Do Robots Increase Wealth Dispersion?*

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Abstract

We demonstrate that increased automation has a significant impact on both static and dynamic aspects of wealth distribution. Households who are more exposed to 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 in saving rates. We argue and provide evidence that the adverse effects of rapid robotization on individual workers' human capital, and thereby, on their financial risk taking behavior and investment choices appear to be an additional operative channel.

Keywords: Wealth inequality, portfolio choice, financial wealth, robots, automation, labor income uncertainty.
JEL Codes: D31, J24, E21, D1, G11

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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 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, 2017; Graetz and Michaels, 2017; 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 (2017) and the references therein.

[2] Indeed, 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, 2017), automation and advances in production methods negatively affect wages and employment opportunities of individual workers (Acemoglu and Restrepo, 2017; Autor and Salomons, 2018), and further correlate with increases in labor income risk and wage inequality (Kogan et al., 2018).

We provide evidence that increased automation has indeed negative effects on both static and dynamic 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 2.5 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 first investigate whether the impact of robots on household wealth operates through its direct effects on earnings of individuals. Even though we find negative wage effects of automation, our analysis suggests that differences in earned incomes alone do not explain the variation in levels and dynamics of household wealth.

Next, we examine the potential role of heterogeneity in saving rates across households to explain the observed patterns in the wealth distribution, and find no support for this explanation. Specifically, we observe that exposure to robots variable still exhibits negative significant effects on household wealth variables even after conditioning on the total saving rates of households along with other control variables.

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 operative 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 their work, and hence, face increased uninsurable risk in their human capital are more likely to exit from the stock market. Specifically, ceteris paribus, a one-standard-deviation exogenous rise in the robot density in their industry of employment leads to an 11.4% increase in the exit probability of households from the stock market. As these individuals fully rebalance their financial portfolio away from (both direct and indirect) stocks, they also forgo substantial equity returns up to 4.3% on a year during the observation period (Calvet et al., 2007), and thereby, experience a substantial drop in the growth of their financial wealth and accumulate less financial wealth relative to their income.

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 et al., 2015; Berg et al., 2018). For example, Acemoglu and Restrepo (2018b) 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 US Council of Economic Advisers, more than 80 percent of jobs paying less than 20 USD per hour in the US 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

[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.

[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.

methods can 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 only observe negative significant wealth effects for low-skill individuals (i.e., proxied by lower-educational attainment), while we find no effect for high-skills individuals. Similarly, the reduced financial risk taking channel is 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. To overcome this endogeneity issue, following a similar identification strategy as in Autor et al. (2013) and Acemoglu and Restrepo (2017), 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 these eleven developed countries represents the advances in global technological frontier (Acemoglu and Restrepo, 2017). Hence, our instrumental variable 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 and to pin down its causal effects on household wealth accumulation.

Our paper complements a small but growing literature which analyzes the economic consequences of increased automation.[5] For example, Acemoglu and Restrepo (2017) find that penetration of industrial robots across US local labor markets reduce aggregate employment and wages, while, in an international sample, Graetz and Michaels (2017) document positive productivity effects of automation, which, however, reduce the employment of low-skill workers. We contribute to this literature along several dimensions. First, 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. Second, and more importantly, 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.[6]

Our paper also relates to the empirical literature on the importance of uninsurable background risk in the demand for risky assets (Fagereng et al., 2017; Betermier et al., 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.

The remainder of the paper proceeds as follows. Section 2 introduces the data sources, and presents information 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. Section 4 presents the impact of increased automation on labor market. In Section 5 we present the results on the wealth analysis and further discuss and explore mechanisms. Section 6 reports the findings on the distributional effects of robots. In Section 7 we present the results of additional robustness and sensitivity checks. Section 8 concludes the paper.

[5] See also Acemoglu and Restrepo (2018a); Aghion et al. (2017); Freeman (2015); Benzell et al. (2015); Sachs and Kotlikoff (2012).

[6] It is, however, important to note that the focus of our paper is on the direct effects of automation on economic and financial outcomes of households who are exposed to robots at work rather than the aggregate impact of robots as in, for example, Acemoglu and Restrepo (2017).

2 Data, Variable Definitions, and Descriptive Statistics

In the analysis of the effects of automation on economic behavior and wealth accumulation of households, we make use of various 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). The IFR collects annual information on the total stock of robots and new robot installations, 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, 2017; Acemoglu and Restrepo, 2017; IFR, 2017).[7] For Sweden, on which we focus our investigation, we observe the total stock of robots for 14 industries on a yearly basis for the time period between 1993 and 2016.[8] 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.[9] 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 (2017), 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:

[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.

[8]See World Robotics 2017 report from the IFR for the details on the calculation of the inventory of robots.

[9]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.

