersectoral transferability. For example, we observe that educational majors such as medicine, dentistry, and nursing have very low intersectoral transferability, while majors including engineering, information technology, and business administration have very high intersectoral transferability. Furthermore, in tests tabulated in Table O.A.8, we validate the measure by showing that individuals with lower intersectoral human capital are indeed less likely to switch industries between 1999 and 2007, suggesting that our measure reasonably captures the sectoral specificity of human capital.

To identify individuals with higher industry-specific human capital (and who are more

[18]The SUN 2000 classification of Statistics Sweden for educational majors is similar to that of the International Standard Classification of Education 1997 (ISCED-97). We use the 3-digit SUN 2000 category that consists of 117 educational orientations such as economics and economic history, mining and mineral engineering, nursing and many others.

prone to adverse effects of robotization), we define an indicator variable $Low\_Transfer_{ij}$, which equals one if the HHI of household i's educational major is above the median HHI across individuals working in industry j, and equals zero otherwise. In principle, we intend to compare individuals with similar (financial and demographic) characteristics working in the same industry, some of whom are more affected by increased automation, and some of whom are not or less affected. As shown in Figures O.A.II and O.A.III, the distributions of annual income and net wealth of individuals in both groups are very similar, suggesting that we have a sample of fairly balanced treatment and control individuals.

We then estimate (within-industry) regressions of the following form where we interact the changes in robot density between 1999 and 2007 and (household-level) indicator variable for having less transferable human capital:

$$\begin{aligned}\Delta Y_{ij}^{99\rightarrow 07} = \beta_1 \cdot \Delta Robot\_Density_j^{99\rightarrow 07} \times Low\_Transfer_{ij} + \beta_2 \cdot Low\_Transfer_{ij} \\ + \theta \cdot \Delta HH\_Controls_i^{99\rightarrow 07} + \delta_j + \epsilon_{ij}\end{aligned} \tag{5}$$

Note that industry fixed effects, as denoted by δ_j, subsume the direct effect of robotization and control for all sources of variation in differential industry factors and trends. Table IV reports the results of the wealth analysis.

Consistent with our results from baseline analysis, we still observe a negative and significant effect of robots on wealth accumulation of individuals even after the inclusion of industry fixed effects. For example, a one-standard deviation increase in the robot density in a given industry reduces the wealth rank of individuals with more industry-specific human capital by 1.21 percentiles (t-stat. = -2.46) as compared to those in the control group working in the same industry. These results are also robust to controlling for changes in household characteristics between 1999 and 2007. Overall, the sensitivity analysis implies that our findings on the adverse effects of automation are not simply an artefact of unobserved industry factors.

4.3 Additional Robustness and Sensitivity Analysis

In this section, we perform several additional tests to ensure the robustness of our findings. We present these results in the Online Appendix. First, we address the potential sorting of households into different industries. In particular, individuals may anticipate the increased adoption of industrial robots at their workplace in the beginning of the observation period. Hence, they may sort themselves into sectors that have a lower potential for increased use of robots. The non-randomness in the sorting of individuals to different industries could bias the coefficient estimates on the exposure to robots variable. To address this concern, we next repeat our benchmark analysis focusing only on households who have been employed in the same industry since 1995 or earlier (i.e., when concerns over robotization have not yet gained much prominence). This restriction reduces the sample size by approximately 11,200 from 30,375 to 19,178 households. As shown in Table O.A.9, we observe that our findings are robust to basing our exposure variable on the households' industry of employment from the prior decade, indicating that endogenous selection of individuals to different industries do not drive our results. In untabulated tests, we also verify these findings using industry of employment information from 1993.

Second, we verify our results excluding from the sample those individuals who are working in the automative industry, which has historically the highest robot density per thousand workers in Sweden. The results, tabulated in Table O.A.10, are consistent with those of our baseline regressions, indicating that our results are not merely driven by the automative industry.

Third, we reestimate our base analysis using the full set of industries (rather than focussing only on those that are directly affected by increased automation). Specifically, we now consider those households who are employed in industries that are not directly affected by adoption of industrial robots and for which the IFR does not provide any information about the number of robot stock by setting the robot adoption in those industries to zero. The relaxation of this constraint increases the sample size to 82,424 households. As shown in Table O.A.11, the results are qualitatively similar (though, not surprisingly, smaller in magnitude) to what we observe in our main specifications, which alleviates any concerns of sample selection bias.

Fourth, we eliminate individuals working in the rubber and plastic industry that experienced the largest growth in robot use across industries in Sweden during the observation period. As presented in Table O.A.12, we find qualitatively and quantitatively similar results even after the exclusion of this industry from the sample, suggesting that our results are not affected by any outliers.

Finally, following Brunnermeier and Nagel (2008), we augment the base estimation model by allowing for additional life-cycle controls and preference shifters specific to the household. The additional control variables include age and age squared, their interactions with education variables, gender, and its interaction with age and age squared, household size, changes in household size, log disposable income in 1995, dummy variable for being unemployed in any year between 1999 and 2007, (percentage) change in income between 1995 and 1997 as well as change in income between 1997 and 1999, set of indicator variables for homeownership, business ownership, positive labor income for both in 1999 and 2007. We observe that our findings are robust to controlling for life-cycle effects and additional preference shifters, as presented in Table O.A.13.

5 Understanding the Mechanism

In what follows we discuss and explore mechanisms through which increased use of robots at work can affect household wealth accumulation and distribution of wealth.

5.1 Robots, Differences in Earned Incomes, and Saving Behavior

Recent empirical literature documents significant negative effects of increased use of robots at workplace on wages and employment prospect of individuals (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). Hence, a natural explanation for the negative wealth effects of automation could be the differences in earned incomes of households. To address this explanation, we first consider the effects of rapid robotization on labor market outcomes of households.[19]

We begin our analysis with investigating the effects of increased automation on changes in household income, which is defined as the log differences in earnings (net of any transfers or capitals gains) between 1999 and 2007. Consistent with the existing evidence, we also document that individuals who are working in industries with a higher rate of robot adoption on average experience lower income growth, as presented in columns (1) and (2) in Table V.[20]

Next, we turn to the impact of automation on the unemployment risk of households. Our dependent variable is now an indicator variable that takes the value of 1 if a given household was employed in 1999, and is unemployed in 2007. In other words, we estimate the transition probability from employment to unemployment during the observation period. As noted by Fagereng, Guiso, and Pistaferri (2017), unemployment risk represents one of the most important sources of background risk - a risk that is non-tradable and not fully insurable due to market illiquidity or incompleteness (Kimball, 1993; Aiyagari, 1994; Heaton and Lucas, 2000).

[19]Our analysis of the effect of robots on labor market parallels two recent pioneering papers that analyze the effects of penetration of robots on productivity, aggregate employment and wages. Using the same dataset on industrial robot stock from the IFR, Graetz and Michaels (2018) analyze the effects of automation on labor productivity in a sample of 17 countries, and find that gains in labor productivity are significantly more pronounced for those country-industry pairs that experienced a higher adoption of robots between 1993 and 2007. The authors also show that robots reduce the employment share of low-skill workers, albeit, they find no effects on aggregate employment shares. In an another key contribution, Acemoglu and Restrepo (2020) analyze the equilibrium effects of automation on aggregate wages and employment shares across U.S. commuting zones. They find that each additional robot per thousand workers decreases the aggregate employment rate by 37 and aggregate wages by 73 basis points, respectively.

[20]In an additional test, we re-define the dependent variable, including the transfers received by the households such as unemployment benefits or social welfare payments for the alleviation of poverty in the income definition, and consider the effects of automation on the log differences in household disposable income (that is net of taxes and excludes capital income) between 1999 and 2007. The results, tabulated in Table O.A.14 in the Online Appendix, show that the effects of robots remain statistically significant while, not surprisingly, they decline in magnitude. This finding indicates that the negative contribution of automation to household income seems not to be fully offset by transfers from the government.

Columns (3) and (4) of Table V report the estimation results. The regression estimates indicate that, ceteris paribus, a one-standard deviation increase in the robot density increases the probability of becoming unemployed by 1.4 percentage points. The effect is statistically highly significant (t-stat. = 5.05), and meaningful in economic terms. To put this into context, our estimates imply an 32% increase in the unemployment probability, as the unconditional unemployment rate in our samples accounts for 4.2%, indicating that the impact of automation on job-loss risk is significant in magnitude.[21] In summary, we establish negative and significant effects of robots on labor market outcomes of households.

To test whether the negative impact of automation on household wealth operates through its direct effects on the labor market outcomes of individuals, we would in principle like to estimate the wealth regressions by including both changes in robotization and realized income growth of households over the observation period in the right-hand side of the model. Since income growth is endogenous in this setting, such a model would lead to biased estimates. Hence, we rely on out-of-sample information and use realized income growth of households between 1995 and 1998 as an instrument for the realized income growth over the sample period (Zeldes, 1989; Shea, 1995). Specifically, we augment our base estimation model by including the deciles of household disposable income in 1999 and realized income growth between 1995 and 1998 as additional regressors (that corresponds to the reduced form of an IV regression where we instrument current income growth by lagged income growth). As presented in Table VI, we still observe that the exposure to robot variable remains significant with a negative sign. We obtain similar results when we use the average disposable income over the 5 year period prior to 1999 in lieu of income deciles in 1999 in these regressions (see Table O.A.15) (Guvenen, Schulhofer-Wohl, Song, and Yogo, 2017).[22]

[21]The positive contribution of robots to jobloss risk is consistent with Kogan et al. (2018) who document that advances in production methods are associated with substantial increases in the labor income risk of individual workers. Still, it is important to note that our analysis is silent on the general equilibrium spillover effects of automation on wages and employment in other sectors, as we focus on households who are directly exposed to robots at work. Hence, we note that the displacement effect of robots may be partly offset by their reinstatement effect (Acemoglu and Restrepo, 2018b), which would in turn mitigate the adverse effects of automation on overall employment.

[22]Note that Guvenen et al. (2017) use the 5-year average income as a proxy for permanent income in their

In Table O.A.16, we repeat the estimation, but excluding unemployed households in 2007, to mitigate concerns that our wealth results are merely a consequence of households who became unemployed. We find that, not surprisingly, the coefficient on changes in robot density declines, but retains its economic and statistical significance. Finally, in untabulated analysis, we also split the sample into two subsamples by the median value of the realized income growth between 1999 and 2007, estimate separately the wealth regressions. We document negative and significant effects of automation on household wealth in both subsamples with comparable coefficient estimates, which further suggests that the negative wealth effects of robots do not only operate through their impact on labor market outcomes of households.

A further potential consideration is that observed differences in wealth arise from the heterogeneity in saving behavior across households from different industries, as argued by the standard models (De Nardi and Fella, 2017). According to this explanation, individuals who are employed in more automated industries may have systematically lower active saving rates than those who work in industries with a lower rate of robotization. Hence, they end up in relatively lower ranks of the wealth distribution, and experience greater downward mobility. We address this alternative explanation in a number of ways. First, we calculate the initial active saving rate of each sampled household and include this variable as an additional covariate in the wealth analysis.[23] The results, tabulated in Table VII, show that the exposure to robots variable still exhibits a negative significant effect even after controlling for heterogeneity in saving behavior. We verify these results using the ini-

analysis. By the same logic, one can argue that the negative wealth effects of robots that we document are robust to controlling for differences in (initial) permanent income across people.

[23]To calculate the active saving rates, we make use of an auxiliary dataset provided by Statistics Sweden, which includes individual-level security information on the portfolio holdings of each (and every) individual in the LINDA dataset. Using standard financial databases (*inter alia* Bloomberg, Thomson Reuters Datastream, Factset, Compustat, Thomson Reuters Mutual Funds), we next collect end-of-year adjusted prices for (sampled) single stocks and mutual funds, and calculate their annual raw returns. We then compute the one year value-weighted buy-and-hold returns for each household's equity portfolio using the weighted-sum of the portfolio share of each stocks or mutual fund from the prior year and their annual returns. Here, we assume that all portfolio inflows and outflows occur at the end of each year. Using this information, we then decompose the changes in the financial wealth into two components: (i) active changes (i.e., due to new savings), and (ii) passive changes (i.e., due to returns on risky investments). Finally, we calculate the active saving rate of a given household a given year by dividing the active changes in the financial wealth by the contemporaneous disposable household income. To alleviate any concerns about the outliers, we winsorize this variable at 1%.

tial total saving rate in lieu of active saving rates as shown in Table O.A.17 and O.A.18. In another robustness exercise, we include initial wealth of households (as of 1999) in our wealth regressions.[24] This analysis is motivated by Bach et al. (2017) who document a negative robust correlation between active saving rates of households and their wealth levels in Sweden. As presented in Tables O.A.19 and O.A.20, the IV estimates indicate a negative significant effect of increased automation on household wealth variables. This finding is robust to measuring the initial wealth either in levels or using quartile wealth dummies.

Taken together, our results suggest that wealth differences across households appear not to be merely a consequence of income differences or heterogeneity in saving behavior of individuals across industries. In Section 5.3, we also perform a quantification exercise and provide additional results on the relative importance of these mechanisms for the observed differences in household wealth using causal mediation analysis.

5.2 Robots, Financial Risk Taking, and Financial Wealth

Another potential mechanism through which increased automation can affect wealth accumulation is through its potential effects on financial risk taking and investment choices of households. Even though early models of wealth inequality assumes homogeneous rates of return (Bewley, 1977), recent empirical literature documents considerable heterogeneity in returns to wealth (Bach et al., 2020; Fagereng et al., 2020), which emerges as an important channel to explain the variation in household wealth (Benhabib et al., 2011; Gabaix et al., 2016; Hubmer et al., 2016; Benhabib et al., 2019). In the following, we examine this potential mechanism.

How can increased automation affect returns to wealth? The rapid adoption of robots at work leads individuals to face higher background labor income risk, as shown by our labor

[24] We calculate the total saving rate of a household in the following way: We first calculate the annual differences in the household net wealth, and scale it by the household net wealth from the prior year. Following Bach, Calvet, and Sodini (2017), we only consider those households with non-zero or non-negative net wealth in the analysis. Finally, we winsorize the saving rate variable at 1% level to eliminate any concerns about the outliers. We also compute the total saving rates by scaling the total savings by current household income.

market analysis in Section 5.1. The theory argues that increased background risk reduces the willingness of investors to take other types of risk, such as holding risky financial assets (Eeckhoudt, Gollier, and Schlesinger, 1996).[25] As returns to wealth are directly affected by willingness of households to take financial risk (Ameriks, Caplin, and Leahy, 2003), reducing or completely eliminating the exposure to the stock market (in response to increased human capital risk) would lead to accumulating less wealth over time, which is also supported by the data. For example, using household data from Sweden, Bach et al. (2020) find that individuals in the top 1% of the wealth distribution earn on average 400 basis points higher annual returns on their financial wealth compared to the median household, which, as the authors argue, are primarily compensations for their exposure to higher levels of systematic risk.[26]

Given this background, we now turn to analysis of the effects of exposure to robots on financial risk taking of households and financial wealth accumulation, respectively. Table VIII reports the regression results. In Columns (1) and (2), the dependent variable is the stockholding status of a given household, which takes the value of 1 if household i holds directly or indirectly stocks in 2007, and 0 otherwise. In other words, we first focus on the static aspect of the household financial behavior, and estimate the probability of *being* a stockowner at the end of the observation period.