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

As presented in Table I, 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 dataset, which is provided by Statistics Sweden.[10] LINDA consists of an annual cross-sectional sample of around 300,000 individuals, or approximately 3% of the entire Swedish population. The data contain highly accurate information on financial (e.g., detailed decomposition of household wealth at the asset class level) and demographic characteristics (e.g., age, marital status, educational attainment) of each sampled individual as well as very detailed information on their labor market outcomes such as earnings, employment status, and industry of occupation (i.e., detailed at the three-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 or measurement errors. First, we only focus on working-age households who age between 22 and 60 during the sample period (Hurst and Lusardi, 2004; 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.[11]

[10] 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 (2017). We provide further details about the matching procedure in Table O.A.1 in the Online Appendix.

[11] In other words, 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.

According to the employment counts from the *EU KLEMS* database, the number of employees in the industries that 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, however, we allow for the sampled households to switch industries or become unemployed or move to different locations in the following years. Finally, out of this conservatively constructed sample, we eliminate households with any missing information on labor market outcomes, financial assets and 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.[12]

The key variable of interest in our analysis is the household's exposure to 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, 2017).[13] Panel B of

[12]It is important to note that, as of now, we only consider the household head's exposure to robots (rather than each household member's exposure to robots) when analyzing the effects of automation on household economic behavior.

[13]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.

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 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. The import data are collected from Statistics Sweden, and information on employment levels again comes from the *EU KLEMS* database. Second, following Acemoglu and Restrepo (2017), we control for whether a given industry is declining in terms of change in the nationwide employment levels between 1993 and 1998. Finally, 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 some 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, relevant industry trends, and local economic conditions through regional fixed effects. Our base model takes the following form:

$$\Delta Y_{ijk}^{99\to 07} = \alpha \cdot \Delta Robot\_Density_{j}^{99\to 07} + \beta \cdot HH\_Controls_{i}^{99} + \gamma \cdot \Delta IND\_Controls_{j}^{99\to 07} + \delta_k + \epsilon_{ijk} \tag{4}$$

where $\Delta Y_{ijk}^{99\to 07}$ 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 highly accurate information on numerous household demographic and financial characteristics, which are represented by vector $HH\_Controls_{i}^{99}$. In our regressions, we control for household age and age squared to capture the hump-shaped profile of wealth and financial decisions, educational attainment measured by three different indicator variables (i.e., less than high school, high school graduate, and college and more), gender, marital status of the household head, separate variables for number of adults and number of children in the household, a dummy variable for whether the household is an immigrant, (inverse hyperbolic sine of) household disposable income, and quartile dummies for household net wealth. Note that all household controls are defined for the initial time period, which is 1999.

In addition to household characteristics, we account for several relevant industry controls (i.e., $IND\_Controls_{j}^{99\to 07}$) so as to isolate the effect of automation from other industry level trends and changes. The vector $IND\_Controls_j^{99\rightarrow 07}$ includes changes in exposure to Chinese imports between 1999 and 2007; 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 and environment. In Sweden, there are a total 290 municipalities, which are responsible for various tasks such as social services or physical planning. Hence, the municipality fixed effects account for possible latent regional characteristics and capture the direct effects of the location of households.[14] In our main specifications, we also control for initial robot density (measured in our base year that is 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 changes and trends that can be correlated with growth in robot density and wages and employment prospects in that industry. This would pose a threat to our identification. For example, a rapid increase in unionization in 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.[15]

To pin down the causal effects of increased exposure to robots on economic outcomes of households, 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) and Acemoglu and Restrepo (2017), we instrument for changes in robot density between 1999 and 2007 in the Swedish industries using the contemporaneous median changes in robot density across

[14] Also, note that municipalities represent the most disaggregated geographic level in Sweden for which macroeconomic information is collected and calculated.

[15] 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.

eleven other developed Western European countries.[16] Building on the same ideas as in Acemoglu and Restrepo (2017), 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.[17] Indeed, the first-stage regressions 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.[18]

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 further allows us to isolate the effect of an (exogenous) increase in robot density on the economic outcomes of households.

Finally, recall that Equation 4 is defined and estimated in first differences (i.e., changes between 1999 and 2007). Also, it is important to note that we correct standard errors for potential spatial correlation across households within a municipality by clustering at the municipality level. We obtain similar results when we account for possible serial correlation and heteroskedasticity within municipality-industry level (i.e., there is a total of 2,942 municipality-industry cells), which we present in the Online Appendix.

[16]The eleven other developed countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Portugal, and the United Kingdom.

[17]To the latter, we are unable to perform any over-identification tests such as the Hansen-J statistic to test the statistical exogeneity of the excluded instrument since our model is exactly identified.

[18]As in almost every IV estimation, we acknowledge that our identification strategy may be subject to some potential limitations. For example, the IV estimates may be contaminated if there is a negative correlation between the excluded instrument, i.e., changes in robot exposure in the (non-Swedish) European countries, and changes in the economic outcomes of Swedish households. Such a negative correlation may arise if any negative shock to the Swedish industries (that affect the labor market and financial outcomes of the Swedish workers) is positively correlated with the adoption of robots in other advanced countries. To overcome, or at least to minimize, the severity of this problem, we account for various industry level trends in Sweden such as the contemporaneous changes in exposure to Chinese imports, percentage changes in the capital intensity and IT capital, and early trends in employment growth and adoption of robots of a given industry in all our regressions.