Even after controlling for endogeneity of the robot exposure variable and other well-known predictors of stockholding, we find that increased exposure to robots in an industry significantly reduces the probability of households in that industry to hold stocks (t-stat.= -

[25] In a key contribution, Cocco et al. (2005) build and simulate a life-cycle model of consumption and portfolio choice with non-tradable labor income, and show that individuals who are exposed to more idiosyncratic labor income risk invest less in stocks. They also estimate the welfare losses incurred by ignoring labor income when investing in risky assets, and find them to be up to 2% of annual consumption of investors. The recent empirical literature also provides evidence that is consistent with the predictions of the theory (Betermier et al., 2012; Fagereng et al., 2017). For example, using a similar administrative dataset to ours, Fagereng et al. (2017) find that individuals respond to increased labor income risk by reducing their financial risk exposure, with the effect being more pronounced among less wealthy households.

[26] In another important contribution, Fagereng et al. (2020) document a return spread of 260 basis points between the 90th and 10th percentile of the financial wealth distribution in Norway. See also Campbell, Ramadorai, and Ranish (2019) who document that heterogeneity in returns to equity wealth contributes to increased equity wealth inequality in India.

3.80). In terms of economic magnitude, ceteris paribus, a one-standard-deviation increase in the robot density lowers the likelihood to be a stockowner by approximately 1.7 percentage points. In fact, the economically (relatively) weaker results using the stockholding status as the dependent variable is consistent with the previous findings of the literature. For example, in their analysis of the effect of labor income risk on asset allocation, Betermier, Jansson, Parlour, and Walden (2012) find weaker effects when they consider level of risky share rather than the changes in risky share. The authors attribute this difference to the cross-sectional unobserved "taste" differences.

To address this concern, in Columns (3) to (6), we next consider changes in financial risk taking using two different measures. In Columns (3) and (4), we first focus on the exit decisions of households from the stock market using an indicator variable that equals to 1 if household i held directly or indirectly stocks in 1999 but liquidiated all her stock holdings by 2007. In Columns (5) and (6), we use changes in risky share over the sample period as our dependent variable. In the financial risk taking analysis, following the standard in the literature, we restrict the sample to stock market participants in 1999, which reduces the sample size by approximately 8,250 to 22,125 households.

Consistent with the theoretical expectations, we document that increased robotization significantly decreases the risky share of households and increases the probability of stock market exit, respectively. The estimated effects are not only statistically significant but also economically highly meaningful. For example, the coefficient estimate in Column (3) implies that a one-standard-deviation exogenous rise in robot use, that again corresponds to a 3.27 robot increase per thousand workers between 1999 and 2007, increases the likelihood of exiting from the stock market by approximately 1.25 percentage points.[27] The magnitude of the coefficient estimate might appear at first glance relatively small in economic terms. Though, this estimate implies an 15% increase in the exit probability, as the stock market exit rate in our sample equals to 8.20%. Overall, these findings conform to our proposed

[27] In untabulated analysis, we also consider the impact of increased exposure to robots at workplace on stock market entry, and find no significant effect of robots on the decision to enter into the stock market.

mechanism that increased adoption of robots at work, and hence, the higher human capital risk makes households less willing to take financial risks. Consequently, investors (fully) rebalance their financial portfolio away from stocks, and forego substantial equity returns up to 4.3% on a year by not participating in the stock market (Calvet et al., 2007).[28]

When interpreting the results of financial risk-taking regressions, we emphasize the role of labor income risk as the underlying channel. Alternatively, one can argue that expected changes in human capital could also generate the observed patterns, as shown by Calvet and Sodini (2014). We address this explanation in a number of ways. First, assuming perfect foresight, we control for income-growth expectations between 1999 and 2007 in the stock market regressions. As presented in Table O.A.21, consistent with Calvet and Sodini (2014), we find that expected human capital is positively associated with financial risk taking. Still, the exposure to robot variable retains its economic and statistical significance. We also verify this finding, tabulated in Table O.A.22, assuming adaptive expectations. Finally, in untabulated analysis, we estimate separately the financial risk taking regressions for two subsamples split by the median value of the realized income growth between 1999 and 2007. Again, we find significantly negative and economically comparable effects of pervasive automation on financial risk taking behavior of individuals in both subsamples. Overall, these additional tests imply that the negative effects of robots on financial risk taking do not only run through their impact on mean earnings and further suggest that second moment effects matter for financial risk-taking.

Motivated by our findings on financial risk taking, we finally investigate whether automation also contributes to differences in accumulation of financial wealth across households. To do so, we first regress percentage changes in financial wealth (defined as the log

[28]As a potential policy recommendation, Freeman (2015) argues that being a capital owner (e.g., either by directly or indirectly - through private pension funds or mutual funds - investing in the stocks of companies that produce or employ robots that can substitute for human workers) could limit the adverse impact of automation on economic well-being of individuals if they were to earn a higher share of their income from capital ownership. However, our findings indicate that automation not only exerts direct downward pressure on wages of individual workers, but also prevents them to receive a share of potential productivity gains by discouraging individuals to invest in the stock market.

differences in financial wealth between 1999 and 2007) on the changes in robot density over the sample period, and other household and industry controls.[29] As presented in columns (1) and (2) of Table IX, we observe that increased exposure to robots at work indeed negatively contributes to the changes in household financial wealth between 1999 and 2007. In terms of magnitude, a one-standard deviation exogenous increase in the robot density reduces the rate of financial wealth accumulation by 15.2% over the observation period (t-stat. = -5.26). Finally, we consider the effects of increased automation on the financial wealth to income ratio of individuals in 2007.[30] Column (3) and (4) of Table IX report the estimation results. The coefficient on changes in the robot density variable is negative and statistically highly significant (t-stat. = -3.47), suggesting that households who are working in industries with a higher rate of robot adoption end up accumulating less financial wealth relative to their income over time.[31] Taken as a whole, these findings support the notion that individuals who reduce their exposure to the stock market in response to increases in their human capital risk experience a substantial drop in their financial wealth growth and accumulate less financial wealth relative to their income.

5.3 Quantifying the Relative Importance of Different Mechanisms

Our analysis thus far suggests that the negative impact of robots on household wealth does not only operate through its direct effects on earnings or saving behavior of individuals. In addition, we provide evidence that the portfolio channel appears to amplify the inequality-enhancing effects of automation. Still, a natural concern pertains to the relative importance

[29]Financial wealth is defined as the sum of the value of direct and indirect stocks, bonds, bond and mixed mutual funds, and cash holdings in the savings and checking accounts. Note that percentage change in financial wealth can be either due to passive changes (i.e., returns on financial wealth) or active changes. Finally, it is important to mention that we winsorize this variable at the 1 percent level.

[30]We divide the financial wealth by the household earnings net any any transfers and capital gain. Again, we winsorize the financial wealth-to-income ratio at the 1 percent level to alleviate any concerns that our results might be driven by outliers.

[31]In fact, models of precautionary saving imply that prudent households would accumulate more assets when they are confronted with greater income uncertainty (Kimball, 1990; Carroll, 1998; Lusardi, 1998). Our findings suggest that this effect (i.e., the precautionary saving motive) appears to be offset (or even reversed) by the relative price effects due to differences in the composition of financial portfolio and thereby generate an overall negative effect of automation on financial wealth.

of these alternative mechanisms for household wealth accumulation. For example, if the negative wealth effects of robotization are predominantly driven by its effect on wages (as it is previously documented in the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020)), then our findings that increased use of robots negatively affects household wealth may not be unexpected.

To address this issue, we next perform causal mediation analysis to estimate the share of the effect of increased automation on household wealth that runs through realized income growth. In principle, the causal mediation analysis allows to disentangle the average causal effect of a treatment variable (automation growth) on an outcome variable (changes in net wealth) running through an observed intermediate outcome, i.e., indirect effects (realized income growth) and through other mechanisms, i.e., direct effects (such as the portfolio channel) (Imai et al., 2010, 2011; Heckman et al., 2013; Heckman and Pinto, 2015).[32] To do so, we use the identification framework of Pinto et al. (2019) that enables, given some assumptions, such a decomposition in IV settings where both treatment and intermediate outcome are endogenous.[33]

Specifically, the estimation framework of Pinto et al. (2019) uses three separate 2SLS regressions to decompose the average causal effect of increased automation on household wealth into direct and indirect effects. The second-stage of these three equations are described as follows:

$$\Delta Net\_Wealth_{ijk}^{99\to 07} = \beta_1 \cdot \Delta \widehat{Robot\_Density}_j^{99\to 07} + \beta_2 \cdot \Delta X_{ij} + \delta_k + \epsilon_{ijk}, \tag{6}$$

$$\Delta Income_{ijk}^{99\to 07} = \gamma_1 \cdot \Delta \widehat{Robot\_Density}_j^{99\to 07} + \gamma_2 \cdot \Delta X_{ij} + \delta_k + \theta_{ijk}, \tag{7}$$

$$\Delta Net\_Wealth_{ijk}^{99\to 07} = \lambda_1 \cdot \Delta \widehat{Income}_{ijk}^{99\to 07} + \lambda_2 \cdot \Delta Robot\_Density_j^{99\to 07} + \lambda_3 \cdot \Delta X_{ij} + \delta_k + \eta_{ijk} \tag{8}$$

[32]Recent application of this method to quantify the empirical importance of different mechanisms (underlying a causal effect) include Heckman et al. (2013), Fagereng et al. (2020), Dippel et al. (2017, 2019).

[33]A novel property of the identification framework of Pinto et al. (2019) is that it requires a single instrument for identification, whereas earlier methods require separate instruments for treatment and mediator.

where $\Delta Income_{ijk}^{99\to07}$ is the mediator variable of interest, that is, the realized income growth of household i between 1999 and 2007, $\Delta Net\_Wealth_{ijk}^{99\to07}$ is the outcome variable, which is the change in net wealth rank of household i within her birth cohort-year distribution, and finally, $\Delta Robot\_Density_j^{99\to07}$ represents the changes in industrial robots per thousand workers in industry j (the treatment variable). Equations (6)-(8) are the second-stage of three separate 2SLS regressions where we use the median changes in robot density across the European countries as an instrument. Accordingly, $\Delta\widehat{Robot\_Density}_j^{99\to07}$ and $\widehat{Income}_{ijk}^{99\to07}$ are estimated values from the corresponding first-stage regressions.[34] Analogous to our base regressions, we also account for all the relevant household and industry controls, as denoted by vector ΔX_{ij}, and regional fixed effects.

The point estimate, $\hat{\beta}_1$, in Equation (6) is the total effect of increased automation on changes in net wealth rank, as presented in Column (5) and (6) of Table III. Using the parameter estimates of $\hat{\gamma}_1$, $\hat{\lambda}_1$ and $\hat{\lambda}_2$ from Equations (7) and (8), we are able to quantify how much of the effect of increased automation on net wealth rank of households (i.e., $\hat{\beta}_1$) is explained by the effect of automation on wage growth of households. Put differently, the product $\hat{\gamma}_1 \times \hat{\lambda}_1$ yields the indirect effect, and $\hat{\lambda}_2$ is the direct effect of increased robotization that affects household wealth accumulation through channels others than income growth.[35]

Table X reports the estimated decompositions. Based on the parameter estimates presented in Column (1), where we use the base specification as in Equation (4), we find that income growth as a mediator can explain slightly more than one-third of the total effect of increased exposure to robots at work on household wealth accumulation. This result is consistent with our earlier findings that negative wealth effects of automation cannot be only attributed to its negative effects on wages. Next, to isolate the effects of heterogeneity in

[34]It is important to note that the parameters, β_1 and γ_1, can be estimated using standard 2SLS regressions. As shown in Pinto et al. (2019), the identification of λ_1 and λ_2 is achieved by the identifying assumption that any potential confounders that bias the relationship between the treatment and outcome variable are primarily because of the confounders that jointly affect the treatment and intermediate outcome variable. This uncorrelatedness assumption generates a new exclusion restriction to identify the causal effect of the treatment on outcome variable running through the mediator variable.

[35]Note that the sum of the indirect and direct effects (i.e., $\hat{\gamma}_1 \times \hat{\lambda}_1 + \hat{\lambda}_2$) equals to $\hat{\beta}_1$, that is, the total effect of robots on household wealth.

saving behavior across households, we augment the base estimation model by including the initial active saving rate of households as an additional regressor. The results are reported in Column (2) of Table X. Controlling for differential saving behavior indeed reduces the overall effect of automation on household wealth (by approximately 5%) as well as the mediating effect of the income growth channel (to approximately 30 percent of the total effect). Overall, the analysis presented in this section suggests that, in addition to the labor income and savings channel, the portfolio channel is also at play, and it represents an important and relevant wealth accumulation factor.

6 Distributional Effects of Robots

Up until now in our base analysis, we have worked under the assumption that all employees within an industry are to a similar degree affected by increased use of robots in that industry. However, it is conceivable to argue that automation can have differential effects on the economic and financial outcomes of households, depending on the required skill-level or type of their occupations. Consistent with this conjecture, Acemoglu and Restrepo (2018c) show that middle-aged workers who perform blue-collar tasks are more likely to be replaced by industrial robots relative to older workers who are specialized in non-production services.

To study the distributional effects of automation, we next focus on the economic behavior and wealth accumulation of households by skill-level. Following the standard in the literature (see e.g., Card and Lemieux, 2001; Acemoglu, Autor, and Lyle, 2004), we use the level of educational attainment of households, and define a low-skill group that corresponds to either being a high-school graduate or less, and a high-skill group that includes households with a college education and more. We then rerun our benchmark model given in Equation 4 for these groups separately. We argue that education level of households should serve as a good proxy for their skill-level, with the less-educated being more likely to perform blue-collar tasks, and hence, more prone to the adverse effects of robots.

Table XI presents the key results for our cross-sectional analysis. In Panel A, we first focus on the labor market outcomes of households. As shown in columns (1) and (3), we find that less-educated households indeed experience a decline in income growth and a higher employment risk due to the increased number of industrial robots in their industry of employment. Interestingly, negative wage and employment effects are also present for the better-educated households, albeit, the estimates are only marginally significant. The latter result is somewhat surprising but consistent with the findings of Acemoglu and Restrepo (2020) who argue that industrial robots appear not to complement any particular skill-group of workers, unlike other types of recent technologies such as computerization (Autor and Dorn, 2013; Tuzel and Zhang, 2018).