4 The Effect of Robots on Earnings and Unemployment Risk

We begin our empirical analysis with investigating the relationship between labor market outcomes of households and changes in their exposure to robots at work by considering two important dimensions of labor market outcomes. Specifically, we analyze whether working in an industry that experienced a higher robot adoption over the observation period affects the income growth and job-loss risk of households in that industry. 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, aggegate employment and wages (Graetz and Michaels, 2017; Acemoglu and Restrepo, 2017).[19]

Table III presents the regression results on labor market outcomes.[20] In columns (1) and (2) of Table III, we consider 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. We find that both the OLS and the IV coefficients on robot exposure variable are negative and statistically significant, albeit, the IV coefficient is larger in magnitude, -0.009 versus -0.016. More specifically, based on the IV coefficient, 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, reduces the income growth

[19] Using the same dataset on industrial robot stock from the IFR, Graetz and Michaels (2017) 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 (2017) analyze the equilibrium effects of automation on aggregate wages and employment shares across US commuting zones. Specifically, the authors first formally model the interactions between robots and workers in the production of different tasks, and derive testable predictions on how robots can affect aggregate labor market outcomes. 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] A key distinction of our labor market analysis from the existing papers is that we use an extensive individual-level panel data and focus on the direct effects of automation on labor market outcomes of households who are exposed to robots at work rather than the aggregate impact of robots. Furthermore, our dataset enables us to track the economic outcomes of the same individuals over a nine year period. Hence, both the panel dimension and rich nature of our dataset allow us to control for a wide range of individual characteristics and to isolate the effects of automation from other industry-level trends and region specific macro shocks.

of individuals by 5.2% (t-statistics: 2.60). This effect is economically meaningful, given that the average (nominal) income growth between 1999 and 2007 accounts for 19%.[21]

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 et al. (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).

Columns (3) and (4) of Table III report the estimation results. The IV estimates indicate that, ceteris paribus, a one-standard deviation increase in the robot density increases the probability to become unemployed by 1.5 percentage points. The effect is statistically highly significant (t-statistics: 5.52), and meaningful in economic terms. To put this into context, we compare the effect of automation with that of educational attainment. Our estimates imply that a one-standard deviation increase in robot density would fully offset the effect of having a high school degree (as compared to being a high-school dropout) on becoming unemployed, indicating that the impact of automation on job-loss risk is significant in magnitude. The positive contribution of robots to unemployment probability 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.

It is also worth briefly discussing some of the other controls in the regressions and their importance. First, and not surprisingly, we find that increased exposure to Chinese imports reduces the income growth and increases the unemployment probability of households. The

[21] 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.2 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 the transfers from the government.

negative and significant effect of exposure to imports from China on wages and employment is consistent with the findings of the prior literature (Autor et al., 2013; Bloom et al., 2016). More interestingly, we observe that changes in ICT capital in a given industry is positively correlated with the income growth. This result is in line with the findings of Acemoglu and Restrepo (2017) who note that the effect of robots on wages may be distinct from that of ICT capital and other related information technologies (Acemoglu and Restrepo, 2017). When we turn to household controls, we observe that educational attainment and being a male positively contribute to income growth and employment, while immigrants tend to experience a lower income growth and face a higher job-loss risk than the natives during the observation period.

In summary, we establish negative and significant effects of robots on labor market outcomes of households. Next, we go beyond the labor market and investigate the effects of robots on household wealth accumulation.

5 Beyond the Labor Market: The Effect of Robots on Household Wealth

This section presents the results of household wealth regressions, and further discusses and explores mechanisms.

5.1 Robots and Distribution of Wealth

We next analyze the effects of automation on both static and dynamic aspects of the wealth distribution. 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 et al., 2015; Chetty et al., 2014).[22] This wealth measure, by definition, accounts for life-cycle differences across households (Black et al., 2015). Also, it can be defined for zero or negative values of net wealth, which is, for example, not feasible with a log transformation. 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 households in the LINDA dataset with non-missing wealth information.

Before presenting the formal econometric estimates, we first provide some suggestive evidence on the relationship between increased use of robots and household wealth. In Figure I, we depict 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.[23] As illustrated in the graph, all three groups exhibit increased wealth dispersion throughout the observation period. Interestingly, the rise in wealth dispersion monotonically increases in the changes in robot density, indicating potential effects of automation on household wealth accumulation. While Figure I is suggestive, we now formally analyze the relationship between automation and household wealth dynamics.

First, we use the net wealth percentile rank of a household in 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 IV present the regression results. Both OLS and IV estimates imply a negative and statistically highly significant effect of exposure to robots on the rank of households in the wealth distribution (t-statistics: -8.15). To give an idea of the magnitude of automation

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

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

effects, a one-standard-deviation increase in the robot density in an industry reduces the rank of individuals in the wealth distribution by 2.5 percentiles. To put this into context, we again contrast it with the effect of educational attainment level on the wealth rank of households. We observe that the effect of robots is equivalent to one-fifth of that of having a college degree (where high school drop-outs being the reference group). Hence, the magnitude of the automation effects is quite considerable, given the importance of educational attainment in the wealth accumulation (Huggett et al., 2011; Epper et al., 2018).

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. In particular, 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. Note that this measure enables 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) and (4) of Table IV present our OLS and IV estimates. We find that households who are more exposed to industrial robots at work also experience greater downward mobility in the 1999-2007 period. The IV estimate in column (4) of 0.004 indicates that a one-standard-deviation exogenous rise in the robot use in an industry leads to a 1.2 percentage points increase in the probability of a household falling in the wealth distribution over the sample period (t-statistics: 2.41). 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 are consistent with the patterns observed in Figure 1, indicating that rapid automation can contribute to a more dispersed wealth distribution.

Controlling for other household variables, we find that educational attainment and household income both negatively contribute to downward mobility, while they have a positive effect on the household rank in the wealth distribution. Interestingly, we observe that immigrants tend to be in lower ranks of the wealth distribution, however, they do not experience any downward mobility relative to natives during the observation period.

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 conditioning on homeownership. Also, 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., 2018). 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 et al. (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 appears to affect 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 both static and dynamic aspects of wealth distribution.

A natural explanation for our findings could be the differences in earned incomes of households. Recall our findings that individuals who are working in industries with a higher rate of robot adoption on average experience lower income growth. Accordingly, wealth accumulation behavior of households could differ from each other, with those who are less exposed to robots accumulating higher levels of wealth over time.[24] To address this concern, we rerun our wealth regressions by including (the inverse hyperbolic sine of) household disposable income in 1999 and realized income growth between 1999 and 2007 as additional regressors in our analysis, both of which enter positively and significantly in the wealth regressions. As presented in Table O.A.7, we still observe that the exposure to robot variable remains significant with a negative sign. We obtain similar results even when we use the average disposable income over the 5 year period prior to 1999 in lieu of income levels in 1999 in these regressions (Guvenen et al., 2017).[25]

A further potential consideration is that observed differences in wealth can arise from the heterogeneity in saving rates across households from different industries, as argued by the standard models (De Nardi and Fella, 2017).[26] 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 several ways. First, we calculate the total saving rate of each sampled household and include this variable as an additional covariate in the wealth analysis.[27] The results, tabulated in Table O.A.8, show that exposure to robots

[24]To illustrate this channel, consider two identical households owning the same initial level of wealth, earning the same (initial) income, and having identical savings rate. Under the assumption of homogeneous rates of returns to savings, as households from different industries experience different income growth due to robots, the one household that is less exposed to automation would accumulate higher levels of wealth over time.

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

[26]The existing theories argue that there can be various reasons for the heterogeneity of saving behavior. For example, the variation in the saving rates can be related to the heterogeneity in time preferences (Krusell and Smith, 1998) or to the differences in the levels of household wealth (Carroll, 1998).

[27]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 et al. (2017), we only consider those households with non-zero or non-negative net wealth in the analysis.

variable still exhibits a negative significant effect even after controlling for total saving rates of individuals along with other control variables. In another robustness exercise, we include initial wealth of households (as of 1999) in our wealth regressions, which is motivated by the recent contribution of 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.9 and O.A.10, both the OLS and 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 differential saving rates of individuals across industries.

Finally, increased automation in an industry can affect household wealth 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., 2016; Fagereng et al., 2018). In sum, choice of investment options and heterogeneity in returns to financial wealth emerge as an important mechanism to explain the variation in household wealth. In the next section, we discuss and explore this mechanism.

5.2 Robots, Financial Risk Taking, and Financial Wealth

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 market analysis in Section 4. The theory argues that increased background risk and its associated costs reduce the willingness of investors to take other types of risk, such as

Finally, we winsorize the saving rate variable at 1% level to eliminate any concerns about the outliers. It is also worthwhile to mention that we obtain similar results even when we scale the total savings by lagged household income instead of their net wealth from prior year.

holding risky financial assets (Eeckhoudt et al., 1996).[28] As returns to wealth are directly affected by willingness of households to take financial risk (Ameriks et al., 2003), reducing or completely eliminating the exposure to stock market (in response to increased human capital risk) would lead to accumulating lower levels of wealth over time, which is also supported by the data. For example, using household data from Sweden, Bach et al. (2016) find that individuals in the top 1% of the wealth distribution earn 400 basis higher annual returns on their financial wealth than the median household, which, as the authors argue, are primarily compensations for their exposure to higher levels of systematic risk.[29]

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 V reports our OLS and IV estimates. In Columns (1) and (2), the dependent variable is the stockholding status of a given household that is an indicator variable, which takes the value of 1 if household i holds directly or indirectly stocks in 2007. In other words, we first focus on the static aspect of the household financial behavior, and estimate the probability of *being* a stockowner.