When we analyze the wealth effects by skill-level, an interesting pattern emerges. As presented in Panel B of Table XI, we observe that negative wealth effects of automation is significantly more pronounced among low-educated households who also face greater probability of experiencing downward mobility in the wealth distribution over the sample period. A similar perspective also applies to household financial risk taking. As presented in Panel C, for the low-educated households, increased exposure to robots significantly reduces the risky share and increases the exit probability from the stock market, whereas we find no significant effects for better-educated households.[36]

The potential implications of these results are mirrored in Figure I where we depict the evolution of wealth inequality, measured by the interquartile range of net wealth, between 1999 and 2007. Specifically, we sort the sampled households into three groups based on the automation growth of their industry of employment during the sample period, and compute the interquartile ranges of net wealth for each group in each year.[37] As illustrated in the graph, all three groups exhibit increased wealth dispersion throughout the observation

[36] One possible explanation for this finding may be the differences in financial literacy levels of high- and low-skill households. For example, better-educated individuals may better assess the diversification benefits of being a capital owner (against the adverse effects of robotization), and hence, earning a higher share of their income from capital ownership as compared to low-educated individuals.

[37] For comparison, we normalize these values by the initial IQR value.

period. Interestingly, the rise in wealth dispersion monotonically increases in the changes in robot density, which suggests that rapid automation is likely to play a role in increased wealth dispersion.

In summary, there appears to be asymmetric wealth effects of robots across different segments of the population, which have important implications. For example, expert opinion suggests that global robot stock could reach to three to four times larger levels (relative to its current level) over the next decade (see for example Acemoglu and Restrepo, 2020 and the references therein). According to our results, such a rapid growth in robotics could contribute to widening, the already large and persistent, wealth gap across households with different educational attainment levels, which can in turn create distributional challenges in the future.

7 Conclusions

This paper uses an extensive administrative panel and auxiliary data on stock and new installations of industrial robots to estimate the effect of increased automation on household wealth dynamics. We find evidence of statistically and economically significant effects of rapid adoption of industrial robots on distribution of wealth. In particular, exposure to robots reduces the percentile wealth rank of an individual within her birth cohort-year distribution, and significantly increases the probability of downward mobility between 1999 and 2007. Our findings are robust to correcting for the endogeneity of exposure to robots, and controlling for a rich set of household characteristics, macroeconomic and institutional regional factors, as well as a range of industry trends.

We consider a number of alternative explanations for our results in the process of exploring the mechanism through which industrial robots can affect household wealth accumulation. We show that differences in earned incomes or differential saving rates alone do not explain the differences in levels and dynamics of household wealth. In addition, we provide evidence that the negative impact of automation (through increasing uninsurable human capital risk) on financial risk taking and investment behavior of households appear to be an additional channel, which amplifies the inequality-enhancing effects of increased automation. We also find that the wealth effects of automation are only operative for the subsample of households with low levels of education. The asymmetric wealth effects of robots across low- and high-skill workers caution against distributional challenges of automation.

All in all, our findings suggest the presence of significant effects of automation that extend beyond labor market to the distribution of wealth, and contribute to the current discussion on the economic consequences of automation.

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Table I: Use of Industrial Robots in the Swedish Industries

This table presents descriptive statistics on the use of industrial robots in Swedish industries. In column (1), we report the number of sampled households who are working in the industries that we consider in our analysis. Column (2) presents the number of workers in thousands in each industry in 1995. Columns (3) and (4) present the number of industrial robots for 1999 and 2007, respectively. In columns (5) and (6), we report the robot density per thousand workers for 1999 and 2007, respectively. Finally, column (7) presents the changes in robot density between 1999 and 2007 for each industry separately. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS database.

Name of Industry	No of obs	No of Workers 1995	No of Robots 1999	No of Robots 2007	Robot Density 1999	Robot Density 2007	Change in Robot Density 1999-2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agriculture, forestry, fishing	1,215	46	0	1	0	0.022	0.0217
Food and beverages; tobacco	1,699	69	96	416	1.391	6.029	4.637
Textiles	320	15	7	0	0.467	0	-0.467
Wood and furniture, Paper	3,863	112	82	189	0.732	1.687	0.955
Pharmaceuticals, cosmetics; other chemical products	1,275	42	0	80	0	1.904	1.905
Rubber and plastic products; chemical products	1,180	46	260	790	5.652	17.173	11.521
Basic metals; Metal products	3,483	110	1249	1943	11.354	17.663	6.309
Industrial machinery	3,142	88	551	576	6.261	6.545	0.284
Electrical/electronics	2,723	91	356	569	3.912	6.252	2.340
Automotive; Other vehicles	3,263	87	2424	3089	27.862	35.505	7.643
Education/research/development	1,666	398	129	93	0.324	0.234	-0.0904
Construction	5,372	187	39	49	0.209	0.2620	0.0534
Electricity, gas, water supply	878	41	1	1	0.024	0.024	0
Mining and quarrying	296	10	0	0	0	0	0

Table II: Summary Statistics For the Final Sample

This table presents the number of observations, mean, and standard deviation of variables used in the empirical analysis. In Panel (A), we present the descriptive statistics for the household control variables that are defined in 1999. In Panel B, we report the summary statistics for the main variables of interest in our analysis, that are the changes in robot density in Swedish industries and the median change in the eleven developed Western European countries that we use as an excluded instrument. Panel C presents the descriptive statistics for the dependent variables that we consider in our empirical analysis, and Panel D reports summary statistics for the industry-level control variables. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	No of Obs	Mean	Std. Dev.
	(1)	(2)	(3)
Panel A. Household Demographics			
Age	30,375	38.8532	7.5261
Male	30,375	0.8699	0.3365
Married	30,375	0.5507	0.4974
College and more	30,375	0.2424	0.4286
High school	30,375	0.5581	0.4966
Number of adults	30,375	1.9267	0.6273
Number of children	30,375	1.4168	1.1490
Net wealth (in SEK)	30,375	524553.4	1730830
(IHS) Disposable income	30,375	13.2065	0.4075
(IHS) Labor income	30,375	12.7125	0.5225
Immigrant	30,375	0.0995	0.2994
Panel B. Variables of Interest			
$\Delta Robot\_Density^{99\rightarrow 07}$	30,375	2.6927	3.2744
$\Delta Robot\_Density_{EU}^{99\rightarrow 07}$	30,375	0.4225	0.5255
Panel C. Dependent variables			
Stockholding status (2007)	30,375	0.7808	0.4137
Exit from the stock market	22,125	0.0819	0.2744
Change in risky share	30,375	-0.1630	0.4069
Transition to unemployment	30,375	0.0423	0.2014
Change in log earnings	30,375	0.1955	1.5471
Downward wealth rank mobility	30,375	0.5279	0.4992
Net wealth rank (2007)	30,375	52.9843	27.1651
Change in net wealth rank	30,375	0.1948	21.2564
Change in financial wealth	30,375	2.1391	3.7284
Wealth-to-income ratio (2007)	29,955	0.8728	1.8076
Panel D. Industry controls			
ΔNo of Employees (1993-98)	30,375	-1.6201	15.5676
$\Delta Chinese\_Import^{99\rightarrow 07}$	30,375	2.4709	4.4889
ΔCapital Intensity	30,375	0.2019	0.1145
ΔICT Capital	30,375	0.3863	0.1853
Initial Robot Density (1995)	30,375	4.3988	6.2528
$\Delta EU\_Import^{99\rightarrow 07}$	30,375	14765.15	21930.88
$Labor\_Intesity$ (1999)	30,375	0.3001	0.1843
$\Delta Profits$	30,375	0.4664	0.3594

Table III: Exposure to Robots and Household Net Wealth

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. In (5) and (6), the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.25553***	-1.25553**	0.00817***	0.00817**	-0.21784***	-0.21784**
	(0.1238)	(0.5003)	(0.0017)	(0.0034)	(0.0716)	(0.0877)
Married	0.75507	0.75507	-0.02366***	-0.02366**	1.31402***	1.31402**
	(0.4655)	(0.5739)	(0.0089)	(0.0104)	(0.4318)	(0.5193)
College	-5.66093***	-5.66093***	0.06513**	0.06513***	-4.17804***	-4.17804***
	(1.2679)	(1.1723)	(0.0266)	(0.0235)	(1.3206)	(1.1815)
High School	-8.53814***	-8.53814***	0.03487*	0.03487	-1.08866	-1.08866
	(1.0305)	(0.9931)	(0.0207)	(0.0212)	(0.8957)	(0.8852)
ΔNumber of adults	2.12619***	2.12619***	-0.01780***	-0.01780***	1.08315***	1.08315***
	(0.2165)	(0.1928)	(0.0040)	(0.0040)	(0.1678)	(0.1714)
ΔNumber of children	1.22087***	1.22087***	-0.02284***	-0.02284***	1.42522***	1.42522***
	(0.1526)	(0.1891)	(0.0029)	(0.0034)	(0.1373)	(0.1723)
ΔNo of Employees (1993-98)	0.16975***	0.16975	-0.00051	-0.00051	-0.01349	-0.01349
	(0.0424)	(0.1539)	(0.0007)	(0.0011)	(0.0291)	(0.0361)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.27908***	-0.27908	0.00315***	0.00315*	-0.07535**	-0.07535
	(0.0547)	(0.1889)	(0.0009)	(0.0016)	(0.0336)	(0.0485)
ΔCapital Intensity	-5.18301	-5.18301	0.27886***	0.27886**	-10.32084*** -	-10.32084***
	(3.5860)	(12.4279)	(0.0596)	(0.1103)	(2.6188)	(3.9865)
ΔICT Capital	11.95866***	11.95866*	-0.06737***	-0.06737	1.51364*	1.51364
	(1.4717)	(6.2946)	(0.0218)	(0.0476)	(0.9031)	(1.2834)
Initial Robot Density (1995)	-0.23779***	-0.23779	-0.00058	-0.00058	0.07497*	0.07497
	(0.0659)	(0.1998)	(0.0010)	(0.0013)	(0.0414)	(0.0487)
$\Delta EU\_Import^{99\rightarrow07}$	-0.30151**	-0.30151	-0.00498***	-0.00498**	0.36527***	0.36527***
	(0.1193)	(0.2948)	(0.0018)	(0.0025)	(0.0849)	(0.0818)
$Labor\_Intesity$ (1999)	-1.69119	-1.69119	-0.08381**	-0.08381	4.45408**	4.45408**
	(2.4108)	(5.8685)	(0.0399)	(0.0515)	(1.7811)	(2.0822)
$\Delta Profits^{99\rightarrow07}$	-0.00798***	-0.00798	0.00004	0.00004	0.00027	0.00027
	(0.0020)	(0.0056)	(0.0000)	(0.0001)	(0.0012)	(0.0014)
Constant	37.60002***	37.60002***	0.60586***	0.60586***	-4.53833	-4.53833
	(5.4998)	(6.3416)	(0.0837)	(0.0944)	(3.6323)	(3.6657)
Observations	30,375	30,375	30,375	30,375	30,375	30,375
R-squared	0.1876	0.1876	0.0644	0.0644	0.0688	0.0688
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table IV: Intersectoral Transferability of Human Capital and Robots

This table presents coefficient estimates from the within-industry regressions. In all specifications, wealth measures are regressed on the interaction term between changes in robot density between 1999 and 2007 and (household-level) indicator variable for having a lower portable human capital, and changes in observable household characteristics between 1999 and 2007. Note that we control for industry fixed effects that subsume the direct effect of robotization and control for all sources of variation in differential industry trends and changes. In all specifications, the standard errors are clustered at the industry-treatment level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR).

	Percentile Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99 \rightarrow 07}$ x $Low\_Transfer$	-0.47452***	-0.36857**	0.00495***	0.00402**	-0.22567**	-0.18439**
	(0.1683)	(0.1497)	(0.0017)	(0.0015)	(0.0917)	(0.0850)
Observations	30,375	30,375	30,375	30,375	30,375	30,375
Household Controls	No	Yes	No	Yes	No	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering			Low_Transfer-Industry			

Table V: Exposure to Robots and Labor Market Outcomes

This table presents coefficient estimates from the second-stage of the IV regressions for labor market outcomes. In all specifications, labor market measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the log changes in household earnings between 1999 and 2007. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if a household is unemployed in 2007, and zero otherwise. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Change in Earnings		Transition to Unemployment	
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\to07}$	-0.01715***	-0.01715**	0.00422***	0.00422***
	(0.0062)	(0.0079)	(0.0008)	(0.0013)
Married	0.20977***	0.20977***	-0.01703***	-0.01703***
	(0.0234)	(0.0278)	(0.0036)	(0.0035)
College	0.03751	0.03751	0.04797***	0.04797***
	(0.0561)	(0.0465)	(0.0153)	(0.0156)
High School	-0.18642**	-0.18642*	0.08787***	0.08787***
	(0.0890)	(0.0972)	(0.0150)	(0.0151)
ΔNumber of adults	0.31139***	0.31139***	-0.00462***	-0.00462***
	(0.0129)	(0.0185)	(0.0016)	(0.0016)
ΔNumber of children	0.04933***	0.04933***	-0.00098	-0.00098
	(0.0066)	(0.0068)	(0.0010)	(0.0011)
ΔNo of Employees (1993-98)	-0.00688***	-0.00688	0.00003	0.00003
	(0.0021)	(0.0048)	(0.0003)	(0.0005)
$\Delta Chinese\_Import^{99\to07}$	-0.00771**	-0.00771	0.00110**	0.00110*
	(0.0039)	(0.0062)	(0.0005)	(0.0006)
ΔCapital Intensity	0.77249***	0.77249*	0.01674	0.01674
	(0.2071)	(0.4209)	(0.0267)	(0.0450)
ΔICT Capital	0.02968	0.02968	0.00507	0.00507
	(0.0747)	(0.0978)	(0.0100)	(0.0224)
Initial Robot Density (1995)	0.01043***	0.01043**	-0.00205***	-0.00205**
	(0.0037)	(0.0048)	(0.0005)	(0.0009)
$\Delta EU\_Import^{99\to07}$	0.00405	0.00405	-0.00072	-0.00072
	(0.0056)	(0.0069)	(0.0007)	(0.0011)
$Labor\_Intesity$ (1999)	-0.50544***	-0.50544	-0.03150*	-0.03150
	(0.1417)	(0.3252)	(0.0184)	(0.0289)
$\Delta Profits^{99\to07}$	0.00010	0.00010	-0.00005***	-0.00005***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Constant	0.25366***	0.25366***	0.01610	0.01610
	(0.0711)	(0.0835)	(0.0109)	(0.0166)
Observations	30,375	30,375	30,375	30,375
R-squared	0.0396	0.0396	0.0241	0.0241
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table VI: Exposure to Robots and Household Net Wealth - Controlling for Income Growth