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 reduces the probability of households in that industry to hold stocks, although the IV coefficient is smaller in magnitude and only marginally significant (t-statistics:-1.83). 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 percentage point. In fact, both economically and statistically weaker results using the stockholding status as a dependent

[28] 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.

[29] In another important contribution, Fagereng et al. (2018) document a return spread of 260 basis points between the 90th and 10th percentile of the financial wealth distribution in Norway.

variable is somewhat consistent with the previous findings of the literature. For example, in their analysis of the effect of labor income risk on asset allocation, Betermier et al. (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 Column (3) and (4), we next consider changes in stockholding behavior by focussing on the exit decisions of households from the stock market, shifting our analysis from the static aspect of household financial behavior to its dynamics. In particular, the dependent variable is now a dummy variable that equals to 1 if household i held both directly and indirectly stocks in 1999 but liquidiated all her stock holdings in 2007. We only include those households who remain in the stock market throughout the sample period in the reference group, which reduces the sample size by approximately 8,250 to 22,125 households.

Consistent with the theoretical expectations, our results indicate that an increase in the robot density in an industry increases the probability of stock market exit. The effect is not only statistically significant (t-statistics: 2.43) but also economically highly meaningful: the IV estimate imply that a one-standard-deviation exogenous rise in the robot use growth, 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 percentage point. The magnitude of the coefficient estimate might appear at first glance relatively small in economic terms. Though, this estimate implies an 11.4% increase in the exit probability, as the stock market exit rate in our sample equals to 8.20%. It is important to note that our results are robust to controlling for unobserved household heterogeneity as reported in O.A.14. Overall, this finding conforms to our proposed 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).[30]

The sign and statistical significance of other investor controls in our estimation model is consistent with what has been found in household finance regressions for these variables to date (Brunnermeier and Nagel, 2008). For example, exit probability monotonically decreases in household wealth. Similarly, higher levels of educational attainment and disposable household income also negatively contribute to the decision of households to exit from the stock market.

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 differences in financial wealth between 1999 and 2007) on the changes in robot density over the sample period, and other household and industry controls.[31] As presented in columns (1) and (2) of Table VI, 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, based on the IV coefficient, a one-standard deviation exogenous increase in the robot density reduces the rate of financial wealth accumulation by 15.3% over the observation period (*t*-statistics:-4.71). Finally, we consider the effects of increased automation on the financial wealth to income ratio of individuals in 2007.[32] Column (3) and (4) of Table VI report the estimation results. Both the OLS and IV coefficients on changes in the robot density variable is negative and statistically highly significant (*t*-statistics:-5.85), sug-

[30]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.

[31]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.

[32]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.

gesting 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.[33] Taken as a whole, these findings support the notion that individuals who eliminate their exposure to 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.

6 Distributional Effects of Robots

Up until now in our 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 (2018b) show that middle-aged workers who perform blue-collar tasks are more likely to be replaced by industrial robots relative 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 et al., 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 effects of robots.

[33] In fact, models of precautionary saving imply that 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.

Table VII presents the key results for our cross-sectional analysis.[34] 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 greater 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 and decline in magnitude. The latter result is somewhat surprising but consistent with the findings of Acemoglu and Restrepo (2017) 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).

When we analyze the wealth effects by skill-level, an interesting pattern emerges. As presented in Panel B of Table VII, we only observe negative wealth effects for low-educated households, who experience a greater probability of moving to lower wealth classes and ending up in a lower rank in the wealth distribution. On the other hand, we find no significant effect on both static and dynamic aspects of wealth accumulation for better-educated households. A similar perspective also applies to household financial risk taking. As presented in Panel C, for the low-educated households, the IV coefficient on changes in robot density is negative and significant at the one-percent level, while it is not statistically different than zero for households with at least a college degree. Finally, it is also important to note that the increase in industrial robot use has a more pronounced negative effect on the financial wealth accumulation of the less-educated group.

In summary, there appears to be asymmetric wealth effects of robots across different segments of the population, which can 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, 2017

[34]Note that we present the results of the IV regressions, which represents our preferred estimation model. For brevity, we only report the coefficient estimates on exposure to robot variable, but we of course control for all relevant household characteristics, industry controls, and regional fixed effects in our regression.

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 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 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.11, are consistent with those of our baseline regressions, suggesting that our results are not merely driven by the automative industry.

To further investigate the robustness of our results, we next 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.

Next, 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 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.13, 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 appear not to drive our results. In untabulated tests, we also verify these findings using industry of employment information from 1993.

In an additional robustness exercise, we remove unobserved time-invariant household heterogeneity by first-differencing the wealth and stock market models. The regression results of the first-differenced models are reported in Table O.A.14. When controlling for household fixed effects, we observe that the exposure to robot variable remains its significance in all regressions. It is also important to note that the magnitude of the coefficient estimates increase drastically when we control for fixed effects.

Lastly, we consider an alternative definition of the technological frontier and rerun the IV regressions. In particular, we use the median changes in robot density per thousand workers in the Northern European countries, which are Austria, Belgium, Denmark, Finland, Germany, and the Netherlands. We note that the results, presented in Table O.A.15, are qualitatively similar to our baseline results.

8 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 spread of industrial robots on static and dynamic aspects of wealth distribution. 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 seem to explain the differences in levels and dynamics of household wealth. In addition, we argue and provide evidence that the negative impact of automation (through increasing uninsurable human capital risk) on financial risk taking and investment choices of individuals appears to be an additional channel, which contributes to differences in levels and dynamics of household wealth. 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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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.

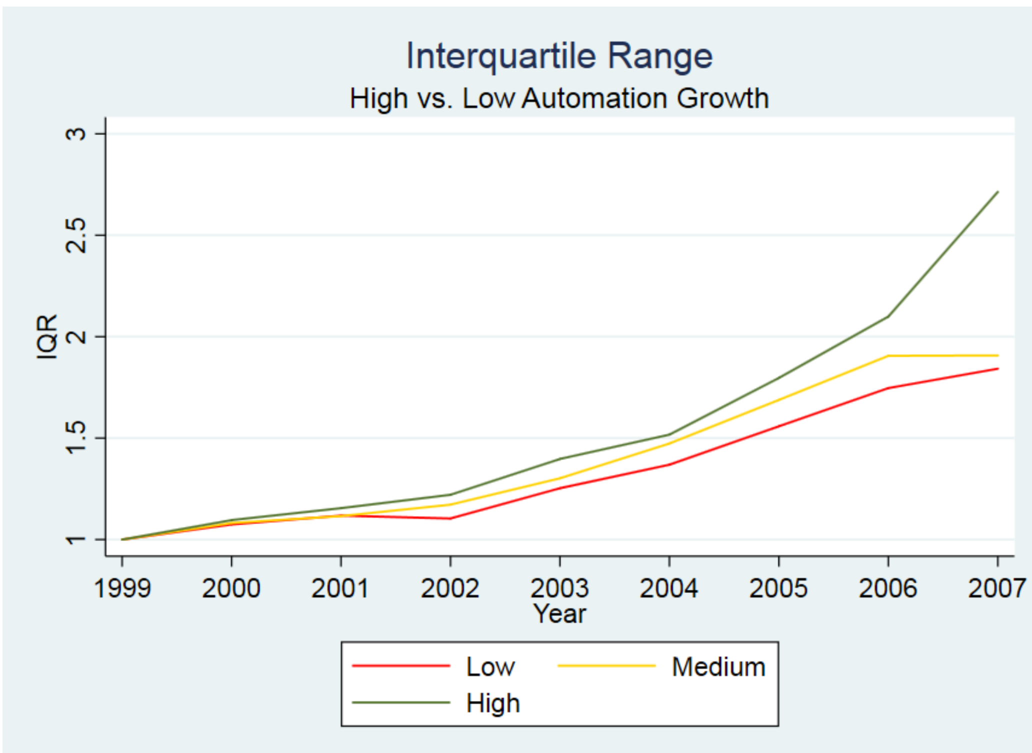

Table I: Use of Industrial Robots in the Swedish Industries

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 11 developed Western European countries that we use as an instrument. Panel C presents the descriptive statistics for the dependent variables that we consider in our empirical analysis, and Panel D report the industry controls. 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	7.526128
Male	30,375	.8698601	.3364628
Married	30,375	.550749	.4974261
College and more	30,375	.2424362	.4285638
High school	30,375	.5581235	.4966183
Nbr of adults	30,375	1.926782	.6272694
Nbr of children	30,375	1.416823	1.149026
Net wealth	30,375	524553.4	1730830
(IHS) Disposable income	30,375	13.2065	.4074581
(IHS) Labor income	30,375	12.71247	.5225056
Immigrant	30,375	.0995226	.2993674
Panel B. Variables of Interest			
$\Delta Robot\_Density^{99\to07}$	30,375	2.692674	3.274397
$\Delta Robot\_Density_{EU}^{99\to07}$	30,375	.4225471	.5255308
Panel C. Dependent variables			
Stockholding status (2007)	30,375	.7808066	.4137068
Exit from the stock market	22,125	.0819887	.2743537
Transition to unemployment	30,375	.0423374	.2013612
Change in log earnings	30,375	.1955055	1.547096
Downward wealth rank mobility	30,375	.5279342	.4992273
Net wealth rank (2007)	30,375	52.9843	27.16513
Wealth-to-income ratio (2007)	29,955	.8727597	1.807638
Panel D: Industry controls			
ΔNo of Employees (1993-98)	30,375	-1.620082	15.56758
$\Delta Chinese\_Import^{99\to07}$	30,375	2.470875	4.488955
ΔCapital Intensity	30,375	.2019738	.1145263
ΔICT Capital	30,375	.3862995	.1852666
Initial Robot Density (1995)	30,375	4.39876	6.252753