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. In (5) and (6), the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. We include realized income growth between 1995 and 1998 as an additional regressor in the regressions (that corresponds to the reduced form of an IV regression where we instrument current income growth by lagged income growth). In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow 07}$	-1.34486***	-1.34486***	0.01013***	0.01013***	-0.28545***	-0.28545***
	(0.1300)	(0.5130)	(0.0019)	(0.0036)	(0.0741)	(0.0963)
Married	1.37437**	1.37437**	-0.02558**	-0.02558**	1.39482***	1.39482**
	(0.5404)	(0.6228)	(0.0103)	(0.0120)	(0.4912)	(0.5462)
College	-5.46032***	-5.46032***	0.08120***	0.08120***	-4.34431***	-4.34431***
	(1.4216)	(1.5777)	(0.0297)	(0.0231)	(1.5019)	(1.2034)
High School	-7.97139***	-7.97139***	0.02216	0.02216	-1.11009	-1.11009
	(1.1264)	(1.1831)	(0.0233)	(0.0243)	(0.9215)	(0.9073)
ΔNumber of adults	2.31511***	2.31511***	-0.01980***	-0.01980***	1.09780***	1.09780***
	(0.2241)	(0.2099)	(0.0041)	(0.0043)	(0.1717)	(0.1699)
ΔNumber of children	1.03196***	1.03196***	-0.02353***	-0.02353***	1.30248***	1.30248***
	(0.1724)	(0.2070)	(0.0032)	(0.0038)	(0.1497)	(0.1687)
ΔNo of Employees (1993-98)	0.19498***	0.19498	-0.00084	-0.00084	-0.01496	-0.01496
	(0.0445)	(0.1565)	(0.0007)	(0.0012)	(0.0298)	(0.0385)
$\Delta Chinese\_Import^{99\rightarrow 07}$	-0.28664***	-0.28664	0.00377***	0.00377**	-0.08848**	-0.08848
	(0.0594)	(0.1953)	(0.0010)	(0.0017)	(0.0345)	(0.0543)
ΔCapital Intensity	-7.51381*	-7.51381	0.30673***	0.30673***	-9.97737***	-9.97737**
	(3.8388) (	(12.8418)	(0.0647)	(0.1111)	(2.6567)	(3.9945)
ΔICT Capital	12.11909***	12.11909*	-0.06517***	-0.06517	0.92690	0.92690
	(1.5697)	(6.4362)	(0.0238)	(0.0500)	(0.9511)	(1.4609)
Initial Robot Density (1995)	-0.24750***	-0.24750	-0.00039	-0.00039	0.09529**	0.09529**
	(0.0686)	(0.2035)	(0.0011)	(0.0014)	(0.0421)	(0.0468)
$\Delta EU\_Import^{99\rightarrow 07}$	-0.23930*	-0.23930	-0.00518***	-0.00518*	0.41645***	0.41645***
	(0.1311)	(0.3074)	(0.0019)	(0.0028)	(0.0879)	(0.0992)
$Labor\_Intesity$ (1999)	0.21781	0.21781	-0.10588**	-0.10588*	4.63440**	4.63440**
	(2.5582)	(6.0175)	(0.0439)	(0.0563)	(1.8122)	(2.2077)
$\Delta Profits^{99\rightarrow 07}$	-0.00856***	-0.00856	0.00004	0.00004	0.00041	0.00041
	(0.0021)	(0.0056)	(0.0000)	(0.0001)	(0.0013)	(0.0016)
$\Delta Income^{95\rightarrow 98}$	-2.07076***	-2.07076***	-0.01755***	-0.01755***	1.12785***	1.12785***
	(0.2785)	(0.3989)	(0.0053)	(0.0061)	(0.2515)	(0.2171)
Constant	37.97558***	37.97558***	0.59784***	0.59784***	-3.10136	-3.10136
	(5.7848)	(7.0526)	(0.0960)	(0.1001)	(3.9472)	(3.5803)
Observations	26,103	26,103	26,103	26,103	26,103	26,103
R-squared	0.1904	0.1904	0.0678	0.0678	0.0696	0.0696
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table VII: Exposure to Robots and Household Net Wealth - Controlling for Differential Saving Rates

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. In (5) and (6), the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. We include active saving rate in 2000 as an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.22554***	-1.22554**	0.00787***	0.00787**	-0.20587***	-0.20587**
	(0.1215)	(0.4870)	(0.0017)	(0.0033)	(0.0712)	(0.0843)
Married	0.85407*	0.85407	-0.02464***	-0.02464**	1.35381***	1.35381***
	(0.4622)	(0.5646)	(0.0089)	(0.0103)	(0.4299)	(0.5159)
College	-5.68286***	-5.68286***	0.06535**	0.06535***	-4.18660***	-4.18660***
	(1.2515)	(1.1735)	(0.0264)	(0.0240)	(1.3138)	(1.1784)
High School	-8.19543***	-8.19543***	0.03146	0.03146	-0.95221	-0.95221
	(1.0264)	(0.9964)	(0.0207)	(0.0213)	(0.8969)	(0.8952)
ΔNumber of adults	1.94255***	1.94255***	-0.01597***	-0.01597***	1.01030***	1.01030***
	(0.2158)	(0.1920)	(0.0040)	(0.0040)	(0.1680)	(0.1716)
ΔNumber of children	1.23456***	1.23456***	-0.02297***	-0.02297***	1.43050***	1.43050***
	(0.1514)	(0.1801)	(0.0029)	(0.0034)	(0.1367)	(0.1693)
ΔNo of Employees (1993-98)	0.16372***	0.16372	-0.00045	-0.00045	-0.01586	-0.01586
	(0.0422)	(0.1510)	(0.0007)	(0.0011)	(0.0291)	(0.0349)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.26147***	-0.26147	0.00298***	0.00298*	-0.06828**	-0.06828
	(0.0544)	(0.1850)	(0.0009)	(0.0016)	(0.0332)	(0.0465)
ΔCapital Intensity	-3.80327	-3.80327	0.26513***	0.26513**	-9.77529***	-9.77529**
	(3.5653) (	(12.1679)	(0.0593)	(0.1063)	(2.6059)	(3.8222)
ΔICT Capital	11.41077***	11.41077*	-0.06193***	-0.06193	1.30211	1.30211
	(1.4379)	(6.1504)	(0.0217)	(0.0464)	(0.9003)	(1.2460)
Initial Robot Density (1995)	-0.22367***	-0.22367	-0.00072	-0.00072	0.08064*	0.08064*
	(0.0650)	(0.1949)	(0.0010)	(0.0013)	(0.0413)	(0.0479)
$\Delta EU\_Import^{99\rightarrow07}$	-0.31470***	-0.31470	-0.00485***	-0.00485**	0.35997***	0.35997***
	(0.1143)	(0.2839)	(0.0017)	(0.0025)	(0.0846)	(0.0783)
$Labor\_Intesity$ (1999)	-2.24355	-2.24355	-0.07832**	-0.07832	4.23652**	4.23652**
	(2.4036)	(5.8017)	(0.0398)	(0.0497)	(1.7784)	(2.0159)
$\Delta Profits^{99\rightarrow07}$	-0.00780***	-0.00780	0.00004	0.00004	0.00034	0.00034
	(0.0019)	(0.0055)	(0.0000)	(0.0001)	(0.0012)	(0.0013)
Active Saving Rate (2000)	9.92399***	9.92399***	-0.09879***	-0.09879***	3.94472***	3.94472***
	(0.5160)	(0.4265)	(0.0086)	(0.0083)	(0.3513)	(0.3679)
Constant	37.51174***	37.51174***	0.60675***	0.60675***	-4.57647	-4.57647
	(5.3770)	(6.2195)	(0.0826)	(0.0935)	(3.5864)	(3.6410)
Observations	30,374	30,374	30,374	30,374	30,374	30,374
R-squared	0.2025	0.2025	0.0687	0.0687	0.0726	0.0726
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table VIII: Exposure to Robots and Financial Risk Taking Behavior

This table presents coefficient estimates from the second-stage of the IV regressions for household financial risk taking behavior. In all specifications, measures of financial risk taking wealth are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the stockholding status in 2007. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if a stockholder household in 1999 exits from the stock market as of 2007, and 0 otherwise. In (5) and (6), we consider the changes in risky share between 1999 and 2007. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Stockholding Status		Exit from the Stock Market		Change in Risky Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\to07}$	-0.00517***	-0.00517**	0.00384***	0.00384***	-0.00402***	-0.00402**
	(0.0014)	(0.0020)	(0.0011)	(0.0012)	(0.0014)	(0.0018)
Married	0.04173***	0.04173***	-0.01932***	-0.01932***	-0.00335	-0.00335
	(0.0068)	(0.0055)	(0.0055)	(0.0046)	(0.0079)	(0.0071)
College	-0.00277	-0.00277	0.01392	0.01392	-0.06562***	-0.06562***
	(0.0215)	(0.0203)	(0.0176)	(0.0173)	(0.0232)	(0.0214)
High School	-0.09968***	-0.09968***	0.07894***	0.07894***	-0.03699	-0.03699*
	(0.0196)	(0.0219)	(0.0217)	(0.0213)	(0.0240)	(0.0216)
ΔNumber of adults	0.04793***	0.04793***	-0.03894***	-0.03894***	0.00761**	0.00761*
	(0.0034)	(0.0029)	(0.0031)	(0.0028)	(0.0037)	(0.0041)
ΔNumber of children	0.03598***	0.03598***	-0.02812***	-0.02812***	0.04064***	0.04064***
	(0.0022)	(0.0023)	(0.0021)	(0.0020)	(0.0028)	(0.0027)
ΔNo of Employees (1993-98)	-0.00320***	-0.00320***	0.00049	0.00049	0.00132**	0.00132
	(0.0005)	(0.0008)	(0.0004)	(0.0005)	(0.0006)	(0.0009)
$\Delta Chinese\_Import^{99\to07}$	0.00117*	0.00117	-0.00076	-0.00076	-0.00151**	-0.00151
	(0.0007)	(0.0010)	(0.0006)	(0.0005)	(0.0007)	(0.0015)
ΔCapital Intensity	0.27301***	0.27301***	-0.06073	-0.06073	-0.19025***	-0.19025**
	(0.0475)	(0.0683)	(0.0379)	(0.0402)	(0.0540)	(0.0929)
ΔICT Capital	-0.02164	-0.02164	0.00560	0.00560	0.04075**	0.04075
	(0.0177)	(0.0245)	(0.0139)	(0.0136)	(0.0191)	(0.0263)
Initial Robot Density (1995)	0.00430***	0.00430***	-0.00117*	-0.00117*	-0.00010	-0.00010
	(0.0008)	(0.0014)	(0.0006)	(0.0007)	(0.0008)	(0.0011)
$\Delta EU\_Import^{99\to07}$	0.00573***	0.00573***	-0.00139	-0.00139	0.00197	0.00197
	(0.0015)	(0.0021)	(0.0012)	(0.0011)	(0.0017)	(0.0016)
$Labor\_Intesity$ (1999)	-0.20664***	-0.20664***	0.02750	0.02750	0.10473***	0.10473
	(0.0331)	(0.0512)	(0.0266)	(0.0263)	(0.0374)	(0.0647)
$\Delta Profits^{99\to07}$	0.00002	0.00002	-0.00001	-0.00001	0.00000	0.00000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.24595***	0.24595***	0.36249***	0.36249***	-0.49760***	-0.49760***
	(0.0574)	(0.0605)	(0.0547)	(0.0717)	(0.0448)	(0.0629)
Observations	30,375	30,375	22,125	22,125	22,125	22,125
R-squared	0.1698	0.1698	0.0715	0.0715	0.0800	0.0800
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Wealth Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table IX: Exposure to Robots and Financial Wealth

This table presents coefficient estimates from the second-stage of the IV regressions for financial wealth accumulation. In all specifications, measures of financial wealth are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the log changes in the financial wealth of households between 1999 and 2007. In (3) and (4), the dependent variable is the financial wealth to household income ratio in 2007. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Change in Financial Wealth		Wealth-to-Income Ratio	
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.04645***	-0.04645***	-0.01551***	-0.01551**
	(0.0088)	(0.0160)	(0.0056)	(0.0077)
Married	0.08394*	0.08394*	-0.10511***	-0.10511***
	(0.0431)	(0.0482)	(0.0227)	(0.0229)
College	-0.12464	-0.12464	0.05719	0.05719
	(0.1419)	(0.1411)	(0.1081)	(0.0990)
High School	-0.77540***	-0.77540***	-0.18356***	-0.18356***
	(0.1611)	(0.1583)	(0.0605)	(0.0609)
ΔNumber of adults	0.37220***	0.37220***	-0.13319***	-0.13319***
	(0.0212)	(0.0247)	(0.0134)	(0.0150)
ΔNumber of children	0.24104***	0.24104***	-0.02288***	-0.02288**
	(0.0146)	(0.0151)	(0.0087)	(0.0092)
ΔNo of Employees (1993-98)	-0.00526*	-0.00526	0.00251	0.00251
	(0.0032)	(0.0057)	(0.0022)	(0.0032)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.01059**	-0.01059	0.00059	0.00059
	(0.0049)	(0.0082)	(0.0040)	(0.0048)
ΔCapital Intensity	0.38627	0.38627	-0.37965*	-0.37965
	(0.2867)	(0.5701)	(0.2125)	(0.2854)
ΔICT Capital	0.13602	0.13602	0.01499	0.01499
	(0.1090)	(0.2124)	(0.0781)	(0.1128)
Initial Robot Density (1995)	0.01339***	0.01339*	-0.00337	-0.00337
	(0.0049)	(0.0078)	(0.0030)	(0.0036)
$\Delta EU\_Import^{99\rightarrow07}$	0.01830**	0.01830	0.01555**	0.01555**
	(0.0078)	(0.0134)	(0.0072)	(0.0060)
$Labor\_Intesity$ (1999)	-0.30763	-0.30763	0.12514	0.12514
	(0.1991)	(0.3489)	(0.1341)	(0.1537)
$\Delta Profits^{99\rightarrow07}$	0.00022*	0.00022	-0.00014	-0.00014
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Constant	6.61121***	6.61121***	1.56070***	1.56070***
	(0.3759)	(0.4090)	(0.3177)	(0.2723)
Observations	30,375	30,375	29,955	29,955
R-squared	0.5968	0.5968	0.1881	0.1881
Income Deciles (1999)	Yes	Yes	Yes	Yes
Wealth Deciles (1999)	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table X: Quantifying the Relative Importance of Alternative Mechanisms

This table presents parameter estimates from causal mediation analysis. As described in Equations (6), (7) and (8), we decompose the total effect of increased robotization into direct and indirect effects that run through income channel. In all specifications, we account for changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (2), we include active saving rate in 2000 as an additional regressor in the regressions. The dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. M is the realized income growth between 1999 and 2007; Z represents the excluded instrument, and T is the endogenous automation growth variable. Standard errors are clustered at the municipality-industry level. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Change in Net Wealth	
	(1)	(2)
Total Effects ($\hat{\beta}_1$)	-0.21783	-0.205872
	(0.07159)	(0.07123)
Direct Effects ($\hat{\lambda}_2$)	-0.14334	-0.14142
	(0.0597)	(0.05938)
Indirect Effects ($\hat{\gamma}_1 \times \hat{\lambda}_1$)	-0.0744	(-0.0644)
	(0.06103)	(0.0593)
Household Controls	Yes	Yes
Active Saving Rate in 2000	No	Yes
Municipality FEs	Yes	Yes
Observations	30,375	30,374
Clustering	Muni-Industry	Muni-Industry
First stage (M on Z\T) F-statistics	19.59	19.48

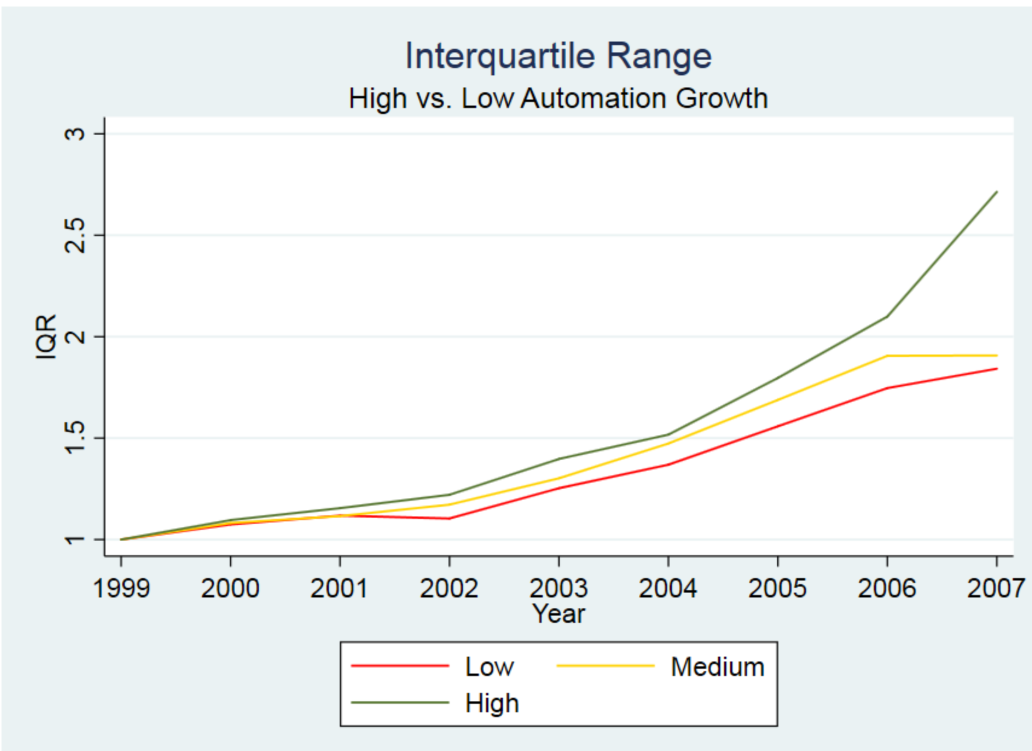
Table XI: Distributional Effects of Robots

This table presents coefficient estimates from the second-stage of the IV regressions for various household economic variables. The *Less-Educated* group includes households where the household head has a high school degree or less; and the *Better-Educated* group comprises households with, at least, some college attendance. We consider labor market and wealth outcomes in Panel A and Panel B, respectively. In Panel C, we report the results of financial risk taking analysis. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. Standard errors are clustered at the municipality-industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Less-Educated	*Better-Educated*	*Less-Educated*	*Better-Educated*
	(1)	(2)	(3)	(4)
	Panel A. Labor Market			
	Change in Earnings		Transition into Unemployment	
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.01296*	-0.01475*	0.00441***	0.00265*
	(0.0071)	(0.0089)	(0.0010)	(0.0014)
Observations	7,364	23,011	7,364	23,011
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow 07}$	-1.30145***	-0.50791***	0.00745***	0.00009
	(0.1330)	(0.1856)	(0.0018)	(0.0037)
Observations	7,364	23,011	7,364	23,011
	Panel C. Financial Risk Taking			
	Change in Risky Share		Exit from the Stock Market	
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.00464***	0.00148	0.00487***	-0.00344**
	(0.0017)	(0.0027)	(0.0014)	(0.0015)
Observations	6,034	16,091	6,034	16,091
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Muni-Industry	Muni-Industry	Muni-Industry
Municipality FEs	Yes	Yes	Yes	Yes

Figure I: Wealth Dispersion over Time

This figure depicts the dynamics of wealth dispersion, measured by the interquartile range of net wealth, between 1999 and 2007. Specifically, we sort the sampled households into three groups based on the automation growth of their industry of employment during the sample period, and compute the interquartile ranges of the net wealth for each group in each year. For comparison, we normalize these values by the initial IQR value. Source: Author computations using household-level LINDA dataset from Statistics Sweden, and data from the International Federation of Robotics (IFR).



Appendix for Online Publication

“Do Robots Increase Wealth Dispersion?”

THOMAS JANSSON and YIGITCAN KARABULUT

September 10, 2020

Abstract

This Online Appendix includes tables and figures referred to but not included in the main body of the paper *Do Robots Increase Wealth Dispersion?* by Thomas Jansson and Yigitcan Karabulut, that provide robustness checks and additional findings.

Table O.A.1: Mathcing the LINDA, IFR, and EU KLEMS Data

This table presents the correspondence list that we use to match industry-level information from the International Federation of Robotics (IFR), EU KLEMS database, and LINDA dataset from Statistics Sweden. Source: Author computations using LINDA dataset from Statistics Sweden, IFR, and EU KLEMS databases.

SNI Code	EU-KLEMS Code	IFR Code	Industry Name (IFR)
01-05	A-B	A-B	Agriculture, forestry, fishing
C	C	C	Mining and quarrying
15 -16	10-12	10-12	Food and beverages; tobacco
17-18-19	13-15	13-15	Textiles
20-21-22	16-18	16-18	Wood and furniture; Paper
23-24	19-21	19-21	Pharmaceuticals, cosmetics; Other chemical products n.e.c.
25-26	22-23	22-23	Rubber and plastic products; Chemical products; Mineral products
27-28	24-25	24-25	Basic metals; Metal products (non-automotive)
29	28	28	Industrial machinery
30-31-32-33	26-27	26-27	Electrical/electronics
34-35	29-30	29-30	Automotive; Other vehicles
E	E	E	Electricity, gas, water supply
F	F	F	Construction
M	M	P	Education/research/development

Table O.A.2: First-Stage Relationship for Labor Market and Wealth Regressions

This table presents coefficient estimates from the first-stage of the IV regressions for labor market outcomes (in (1) and (2)) and household financial behavior and net wealth (in Columns (3) and (4)). In all specifications, the dependent variable is the change in robot density in the Swedish industries. The excluded instrument is the contemporaneous median changes in robot density in the corresponding industries across eleven other developed Western European countries that are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Portugal, and the United Kingdom. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	$\Delta\, Robot\_Density^{99\rightarrow 07}_{SWE}$			
$\Delta Robot\_Density^{99\rightarrow 07}_{EU}$	16.4301***	16.4301***	16.48609***	16.48609***
	(0.5120)	(1.9524)	(0.5107)	(1.9464)
Observations	30,375	30,375	30,375	30,375
R-squared	0.8855	0.8855	0.886	0.886
F-statistics	250.59	3701.59	246.43	1089.24
Household Controls	Yes	Yes	Yes	Yes
Household Wealth Deciles	No	No	Yes	Yes
Household Income Deciles	No	No	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry Level	Industry	Muni-Industry Level	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.3: Exposure to Robots and Household Net Wealth - Upward Mobility

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. The dependent variable is an indicator variable that takes the value of 1 if a household moves up in the within-cohort net wealth distribution between 1999 and 2007, and 0 otherwise. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), standard errors are clustered at the municipality-industry level. In (2), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Upward Mobility	
	(1)	(2)
$\Delta Robot\_Density^{99\to 07}$	-0.00335**	-0.00335
	(0.0017)	(0.0021)
Married	0.02638***	0.02638***
	(0.0088)	(0.0094)
College	-0.05365**	-0.05365**
	(0.0260)	(0.0232)
High School	-0.01833	-0.01833
	(0.0205)	(0.0187)
ΔNumber of adults	0.01640***	0.01640***
	(0.0041)	(0.0038)
ΔNumber of children	0.02502***	0.02502***
	(0.0029)	(0.0033)
ΔNo of Employees (1993-98)	-0.00104	-0.00104
	(0.0007)	(0.0007)
$\Delta Chinese\_Import^{99\to 07}$	-0.00167**	-0.00167
	(0.0008)	(0.0012)
ΔCapital Intensity	-0.15881***	-0.15881*
	(0.0580)	(0.0832)
ΔICT Capital	0.02417	0.02417
	(0.0210)	(0.0236)
Initial Robot Density (1995)	0.00211**	0.00211**
	(0.0009)	(0.0010)
$\Delta EU\_Import^{99\to 07}$	0.00554***	0.00554***
	(0.0018)	(0.0019)
$Labor\_Intesity$ (1999)	0.04911	0.04911
	(0.0392)	(0.0478)
$\Delta Profits^{99\to 07}$	0.00000	0.00000
	(0.0000)	(0.0000)
Constant	0.32827***	0.32827***
	(0.0767)	(0.0816)
Observations	30375	30375
R-squared	0.0630	0.0630
Income Deciles (1999)	Yes	Yes
Clustering	Muni-Industry	Industry
Municipality FEs	Yes	Yes

Table O.A.4: Exposure to Robots and Household Net Wealth - Controlling for Homeownership

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. In (5) and (6), the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. We include an indicator variable for being a homeowner in 1999 as an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow 07}$	-1.05706***	-1.05706**	0.00808***	0.00808**	-0.24719***	-0.24719***
	(0.1104)	(0.4458)	(0.0017)	(0.0034)	(0.0720)	(0.0923)
Married	0.35129	0.35129	-0.02348***	-0.02348**	1.37374***	1.37374***
	(0.4420)	(0.5389)	(0.0089)	(0.0104)	(0.4314)	(0.5216)
College	-4.12488***	-4.12488***	0.06445**	0.06445***	-4.40522***	-4.40522***
	(1.2000)	(0.9303)	(0.0266)	(0.0235)	(1.3218)	(1.1701)
High School	-6.80982***	-6.80982***	0.03410	0.03410	-1.34429	-1.34429
	(0.9370)	(0.7861)	(0.0208)	(0.0211)	(0.8969)	(0.8848)
ΔNumber of adults	2.54244***	2.54244***	-0.01798***	-0.01798***	1.02158***	1.02158***
	(0.2070)	(0.1817)	(0.0040)	(0.0040)	(0.1679)	(0.1687)
ΔNumber of children	2.46463***	2.46463***	-0.02339***	-0.02339***	1.24126***	1.24126***
	(0.1479)	(0.1578)	(0.0029)	(0.0033)	(0.1384)	(0.1717)
Homeowner (1999)	21.11382***	21.11382***	-0.00936	-0.00936	-3.12279***	-3.12279***
	(0.4308)	(0.6455)	(0.0077)	(0.0081)	(0.3515)	(0.2833)
ΔNo of Employees (1993-98)	0.17966***	0.17966	-0.00051	-0.00051	-0.01495	-0.01495
	(0.0384)	(0.1390)	(0.0007)	(0.0011)	(0.0292)	(0.0375)
$\Delta Chinese\_Import^{99\rightarrow 07}$	-0.25117***	-0.25117	0.00314***	0.00314*	-0.07948**	-0.07948
	(0.0498)	(0.1707)	(0.0009)	(0.0016)	(0.0337)	(0.0501)
ΔCapital Intensity	-7.46016**	-7.46016	0.27986***	0.27986**	-9.98404***	-9.98404**
	(3.2981)	(11.4651)	(0.0595)	(0.1103)	(2.6253)	(4.0822)
ΔICT Capital	11.10532***	11.10532*	-0.06699***	-0.06699	1.63985*	1.63985
	(1.3534)	(5.8823)	(0.0218)	(0.0474)	(0.9013)	(1.3019)
Initial Robot Density (1995)	-0.26243***	-0.26243	-0.00057	-0.00057	0.07862*	0.07862
	(0.0564)	(0.1763)	(0.0010)	(0.0013)	(0.0419)	(0.0505)
$\Delta EU\_Import^{99\rightarrow 07}$	-0.30490***	-0.30490	-0.00498***	-0.00498**	0.36577***	0.36577***
	(0.1106)	(0.2924)	(0.0018)	(0.0025)	(0.0841)	(0.0812)
$Labor\_Intesity$ (1999)	-0.48652	-0.48652	-0.08435**	-0.08435	4.27590**	4.27590**
	(2.1869)	(5.0570)	(0.0399)	(0.0513)	(1.7863)	(2.1379)
$\Delta Profits^{99\rightarrow 07}$	-0.00768***	-0.00768	0.00004	0.00004	0.00022	0.00022
	(0.0017)	(0.0052)	(0.0000)	(0.0001)	(0.0012)	(0.0014)
Constant	31.58092***	31.58092***	0.60853***	0.60853***	-3.64809	-3.64809
	(4.7346)	(5.5432)	(0.0834)	(0.0942)	(3.7158)	(3.6979)
Observations	30375	30375	30375	30375	30375	30375
R-squared	0.2837	0.2837	0.0645	0.0645	0.0722	0.0722
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.5: Exposure to Robots and Household Net Wealth - Controlling for Risk Exposure

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. In (5) and (6), the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. We include the initial risk exposure (i.e., share of risky assets in 1999) an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.24333***	-1.24333**	0.00820***	0.00820**	-0.21982***	-0.21982**
	(0.1222)	(0.4981)	(0.0017)	(0.0034)	(0.0717)	(0.0879)
Married	0.49052	0.49052	-0.02429***	-0.02429**	1.35708***	1.35708***
	(0.4622)	(0.5860)	(0.0089)	(0.0103)	(0.4306)	(0.5151)
College	-5.93664***	-5.93664***	0.06447**	0.06447***	-4.13316***	-4.13316***
	(1.2622)	(1.1483)	(0.0266)	(0.0235)	(1.3205)	(1.1765)
High School	-8.47497***	-8.47497***	0.03502*	0.03502*	-1.09894	-1.09894
	(1.0273)	(0.9961)	(0.0208)	(0.0212)	(0.8971)	(0.8883)
ΔNumber of adults	2.08910***	2.08910***	-0.01789***	-0.01789***	1.08918***	1.08918***
	(0.2160)	(0.1903)	(0.0040)	(0.0040)	(0.1679)	(0.1708)
ΔNumber of children	1.29639***	1.29639***	-0.02266***	-0.02266***	1.41292***	1.41292***
	(0.1521)	(0.1859)	(0.0029)	(0.0035)	(0.1375)	(0.1732)
Risky Share (1999)	6.36544***	6.36544***	0.01527**	0.01527*	-1.03604***	-1.03604***
	(0.3845)	(0.4070)	(0.0073)	(0.0082)	(0.3212)	(0.3580)
ΔNo of Employees (1993-98)	0.19161***	0.19161	-0.00045	-0.00045	-0.01704	-0.01704
	(0.0418)	(0.1526)	(0.0007)	(0.0011)	(0.0291)	(0.0360)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.29544***	-0.29544	0.00311***	0.00311*	-0.07269**	-0.07269
	(0.0534)	(0.1881)	(0.0009)	(0.0016)	(0.0335)	(0.0480)
ΔCapital Intensity	-7.83903**	-7.83903	0.27248***	0.27248**	-9.88854***	-9.88854**
	(3.5316) (	(12.3700)	(0.0596)	(0.1091)	(2.6132)	(3.9333)
ΔICT Capital	12.26503***	12.26503*	-0.06663***	-0.06663	1.46377	1.46377
	(1.4569)	(6.3000)	(0.0218)	(0.0475)	(0.9013)	(1.2757)
Initial Robot Density (1995)	-0.25663***	-0.25663	-0.00062	-0.00062	0.07804*	0.07804
	(0.0650)	(0.1968)	(0.0010)	(0.0013)	(0.0414)	(0.0490)
$\Delta EU\_Import^{99\rightarrow07}$	-0.31151***	-0.31151	-0.00500***	-0.00500**	0.36690***	0.36690***
	(0.1189)	(0.2934)	(0.0018)	(0.0025)	(0.0848)	(0.0818)
$Labor\_Intesity$ (1999)	0.00497	0.00497	-0.07974**	-0.07974	4.17801**	4.17801**
	(2.3686)	(5.7197)	(0.0399)	(0.0510)	(1.7782)	(2.0542)
$\Delta Profits^{99\rightarrow07}$	-0.00768***	-0.00768	0.00004	0.00004	0.00022	0.00022
	(0.0020)	(0.0056)	(0.0000)	(0.0001)	(0.0012)	(0.0014)
Constant	35.58746***	35.58746***	0.60104***	0.60104***	-4.21077	-4.21077
	(5.3099)	(6.3096)	(0.0840)	(0.0952)	(3.6518)	(3.6859)
Observations	30375	30375	30375	30375	30375	30375
R-squared	0.1965	0.1965	0.0646	0.0646	0.0692	0.0692
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.6: Exposure to Robots and Changes in Household Debt