Table III: Exposure to Robots and Labor Market Outcomes

This table presents the coefficient estimates from the OLS and second-stage of the IV regressions for labor market outcomes. In all specifications, labor market outcome of interest is regressed on the changes in robot density between 1999 and 2007, initial observable household and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the log changes in household earnings between 1999 and 2007, and in (3)-(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 (1) and (3), OLS regressions are estimated, while we estimate an IV regression in (2) and (4) instrumenting for the change in robot density in Sweden 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, hence, our estimation model is equivalent to a fixed-effects regression. In all specifications, we account for potential spatial correlation across households within a municipality by clustering the standard errors at the municipality 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	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.00859*	-0.01665***	0.00189***	0.00471***
	(0.0048)	(0.0064)	(0.0006)	(0.0009)
Age	0.01290	0.01278	-0.00103	-0.00098
	(0.0127)	(0.0127)	(0.0020)	(0.0020)
Age squared	-0.00053***	-0.00053***	0.00002	0.00002
	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Male	0.34365***	0.34334***	-0.05067***	-0.05056***
	(0.0384)	(0.0381)	(0.0051)	(0.0050)
Married	0.10274***	0.10243***	-0.00749***	-0.00738***
	(0.0176)	(0.0175)	(0.0026)	(0.0026)
College and more	0.30450***	0.30078***	-0.02758***	-0.02628***
	(0.0291)	(0.0285)	(0.0039)	(0.0039)
High school	0.13622***	0.13436***	-0.01090***	-0.01024***
	(0.0261)	(0.0260)	(0.0034)	(0.0033)
Nbr of adults	0.12166***	0.12198***	-0.01361***	-0.01372***
	(0.0211)	(0.0209)	(0.0022)	(0.0022)
Nbr of children	0.15651***	0.15623***	-0.00245*	-0.00235*
	(0.0098)	(0.0097)	(0.0013)	(0.0013)
Immigrant	-0.26335***	-0.26159***	0.03275***	0.03214***
	(0.0578)	(0.0572)	(0.0050)	(0.0050)
ΔNo of Employees (1993-98)	-0.00041	0.00008	0.00022*	0.00005
	(0.0010)	(0.0010)	(0.0001)	(0.0001)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.00898**	-0.00962**	0.00097**	0.00119***
	(0.0039)	(0.0039)	(0.0005)	(0.0005)
ΔCapital Intensity	-0.02452	-0.06565	-0.01709	-0.00267
	(0.0865)	(0.0844)	(0.0125)	(0.0130)
ΔICT Capital	0.14936**	0.13454**	-0.00011	0.00509
	(0.0637)	(0.0665)	(0.0086)	(0.0090)
Initial Robot Density (1995)	0.00005	0.00208	-0.00109***	-0.00180***
	(0.0027)	(0.0032)	(0.0004)	(0.0005)
Constant	-0.20535	-0.16261	0.09676**	0.08178**
	(0.2316)	(0.2299)	(0.0374)	(0.0374)
Observations	30,375	30,375	30,375	30,375
R^2	0.0712	0.0711	0.0346	0.0337
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table IV: Exposure to Robots and Household Net Wealth

This table presents the coefficient estimates from the OLS and second-stage of the IV regressions for household net wealth. In all specifications, net wealth measures are regressed on the changes in robot density between 1999 and 2007, initial observable household and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the percentile rank of the households in the within-cohort distribution, and in (3)-(4), the dependent variable is an indicator variable that takes the value of 1 if a household falls in the within-cohort net wealth distribution between 1999 and 2007, and 0 otherwise. In (1) and (3), OLS regressions are estimated, while we estimate an IV regression in (2) and (4) instrumenting for the change in robot density in Sweden 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, hence, our estimation model is equivalent to a fixed-effects regression. In all specifications, we account for potential spatial correlation across households within a municipality by clustering the standard errors at the municipality 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 (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.44696***	-0.78879***	0.00252**	0.00362**
	(0.0763)	(0.0968)	(0.0012)	(0.0015)
Age	-2.24288***	-2.24956***	0.02977***	0.02980***
	(0.2319)	(0.2289)	(0.0042)	(0.0042)
Age squared	0.02483***	0.02486***	-0.00036***	-0.00036***
	(0.0030)	(0.0030)	(0.0001)	(0.0001)
Male	3.19852***	3.18297***	-0.03508***	-0.03503***
	(0.4642)	(0.4621)	(0.0083)	(0.0082)
Married	2.43364***	2.41704***	-0.00798	-0.00793
	(0.4118)	(0.4087)	(0.0072)	(0.0071)
College and more	12.94445***	12.77618***	-0.10699***	-0.10646***
	(0.6240)	(0.6266)	(0.0097)	(0.0096)
High school	4.70319***	4.62129***	-0.02357***	-0.02331***
	(0.4196)	(0.4194)	(0.0077)	(0.0077)
Nbr of adults	-1.09222***	-1.09446***	-0.01299**	-0.01298**
	(0.4168)	(0.4127)	(0.0064)	(0.0064)
Nbr of children	-0.29157*	-0.30706*	0.00228	0.00233
	(0.1653)	(0.1638)	(0.0029)	(0.0029)
(IHS) Disposable Income	17.68274***	17.72956***	-0.11834***	-0.11849***
	(0.8389)	(0.8262)	(0.0114)	(0.0113)
Immigrant	-11.32475***	-11.24492***	-0.00994	-0.01020
	(0.5602)	(0.5563)	(0.0106)	(0.0106)
ΔNo of Employees (1993-98)	0.10119***	0.12163***	0.00020	0.00014
	(0.0169)	(0.0173)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.14586***	-0.17309***	0.00324***	0.00333***
	(0.0433)	(0.0437)	(0.0008)	(0.0008)
ΔCapital Intensity	-2.88401	-4.63382**	0.15027***	0.15587***
	(1.7537)	(1.8216)	(0.0306)	(0.0316)
ΔICT Capital	9.67114***	9.04501***	-0.04804***	-0.04604**
	(0.9941)	(0.9571)	(0.0184)	(0.0183)
Initial Robot Density (1995)	-0.30682***	-0.22051***	-0.00038	-0.00066
	(0.0539)	(0.0534)	(0.0007)	(0.0008)
Constant	-138.30676***	-137.04243***	1.51765***	1.51360***
	(10.3624)	(10.2412)	(0.1541)	(0.1532)
Observations	30375	30375	30375	30375
R^2	0.2333	0.2326	0.0643	0.0643
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table V: Exposure to Robots and Financial Risk Taking Behavior