This table presents coefficient estimates from the second-stage of the IV regressions for household debt. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. The dependent variable is the log differences in debt outstanding between 1999 and 2007. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), standard errors are clustered at the municipality-industry level. In (2), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Change in Household Debt	
	(1)	(2)
$\Delta Robot\_Density^{99\rightarrow07}$	0.00487	0.00487
	(0.0127)	(0.0112)
Married	0.43927***	0.43927***
	(0.0694)	(0.0567)
College	0.12441	0.12441
	(0.2487)	(0.2370)
High School	0.18815	0.18815
	(0.1616)	(0.1877)
ΔNumber of adults	0.55124***	0.55124***
	(0.0302)	(0.0277)
Δ Number of children	0.61668***	0.61668***
	(0.0242)	(0.0255)
ΔNo of Employees (1993-98)	-0.00069	-0.00069
	(0.0048)	(0.0051)
$\Delta Chinese\_Import^{99\rightarrow07}$	0.00211	0.00211
	(0.0065)	(0.0081)
ΔCapital Intensity	-1.02089**	-1.02089*
	(0.4704)	(0.5952)
ΔICT Capital	0.32476*	0.32476*
	(0.1829)	(0.1726)
Initial Robot Density (1995)	-0.00337	-0.00337
	(0.0069)	(0.0069)
$\Delta EU\_Import^{99\rightarrow07}$	0.01917	0.01917
	(0.0140)	(0.0160)
$Labor\_Intesity$ (1999)	0.46877	0.46877
	(0.3160)	(0.3833)
$\Delta Profits^{99\rightarrow07}$	-0.00016	-0.00016
	(0.0002)	(0.0002)
Constant	0.54296	0.54296
	(0.5172)	(0.5330)
Observations	30375	30375
R-squared	0.0620	0.0620
Income Deciles (1999)	Yes	Yes
Wealth Deciles (1999)	Yes	Yes
Clustering	Muni-Industry	Industry
Municipality FEs	Yes	Yes

Table O.A.7: Educational Majors by Intersectoral Transferability

This table presents the top and bottom 10 educational majors-levels by the degree of their intersectoral transferability. There is a total of 147 educational major-level groups. A higher (lower) HHI would imply lower (higher) levels of intersectoral transferability of an educational major. Source: Author computations using household-level LINDA dataset from Statistics Sweden.

3-Digit Educational Orientation (SUN 2000)	Higher Education	HHI	Rank
Engineering and engineering industries, other / unspecified orientation	0	0.053889	1
Electronics, information technology and automation	0	0.054617	2
Engineering and engineering industries, other / unspecified orientation	1	0.056092	3
Engineering and Engineering Technology	0	0.058537	4
Broad, general education	0	0.05956	5
Business administration, commerce, administration, public educ.	0	0.061519	6
Business, trade and administration, other / unspecified educ.	0	0.062302	7
Energy and electrical engineering	1	0.063842	8
Production of wood, paper, glass / porcelain and plastic products	0	0.065796	9
Marketing	0	0.066667	10
...			
Therapy, rehabilitation and dietary treatment	1	0.73835	138
Medicine	1	0.74245	139
Teacher education for compulsory school ages	1	0.780532	140
Dentistry	1	0.827163	141
Therapy, rehabilitation and dietary treatment	0	0.844249	142
Nursing	1	0.846269	143
Security and Public Safety	1	0.894056	144
Personal services, other / unspecified education	1	1	145
Fisheries and aquaculture	1	1	146
Domestic services and cleaning	1	1	147

Table O.A.8: Industry Switching and Intersectoral Transferability of Educational Majors

This table presents coefficient estimates from Linear Probability Modelsfor industry switchers between 1999 and 2007. In both specifications, industry switcher dummy is regressed on the HHI of the educational major of a household, and initial observable household characteristics. In (1), standard errors are clustered at the municipality level, while in (2) standard errors are clustered at the municipality-industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden.

	Industry Switcher	
	(1)	(2)
HHI (of Education Major)	-0.11350***	-0.11350***
	(0.0314)	(0.0302)
Age	-0.01876***	-0.01876***
	(0.0041)	(0.0041)
Age squared	0.00017***	0.00017***
	(0.0001)	(0.0001)
Male	-0.08564***	-0.08564***
	(0.0094)	(0.0101)
Married	0.01473**	0.01473**
	(0.0063)	(0.0064)
College and more	0.05801***	0.05801***
	(0.0105)	(0.0105)
High school	-0.01222*	-0.01222*
	(0.0069)	(0.0074)
Nbr of adults	-0.00383	-0.00383
	(0.0059)	(0.0061)
Nbr of children	-0.00271	-0.00271
	(0.0031)	(0.0028)
Disposable Income (IHS)	-0.04397***	-0.04397***
	(0.0126)	(0.0111)
Immigrant	0.02724**	0.02724***
	(0.0112)	(0.0105)
Wealth Quartile II	-0.01957***	-0.01957***
	(0.0071)	(0.0075)
Wealth Quartile III	-0.03378***	-0.03378***
	(0.0076)	(0.0076)
Wealth Quartile IV	-0.03167***	-0.03167***
	(0.0095)	(0.0089)
Constant	1.44427***	1.44427***
	(0.1783)	(0.1705)
Observations	29655	29655
R-squared	0.0522	0.0522
Clustering	Muni Level	Muni-Industry Level

Table O.A.9: Exposure to Robots and Household Net Wealth - Addressing Potential Sorting of Households

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We focus only on households who have been employed in the same industry since 1995 or earlier. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	Panel A. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\to07}$	-1.16528***	-1.16528***	0.00905***	0.00905***
	(0.1323)	(0.3530)	(0.0020)	(0.0025)
Observations	19178	19178	19178	19178
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.10: Exposure to Robots and Household Net Wealth - Excluding the Automative Industry

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We exclude from the sample those individuals who are working in the automative industry, which has historically the highest robot density per thousand workers in Sweden. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	Panel A. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow 07}$	-2.56533***	-2.56533***	0.01281***	0.01281*
	(0.2204)	(0.9084)	(0.0028)	(0.0072)
Observations	27112	27112	27112	27112
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.11: Exposure to Robots and Household Economic Behavior - Considering Full Sample

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We now consider the full set of industries (rather than focussing only on those that are directly affected by increased automation). In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	Panel A. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.46839***	-0.46839***	0.00370**	0.00370**
	(0.0791)	(0.1520)	(0.0015)	(0.0015)
Observations	82424	82424	82424	82424
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	No	No	No	No
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.12: Exposure to Robots and Household Economic Behavior - Excluding the Rubber and Plastic Industry

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We eliminate individuals working in the rubber and plastic industry that experienced the largest growth in robot use across industries in Sweden during the observation period. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	Panel A. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow07}$	-1.97864***	-1.97864***	0.01055***	0.01055**
	(0.1708)	(0.7239)	(0.0025)	(0.0052)
Observations	29195	29195	29195	29195
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.13: Exposure to Robots and Household Economic Behavior - Accounting for Life-Cycle Effects and Preference Shifters

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We augment the base estimation model by allowing for additional life-cycle controls and preference shifters specific to the household. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	(1)	(2)	(3)	(4)
	Panel A. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow07}$	-0.80674***	-0.80674**	0.00597***	0.00597**
	(0.1010)	(0.3969)	(0.0017)	(0.0030)
Observations	26504	26504	26504	26504
Household Controls	Yes	Yes	Yes	Yes
Additional Life-Cycle Controls	Yes	Yes	Yes	Yes
Preference Shifters	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.14: Exposure to Robots and Income Growth - Allowing for Transfers

This table presents coefficient estimates from the second-stage of the IV regressions for labor market outcomes. In all specifications, labor market measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the log changes in household disposable income (including transfers received by the households such as unemployment benefits or social welfare payments for the alleviation of poverty) between 1999 and 2007. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), standard errors are clustered at the municipality-industry level. In (2), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Change in Disposable Income	
	(1)	(2)
$\Delta Robot\_Density^{99\to07}$	-0.00547***	-0.00547**
	(0.0012)	(0.0027)
Married	0.04958***	0.04958***
	(0.0060)	(0.0074)
College	-0.01280	-0.01280
	(0.0177)	(0.0178)
High School	-0.03574***	-0.03574***
	(0.0132)	(0.0120)
ΔNumber of adults	0.23467***	0.23467***
	(0.0034)	(0.0056)
ΔNumber of children	0.08962***	0.08962***
	(0.0021)	(0.0028)
ΔNo of Employees (1993-98)	0.00003	0.00003
	(0.0004)	(0.0009)
$\Delta Chinese\_Import^{99\to07}$	-0.00095*	-0.00095
	(0.0006)	(0.0012)
ΔCapital Intensity	-0.02379	-0.02379
	(0.0418)	(0.0862)
ΔICT Capital	0.04756***	0.04756
	(0.0159)	(0.0388)
Initial Robot Density (1995)	-0.00001	-0.00001
	(0.0006)	(0.0011)
$\Delta EU\_Import^{99\to07}$	0.00032	0.00032
	(0.0011)	(0.0018)
$Labor\_Intesity$ (1999)	0.01457	0.01457
	(0.0253)	(0.0412)
$\Delta Profits^{99\to07}$	0.00001	0.00001
	(0.0000)	(0.0000)
Constant	0.42630***	0.42630***
	(0.0207)	(0.0349)
Observations	30,375	30,375
R-squared	0.2341	0.2341
Clustering	Muni-Industry	Industry
Municipality FEs	Yes	Yes

Table O.A.15: Exposure to Robots and Household Net Wealth - Controlling for Income Growth and Permanent Income

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We include average income between 1995 and 1998 and realized income growth between 1995 and 1998 as an additional regressor in the regressions (that corresponds to the reduced form of an IV regression where we instrument current income growth by lagged income growth). In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\to07}$	-1.25779***	-1.25779**	0.00927***	0.00927***	-0.25506***	-0.25506***
	(0.1290)	(0.4997)	(0.0019)	(0.0035)	(0.0741)	(0.0916)
Married	3.24455***	3.24455***	-0.04225***	-0.04225***	2.03159***	2.03159***
	(0.5315)	(0.5723)	(0.0102)	(0.0118)	(0.4850)	(0.5489)
College	-3.98841***	-3.98841**	0.06926**	0.06926***	-3.87848***	-3.87848***
	(1.4499)	(1.5533)	(0.0294)	(0.0233)	(1.4938)	(1.1919)
High School	-8.51775***	-8.51775***	0.02911	0.02911	-1.39274	-1.39274
	(1.1620)	(1.1845)	(0.0234)	(0.0244)	(0.9269)	(0.9013)
ΔNumber of adults	3.11104***	3.11104***	-0.02630***	-0.02630***	1.30534***	1.30534***
	(0.2269)	(0.2016)	(0.0041)	(0.0042)	(0.1726)	(0.1714)
ΔNumber of children	3.28642***	3.28642***	-0.04180***	-0.04180***	1.93274***	1.93274***
	(0.1851)	(0.3285)	(0.0033)	(0.0047)	(0.1569)	(0.1920)
ΔNo of Employees (1993-98)	0.17379***	0.17379	-0.00053	-0.00053	-0.02582	-0.02582
	(0.0437)	(0.1533)	(0.0007)	(0.0012)	(0.0295)	(0.0362)
$\Delta Chinese\_Import^{99\to07}$	-0.25207***	-0.25207	0.00347***	0.00347**	-0.07537**	-0.07537
	(0.0591)	(0.1881)	(0.0010)	(0.0017)	(0.0346)	(0.0511)
ΔCapital Intensity	-3.62614	-3.62614	0.25794***	0.25794**	-8.27825***	-8.27825**
	(3.8080)	(12.9532)	(0.0642)	(0.1099)	(2.6235)	(3.8155)
ΔICT Capital	11.72130***	11.72130*	-0.05828**	-0.05828	0.69527	0.69527
	(1.5514)	(6.2899)	(0.0235)	(0.0475)	(0.9446)	(1.3635)
Initial Robot Density (1995)	-0.25170***	-0.25170	-0.00050	-0.00050	0.09813**	0.09813**
	(0.0674)	(0.1990)	(0.0011)	(0.0014)	(0.0416)	(0.0452)
$\Delta EU\_Import^{99\to07}$	-0.22248*	-0.22248	-0.00550***	-0.00550*	0.42952***	0.42952***
	(0.1264)	(0.2956)	(0.0019)	(0.0028)	(0.0873)	(0.1000)
$Labor\_Intesity$ (1999)	-2.21022	-2.21022	-0.07810*	-0.07810	3.56823**	3.56823
	(2.5133)	(5.9191)	(0.0436)	(0.0567)	(1.7946)	(2.1762)
$\Delta Profits^{99\to07}$	-0.00894***	-0.00894	0.00004	0.00004	0.00038	0.00038
	(0.0021)	(0.0055)	(0.0000)	(0.0001)	(0.0013)	(0.0016)
Income Growth (1995 – 1998)	0.13031	0.13031	-0.03634***	-0.03634***	1.80273***	1.80273***
	(0.2841)	(0.2900)	(0.0052)	(0.0058)	(0.2453)	(0.2175)
Average Income (1995 – 1998)	23.29847***	23.29847***	-0.19159***	-0.19159***	6.83298***	6.83298***
	(0.5386)	(1.4004)	(0.0094)	(0.0136)	(0.3968)	(0.5367)
Constant	-249.14548***	-249.14548***	2.96919***	2.96919***	-88.68176***	-88.68176***
	(9.1629)	(21.6709)	(0.1581)	(0.2184)	(6.5392)	(7.8889)
Observations	26103	26103	26103	26103	26103	26103
R-squared	0.1958	0.1958	0.0673	0.0673	0.0675	0.0675
Income Deciles (1999)	No	No	No	No	No	No
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.16: Exposure to Robots and Household Net Wealth - Excluding Displaced Households

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We exclude those households who become unemployed over the sample period. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.19300***	-1.19300**	0.00762***	0.00762**	-0.19657***	-0.19657**
	(0.1232)	(0.4995)	(0.0017)	(0.0034)	(0.0728)	(0.0892)
Married	0.77125*	0.77125	-0.02732***	-0.02732***	1.42712***	1.42712***
	(0.4649)	(0.5652)	(0.0091)	(0.0105)	(0.4385)	(0.5423)
College	-5.25114***	-5.25114***	0.05585**	0.05585**	-3.75951***	-3.75951***
	(1.3896)	(1.4003)	(0.0278)	(0.0239)	(1.4361)	(1.2816)
High School	-7.52694***	-7.52694***	0.03161	0.03161	-0.67812	-0.67812
	(1.0950)	(0.9938)	(0.0224)	(0.0215)	(0.9712)	(0.8930)
ΔNumber of adults	2.07249***	2.07249***	-0.01775***	-0.01775***	1.04344***	1.04344***
	(0.2191)	(0.1850)	(0.0040)	(0.0042)	(0.1694)	(0.1811)
ΔNumber of children	1.21051***	1.21051***	-0.02284***	-0.02284***	1.44588***	1.44588***
	(0.1550)	(0.1929)	(0.0029)	(0.0034)	(0.1401)	(0.1718)
ΔNo of Employees (1993-98)	0.17267***	0.17267	-0.00066	-0.00066	-0.01104	-0.01104
	(0.0429)	(0.1569)	(0.0007)	(0.0012)	(0.0297)	(0.0371)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.27330***	-0.27330	0.00327***	0.00327**	-0.08022**	-0.08022
	(0.0553)	(0.1907)	(0.0009)	(0.0017)	(0.0349)	(0.0511)
ΔCapital Intensity	-5.12608	-5.12608	0.29405***	0.29405***	-10.61216*** -	-10.61216**
	(3.6436) (	(12.7185)	(0.0614)	(0.1138)	(2.6834)	(4.1660)
ΔICT Capital	12.59888***	12.59888*	-0.07400***	-0.07400	1.74587*	1.74587
	(1.4874)	(6.5035)	(0.0220)	(0.0493)	(0.9239)	(1.3846)
Initial Robot Density (1995)	-0.27921***	-0.27921	-0.00030	-0.00030	0.06826	0.06826
	(0.0661)	(0.2020)	(0.0010)	(0.0014)	(0.0419)	(0.0496)
$\Delta EU\_Import^{99\rightarrow07}$	-0.32603***	-0.32603	-0.00447**	-0.00447*	0.35632***	0.35632***
	(0.1178)	(0.3065)	(0.0018)	(0.0026)	(0.0881)	(0.0886)
$Labor\_Intesity$ (1999)	-2.09004	-2.09004	-0.09158**	-0.09158*	4.45241**	4.45241**
	(2.4420)	(5.9282)	(0.0410)	(0.0527)	(1.8259)	(2.1591)
$\Delta Profits^{99\rightarrow07}$	-0.00887***	-0.00887	0.00004	0.00004	0.00008	0.00008
	(0.0019)	(0.0058)	(0.0000)	(0.0001)	(0.0012)	(0.0015)
Constant	38.84160***	38.84160***	0.60933***	0.60933***	-4.85045	-4.85045
	(5.6351)	(6.5385)	(0.0850)	(0.0970)	(3.7244)	(3.8720)
Observations	29089	29089	29089	29089	29089	29089
R-squared	0.1858	0.1858	0.0644	0.0644	0.0693	0.0693
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.17: Exposure to Robots and Household Net Wealth - Controlling for Total Saving Rate I

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We include total saving rate (normalized by current income) in 2000 as an additional regressor in the regressions.. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.11201***	-1.11201**	0.01248***	0.01248**	-0.35326***	-0.35326***
	(0.1147)	(0.4543)	(0.0019)	(0.0049)	(0.0636)	(0.1164)
Married	1.74741***	1.74741***	-0.02953***	-0.02953***	0.69550*	0.69550
	(0.5320)	(0.5960)	(0.0100)	(0.0108)	(0.4145)	(0.4709)
College	-3.86692***	-3.86692***	0.08801***	0.08801***	-6.18193***	-6.18193***
	(1.4587)	(1.1418)	(0.0305)	(0.0249)	(1.3680)	(1.2487)
High School	-6.21118***	-6.21118***	0.05134*	0.05134*	-3.40313***	-3.40313***
	(1.4181)	(1.2283)	(0.0272)	(0.0282)	(1.0902)	(1.1164)
ΔNumber of adults	2.55760***	2.55760***	-0.01872***	-0.01872***	0.52307***	0.52307***
	(0.2155)	(0.1953)	(0.0045)	(0.0046)	(0.1581)	(0.1614)
ΔNumber of children	1.78635***	1.78635***	-0.01275***	-0.01275***	-0.12799	-0.12799
	(0.1662)	(0.2033)	(0.0034)	(0.0042)	(0.1307)	(0.1238)
ΔNo of Employees (1993-98)	0.22309***	0.22309	-0.00289***	-0.00289*	0.06981***	0.06981
	(0.0404)	(0.1416)	(0.0008)	(0.0016)	(0.0256)	(0.0441)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.32104***	-0.32104*	0.00467***	0.00467**	-0.09141***	-0.09141
	(0.0532)	(0.1812)	(0.0011)	(0.0021)	(0.0315)	(0.0565)
ΔCapital Intensity	-13.96613***	-13.96613	0.39012***	0.39012***	-12.22866*** -	-12.22866***
	(3.4945)	(11.7771)	(0.0675)	(0.1419)	(2.3050)	(4.2353)
ΔICT Capital	12.66395***	12.66395**	-0.12964***	-0.12964*	4.09051***	4.09051**
	(1.4505)	(6.3381)	(0.0252)	(0.0679)	(0.8825)	(1.7162)
Initial Robot Density (1995)	-0.33051***	-0.33051*	0.00293***	0.00293	-0.04342	-0.04342
	(0.0615)	(0.1855)	(0.0011)	(0.0020)	(0.0364)	(0.0625)
$\Delta EU\_Import^{99\rightarrow07}$	-0.18046*	-0.18046	0.00085	0.00085	0.05742	0.05742
	(0.1049)	(0.3054)	(0.0023)	(0.0032)	(0.0772)	(0.0907)
$Labor\_Intesity$ (1999)	2.59317	2.59317	-0.12516***	-0.12516**	4.83670***	4.83670**
	(2.3446)	(5.3556)	(0.0455)	(0.0631)	(1.5673)	(2.1786)
$\Delta Profits^{99\rightarrow07}$	-0.01073***	-0.01073*	0.00008**	0.00008	-0.00045	-0.00045
	(0.0017)	(0.0058)	(0.0000)	(0.0001)	(0.0011)	(0.0017)
Total Saving Rate in 2000 (Income)	2.04091***	2.04091***	-0.08253***	-0.08253***	3.82913***	3.82913***
	(0.2147)	(0.3702)	(0.0037)	(0.0074)	(0.1698)	(0.3337)
Constant	56.48096***	56.48096***	0.58892***	0.58892***	-8.08428***	-8.08428**
	(6.1017)	(7.8263)	(0.0720)	(0.1007)	(3.1250)	(3.3296)
Observations	20933	20933	20933	20933	20933	20933
R-squared	0.1971	0.1971	0.1269	0.1269	0.1270	0.1270
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.18: Exposure to Robots and Household Net Wealth - Controlling for Total Saving Rate II

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We include total saving rate (normalized by wealth from prior period) in 2000 as an additional regressor in the regressions.. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-1.09036***	-1.09036**	0.01235***	0.01235***	-0.34722***	-0.34722***
	(0.1140)	(0.4478)	(0.0019)	(0.0048)	(0.0642)	(0.1143)
Married	1.60080***	1.60080**	-0.02448**	-0.02448**	0.46136	0.46136
	(0.5372)	(0.6329)	(0.0100)	(0.0113)	(0.4216)	(0.4940)
College	-3.61369**	-3.61369***	0.09369***	0.09369***	-6.44544***	-6.44544***
	(1.4739)	(1.1135)	(0.0288)	(0.0251)	(1.3092)	(1.2795)
High School	-6.35906***	-6.35906***	0.05505**	0.05505**	-3.57558***	-3.57558***
	(1.4175)	(1.2420)	(0.0272)	(0.0281)	(1.0790)	(1.1410)
ΔNumber of adults	2.58971***	2.58971***	-0.01753***	-0.01753***	0.46820***	0.46820***
	(0.2156)	(0.1969)	(0.0045)	(0.0046)	(0.1586)	(0.1598)
ΔNumber of children	1.69196***	1.69196***	-0.00899***	-0.00899**	-0.30215**	-0.30215**
	(0.1670)	(0.1984)	(0.0033)	(0.0041)	(0.1310)	(0.1251)
ΔNo of Employees (1993-98)	0.21029***	0.21029	-0.00265***	-0.00265*	0.05854**	0.05854
	(0.0402)	(0.1402)	(0.0008)	(0.0015)	(0.0258)	(0.0426)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.31670***	-0.31670*	0.00469***	0.00469**	-0.09254***	-0.09254*
	(0.0530)	(0.1783)	(0.0011)	(0.0020)	(0.0313)	(0.0559)
ΔCapital Intensity	-13.35714***	-13.35714	0.36962***	0.36962***	-11.27740*** -	-11.27740***
	(3.4809)	(11.6689)	(0.0672)	(0.1382)	(2.2832)	(4.1270)
ΔICT Capital	12.47491***	12.47491**	-0.12737***	-0.12737**	3.98534***	3.98534**
	(1.4371)	(6.2195)	(0.0246)	(0.0638)	(0.8504)	(1.5571)
Initial Robot Density (1995)	-0.31461***	-0.31461*	0.00271**	0.00271	-0.03308	-0.03308
	(0.0615)	(0.1844)	(0.0011)	(0.0019)	(0.0371)	(0.0615)
$\Delta EU\_Import^{99\rightarrow07}$	-0.15681	-0.15681	0.00044	0.00044	0.07676	0.07676
	(0.1056)	(0.2996)	(0.0022)	(0.0031)	(0.0756)	(0.0886)
$Labor\_Intesity$ (1999)	2.63464	2.63464	-0.12297***	-0.12297*	4.73517***	4.73517**
	(2.3355)	(5.3248)	(0.0457)	(0.0633)	(1.5868)	(2.1999)
$\Delta Profits^{99\rightarrow07}$	-0.01028***	-0.01028*	0.00007**	0.00007	0.00005	0.00005
	(0.0017)	(0.0058)	(0.0000)	(0.0001)	(0.0011)	(0.0017)
Total Saving Rate in 2000 (Wealth)	-0.32946***	-0.32946***	-0.05108***	-0.05108***	2.36814***	2.36814***
	(0.1140)	(0.1132)	(0.0022)	(0.0018)	(0.1024)	(0.0901)
Constant	56.25061***	56.25061***	0.61141***	0.61141***	-9.12756***	-9.12756***
	(6.2793)	(7.5857)	(0.0754)	(0.0938)	(3.2679)	(3.1844)
Observations	20933	20933	20933	20933	20933	20933
R-squared	0.1910	0.1910	0.1269	0.1269	0.1269	0.1269
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.19: Exposure to Robots and Household Net Wealth - Controlling for Initial Wealth Deciles

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We include dummies for net wealth deciles in 1999 as additional regressors in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.52219***	-0.52219***	0.01265***	0.01265***	-0.48734***	-0.48734***
	(0.0714)	(0.1765)	(0.0017)	(0.0046)	(0.0707)	(0.1684)
Married	1.02538***	1.02538**	-0.01746**	-0.01746*	0.92092**	0.92092*
	(0.3636)	(0.5047)	(0.0081)	(0.0104)	(0.3675)	(0.4947)
College	-4.95333***	-4.95333***	0.07606***	0.07606***	-4.87931***	-4.87931***
	(1.1150)	(0.9343)	(0.0243)	(0.0213)	(1.1126)	(0.9204)
High School	-3.76020***	-3.76020***	0.07600***	0.07600***	-3.68515***	-3.68515***
	(0.7569)	(0.8105)	(0.0197)	(0.0206)	(0.7529)	(0.7328)
ΔNumber of adults	1.47095***	1.47095***	-0.02345***	-0.02345***	1.43479***	1.43479***
	(0.1502)	(0.1277)	(0.0038)	(0.0037)	(0.1505)	(0.1225)
ΔNumber of children	1.28079***	1.28079***	-0.02072***	-0.02072***	1.27862***	1.27862***
	(0.1190)	(0.1398)	(0.0028)	(0.0035)	(0.1185)	(0.1367)
ΔNo of Employees (1993-98)	0.04125	0.04125	-0.00131**	-0.00131	0.03374	0.03374
	(0.0271)	(0.0585)	(0.0006)	(0.0015)	(0.0269)	(0.0556)
$\Delta Chinese\_Import^{99\rightarrow 07}$	-0.13497***	-0.13497*	0.00391***	0.00391*	-0.11972***	-0.11972*
	(0.0316)	(0.0732)	(0.0009)	(0.0020)	(0.0315)	(0.0698)
ΔCapital Intensity	-6.23526***	-6.23526	0.21913***	0.21913	-6.16855***	-6.16855
	(2.3134)	(5.3116)	(0.0564)	(0.1337)	(2.3117)	(5.0531)
ΔICT Capital	4.43708***	4.43708*	-0.11347***	-0.11347*	4.26663***	4.26663*
	(0.8446)	(2.2862)	(0.0220)	(0.0616)	(0.8430)	(2.1771)
Initial Robot Density (1995)	-0.02137	-0.02137	0.00094	0.00094	-0.01616	-0.01616
	(0.0386)	(0.0777)	(0.0010)	(0.0018)	(0.0387)	(0.0739)
$\Delta EU\_Import^{99\rightarrow 07}$	0.10625	0.10625	-0.00116	-0.00116	0.12629*	0.12629
	(0.0779)	(0.1180)	(0.0017)	(0.0030)	(0.0766)	(0.1157)
$Labor\_Intesity$ (1999)	2.10066	2.10066	-0.05050	-0.05050	2.32083	2.32083
	(1.6009)	(2.6718)	(0.0380)	(0.0632)	(1.5992)	(2.5353)
$\Delta Profits^{99\rightarrow 07}$	-0.00181	-0.00181	0.00007**	0.00007	-0.00148	-0.00148
	(0.0013)	(0.0023)	(0.0000)	(0.0001)	(0.0012)	(0.0022)
Constant	20.98461***	20.98461***	0.30271***	0.30271***	15.07221***	15.07221***
	(4.0733)	(3.6962)	(0.0918)	(0.0952)	(4.0727)	(3.7495)
Observations	30375	30375	30375	30375	30375	30375
R-squared	0.5793	0.5793	0.1738	0.1738	0.3167	0.3167
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Wealth Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.20: Exposure to Robots and Household Net Wealth - Controlling for Initial Wealth in Levels

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile wealth rank of the households within their birth cohort-year distributions. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if the household falls into a lower wealth percentile rank within the birth cohort distribution over the sample period, and 0 otherwise. We include net wealth level in 1999 as an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1) and (3), standard errors are clustered at the municipality-industry level. In (2) and (4), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Net Wealth Rank		Downward Mobility		Change in Net Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.87091***	-0.87091**	0.01244***	0.01244***	-0.49054***	-0.49054***
	(0.0957)	(0.3640)	(0.0018)	(0.0046)	(0.0727)	(0.1596)
Married	1.47563***	1.47563***	-0.01565*	-0.01565	0.80311**	0.80311*
	(0.4068)	(0.5325)	(0.0083)	(0.0101)	(0.3829)	(0.4781)
College	-3.45654***	-3.45654***	0.08962***	0.08962***	-5.74104***	-5.74104***
	(1.1289)	(0.8731)	(0.0251)	(0.0232)	(1.1787)	(1.0578)
High School	-3.97793***	-3.97793***	0.08552***	0.08552***	-4.32204***	-4.32204***
	(0.8761)	(0.8172)	(0.0198)	(0.0210)	(0.7791)	(0.7878)
ΔNumber of adults	2.69241***	2.69241***	-0.01151***	-0.01151***	0.68167***	0.68167***
	(0.1818)	(0.1565)	(0.0038)	(0.0039)	(0.1517)	(0.1369)
ΔNumber of children	2.66112***	2.66112***	-0.00684**	-0.00684**	0.40402***	0.40402***
	(0.1330)	(0.1601)	(0.0028)	(0.0031)	(0.1226)	(0.1359)
ΔNo of Employees (1993-98)	0.14126***	0.14126	-0.00082	-0.00082	0.00672	0.00672
	(0.0341)	(0.1145)	(0.0007)	(0.0015)	(0.0277)	(0.0548)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.24210***	-0.24210*	0.00356***	0.00356*	-0.10157***	-0.10157
	(0.0430)	(0.1443)	(0.0009)	(0.0020)	(0.0322)	(0.0664)
ΔCapital Intensity	-8.69378***	-8.69378	0.23986***	0.23986*	-7.83156***	-7.83156
	(2.9145)	(9.7088)	(0.0577)	(0.1323)	(2.3956)	(4.9831)
ΔICT Capital	9.05203***	9.05203*	-0.09965***	-0.09965*	3.57456***	3.57456*
	(1.1670)	(4.9525)	(0.0225)	(0.0597)	(0.8642)	(2.0086)
Initial Robot Density (1995)	-0.19388***	-0.19388	-0.00009	-0.00009	0.04384	0.04384
	(0.0497)	(0.1426)	(0.0010)	(0.0018)	(0.0418)	(0.0729)
$\Delta EU\_Import^{99\rightarrow07}$	-0.03156	-0.03156	-0.00198	-0.00198	0.17386**	0.17386*
	(0.0988)	(0.2451)	(0.0017)	(0.0029)	(0.0764)	(0.1006)
$Labor\_Intesity$ (1999)	1.63611	1.63611	-0.04685	-0.04685	2.09488	2.09488
	(1.9466)	(4.2579)	(0.0387)	(0.0622)	(1.6550)	(2.4995)
$\Delta Profits^{99\rightarrow07}$	-0.00738***	-0.00738*	0.00005	0.00005	-0.00016	-0.00016
	(0.0015)	(0.0044)	(0.0000)	(0.0001)	(0.0012)	(0.0021)
(IHS of) Net Wealth in 1999	1.17375***	1.17375***	0.01304***	0.01304***	-0.83224***	-0.83224***
	(0.0125)	(0.0250)	(0.0003)	(0.0004)	(0.0120)	(0.0180)
Constant	36.69395***	36.69395***	0.59580***	0.59580***	-3.89589	-3.89589
	(5.1984)	(5.4137)	(0.0845)	(0.0940)	(3.6407)	(3.6446)
Observations	30375	30375	30375	30375	30375	30375
R-squared	0.4293	0.4293	0.1512	0.1512	0.2646	0.2646
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.21: Exposure to Robots and Financial Risk Taking Behavior - Controlling for Income Growth Expectations (Perfect Foresight)

This table presents coefficient estimates from the second-stage of the IV regressions for household financial risk taking behavior. In all specifications, measures of financial risk taking wealth are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the stockholding status in 2007. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if a stockholder household in 1999 exits from the stock market as of 2007, and 0 otherwise. In (5) and (6), we consider the changes in risky share between 1999 and 2007. We include income growth between 1999 and 2007 as an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Stockholding Status		Exit from the Stock Market		Change in Risky Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\to07}$	-0.00471***	-0.00471**	0.00351***	0.00351***	-0.00394***	-0.00394**
	(0.0013)	(0.0019)	(0.0011)	(0.0011)	(0.0014)	(0.0018)
Married	0.03817***	0.03817***	-0.01675***	-0.01675***	-0.00398	-0.00398
	(0.0068)	(0.0055)	(0.0055)	(0.0045)	(0.0079)	(0.0071)
College	-0.00405	-0.00405	0.01502	0.01502	-0.06589***	-0.06589***
	(0.0214)	(0.0202)	(0.0176)	(0.0173)	(0.0232)	(0.0214)
High School	-0.09824***	-0.09824***	0.08064***	0.08064***	-0.03740	-0.03740*
	(0.0196)	(0.0221)	(0.0217)	(0.0213)	(0.0240)	(0.0216)
ΔNumber of adults	0.04071***	0.04071***	-0.03428***	-0.03428***	0.00649*	0.00649
	(0.0034)	(0.0029)	(0.0031)	(0.0027)	(0.0037)	(0.0041)
ΔNumber of children	0.03466***	0.03466***	-0.02711***	-0.02711***	0.04040***	0.04040***
	(0.0022)	(0.0023)	(0.0021)	(0.0020)	(0.0028)	(0.0027)
ΔNo of Employees (1993-98)	-0.00314***	-0.00314***	0.00048	0.00048	0.00132**	0.00132
	(0.0005)	(0.0008)	(0.0004)	(0.0005)	(0.0006)	(0.0009)
$\Delta Chinese\_Import^{99\to07}$	0.00135**	0.00135	-0.00091	-0.00091*	-0.00148**	-0.00148
	(0.0007)	(0.0009)	(0.0006)	(0.0005)	(0.0007)	(0.0014)
ΔCapital Intensity	0.27074***	0.27074***	-0.06054	-0.06054	-0.19029***	-0.19029**
	(0.0471)	(0.0659)	(0.0379)	(0.0394)	(0.0540)	(0.0927)
ΔICT Capital	-0.02446	-0.02446	0.00677	0.00677	0.04047**	0.04047
	(0.0174)	(0.0227)	(0.0138)	(0.0130)	(0.0191)	(0.0262)
Initial Robot Density (1995)	0.00416***	0.00416***	-0.00111*	-0.00111*	-0.00011	-0.00011
	(0.0007)	(0.0014)	(0.0006)	(0.0006)	(0.0008)	(0.0011)
$\Delta EU\_Import^{99\to07}$	0.00576***	0.00576***	-0.00140	-0.00140	0.00197	0.00197
	(0.0015)	(0.0021)	(0.0012)	(0.0012)	(0.0017)	(0.0016)
$Labor\_Intesity$ (1999)	-0.20292***	-0.20292***	0.02551	0.02551	0.10521***	0.10521
	(0.0327)	(0.0490)	(0.0265)	(0.0259)	(0.0374)	(0.0646)
$\Delta Profits^{99\to07}$	0.00002	0.00002	-0.00001	-0.00001	0.00000	0.00000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Change in Income (1999 – 2007)	0.02270***	0.02270***	-0.01785***	-0.01785***	0.00431*	0.00431**
	(0.0018)	(0.0021)	(0.0024)	(0.0029)	(0.0023)	(0.0021)
Constant	0.26976***	0.26976***	0.35730***	0.35730***	-0.49634***	-0.49634***
	(0.0573)	(0.0583)	(0.0539)	(0.0692)	(0.0448)	(0.0622)
Observations	30375	30375	22125	22125	22125	22125
R-squared	0.1766	0.1766	0.0777	0.0777	0.0802	0.0802
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Wealth Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table O.A.22: Exposure to Robots and Financial Risk Taking Behavior - Controlling for Income Growth Expectations (Adaptive Expectations)

This table presents coefficient estimates from the second-stage of the IV regressions for household financial risk taking behavior. In all specifications, measures of financial risk taking wealth are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the stockholding status in 2007. In (3) and (4), the dependent variable is an indicator variable that takes the value of 1 if a stockholder household in 1999 exits from the stock market as of 2007, and 0 otherwise. In (5) and (6), we consider the changes in risky share between 1999 and 2007. We include income growth between 1995 and 1998 as an additional regressor in the regressions. In all specifications, we estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model, Equation 4, is defined and estimated in first differences. In (1), (3) and (5), standard errors are clustered at the municipality-industry level. In (2), (4), and (6), standard errors are clustered at the (3-digit) industry level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using household-level LINDA dataset from Statistics Sweden, data from the International Federation of Robotics (IFR) and the EU KLEMS, and OECD's STAN databases.

	Stockholding Status		Exit from the Stock Market		Change in Risky Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_Density^{99\to07}$	-0.00567***	-0.00567***	0.00417***	0.00417***	-0.00438***	-0.00438***
	(0.0015)	(0.0019)	(0.0012)	(0.0013)	(0.0015)	(0.0017)
Married	0.03609***	0.03609***	-0.01978***	-0.01978***	-0.00265	-0.00265
	(0.0078)	(0.0063)	(0.0069)	(0.0056)	(0.0093)	(0.0081)
College	0.00340	0.00340	0.01138	0.01138	-0.05771**	-0.05771**
	(0.0239)	(0.0223)	(0.0191)	(0.0197)	(0.0250)	(0.0252)
High School	-0.08165***	-0.08165***	0.07006***	0.07006***	-0.02700	-0.02700
	(0.0219)	(0.0244)	(0.0242)	(0.0252)	(0.0268)	(0.0248)
ΔNumber of adults	0.05166***	0.05166***	-0.04185***	-0.04185***	0.00945**	0.00945**
	(0.0034)	(0.0029)	(0.0032)	(0.0027)	(0.0038)	(0.0044)
ΔNumber of children	0.03430***	0.03430***	-0.02981***	-0.02981***	0.04153***	0.04153***
	(0.0024)	(0.0024)	(0.0024)	(0.0022)	(0.0030)	(0.0033)
ΔNo of Employees (1993-98)	-0.00332***	-0.00332***	0.00085*	0.00085*	0.00117*	0.00117
	(0.0006)	(0.0008)	(0.0005)	(0.0005)	(0.0006)	(0.0009)
$\Delta Chinese\_Import^{99\to07}$	0.00112	0.00112	-0.00098*	-0.00098*	-0.00121	-0.00121
	(0.0007)	(0.0010)	(0.0006)	(0.0006)	(0.0008)	(0.0015)
ΔCapital Intensity	0.25848***	0.25848***	-0.08043*	-0.08043*	-0.17107***	-0.17107*
	(0.0509)	(0.0714)	(0.0416)	(0.0453)	(0.0582)	(0.0981)
ΔICT Capital	-0.02148	-0.02148	0.01112	0.01112	0.02857	0.02857
	(0.0194)	(0.0261)	(0.0155)	(0.0161)	(0.0199)	(0.0253)
Initial Robot Density (1995)	0.00486***	0.00486***	-0.00202***	-0.00202***	0.00017	0.00017
	(0.0008)	(0.0012)	(0.0007)	(0.0007)	(0.0008)	(0.0010)
$\Delta EU\_Import^{99\to07}$	0.00610***	0.00610**	-0.00142	-0.00142	0.00200	0.00200
	(0.0017)	(0.0024)	(0.0013)	(0.0013)	(0.0019)	(0.0016)
$Labor\_Intesity$ (1999)	-0.20433***	-0.20433***	0.04791*	0.04791*	0.09353**	0.09353
	(0.0358)	(0.0507)	(0.0290)	(0.0291)	(0.0400)	(0.0673)
$\Delta Profits^{99\to07}$	0.00002	0.00002	-0.00002	-0.00002	-0.00000	-0.00000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Change in Income (1995 – 1998)	-0.00567	-0.00567	0.00411	0.00411	0.00531	0.00531
	(0.0047)	(0.0055)	(0.0045)	(0.0040)	(0.0055)	(0.0057)
Constant	0.25464***	0.25464***	0.39095***	0.39095***	-0.50831***	-0.50831***
	(0.0649)	(0.0661)	(0.0561)	(0.0771)	(0.0519)	(0.0652)
Observations	26103	26103	18928	18928	18928	18928
R-squared	0.1733	0.1733	0.0795	0.0795	0.0856	0.0856
Income Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Wealth Deciles (1999)	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Muni-Industry	Industry	Muni-Industry	Industry	Muni-Industry	Industry
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes

Figure O.A.I: Industry-Level Trends and Correlations

This figure presents the industry-level changes in adoption of robots in the European countries, and various other industry level trends, including changes in exposure to imports from China and European countries, percentage changes in the capital intensity and IT capital, changes in the profitability, early trends in employment growth, and labor intensity. Note that we normalize the values of each variable relative to the industry with the largest value for comparison.

Figure O.A.II: Kernel Density of Household Net Wealth (1999)

This figure shows the comparison of distribution of household net wealth in 1999 between treatment group (i.e., the HHI of household's educational major is above the median HHI across individuals working in the same industry) and the control group (i.e., the HHI of household's educational major is below the median HHI across individuals working in the same industry). Source: Author computations using household-level LINDA dataset from Statistics Sweden.

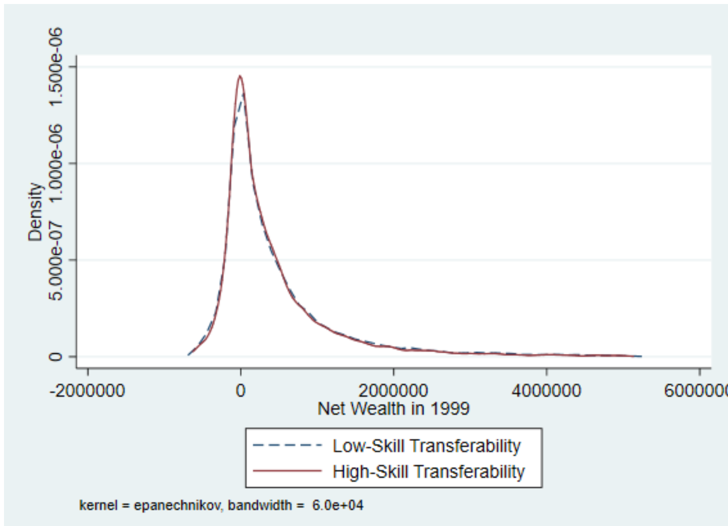


Figure O.A.III: Kernel Density of Annual Houehold Income (1999)

This figure shows the comparison of distribution of household income in 1999 between treatment group (i.e., the HHI of household's educational major is above the median HHI across individuals working in the same industry) and the control group (i.e., the HHI of household's educational major is below the median HHI across individuals working in the same industry). Source: Author computations using household-level LINDA dataset from Statistics Sweden.