This table presents the coefficient estimates from the OLS and second-stage of the IV regressions for household financial risk taking behavior. In all specifications, measures of financial risk taking are regressed on the changes in robot density between 1999 and 2007, initial observable household and contemporaneous industry characteristics and municipality dummies. In (1) and (2), we focus on the stockholding status in 2007, and in (3)-(4), the dependent variable is an indicator variable that takes the value of 1 if an incumbent stockholder household exits from the stock market as of 2007, and 0 otherwise. In (1) and (3), OLS regressions are estimated, while we estimate an IV regression in (2) and (4) instrumenting for the change in robot density in Sweden 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, hence, our estimation model is equivalent to a fixed-effects regression. In all specifications, we account for potential spatial correlation across households within a municipality by clustering the standard errors at the municipality 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	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\to 07}$	-0.00308***	-0.00268*	0.00208**	0.00285**
	(0.0010)	(0.0015)	(0.0009)	(0.0012)
Age	-0.01011***	-0.01010***	0.00163	0.00166
	(0.0037)	(0.0037)	(0.0033)	(0.0033)
Age squared	0.00004	0.00004	0.00001	0.00001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Male	0.02366***	0.02368***	-0.01672***	-0.01671***
	(0.0069)	(0.0068)	(0.0060)	(0.0060)
Married	-0.01734***	-0.01732***	0.01242***	0.01244***
	(0.0049)	(0.0049)	(0.0039)	(0.0038)
College and more	0.13006***	0.13025***	-0.05850***	-0.05816***
	(0.0084)	(0.0083)	(0.0066)	(0.0066)
High school	0.06460***	0.06470***	-0.02446***	-0.02428***
	(0.0068)	(0.0067)	(0.0064)	(0.0063)
Nbr of adults	-0.01320**	-0.01320**	0.00611	0.00613
	(0.0057)	(0.0056)	(0.0045)	(0.0044)
Nbr of children	0.00571**	0.00573**	-0.00407*	-0.00403*
	(0.0026)	(0.0026)	(0.0023)	(0.0022)
Wealth Quartile II	0.07014***	0.07016***	-0.03663***	-0.03662***
	(0.0070)	(0.0069)	(0.0064)	(0.0064)
Wealth Quartile III	0.16863***	0.16867***	-0.07181***	-0.07179***
	(0.0066)	(0.0065)	(0.0058)	(0.0057)
Wealth Quartile IV	0.21055***	0.21066***	-0.08855***	-0.08839***
	(0.0081)	(0.0081)	(0.0067)	(0.0066)
(IHS) Disposable Income	0.23067***	0.23060***	-0.06308***	-0.06327***
	(0.0082)	(0.0081)	(0.0068)	(0.0068)
Immigrant	-0.13690***	-0.13698***	0.04824***	0.04809***
	(0.0113)	(0.0112)	(0.0104)	(0.0103)
ΔNo of Employees (1993-98)	0.00002	-0.00001	-0.00004	-0.00008
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
$\Delta Chinese\_Import^{99\to 07}$	-0.00064	-0.00061	-0.00044	-0.00039
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
ΔCapital Intensity	0.06698***	0.06905***	-0.05477***	-0.05103***
	(0.0225)	(0.0226)	(0.0176)	(0.0178)
ΔICT Capital	0.03484**	0.03557**	-0.00359	-0.00211
	(0.0150)	(0.0152)	(0.0121)	(0.0123)
Initial Robot Density (1995)	0.00086	0.00076	-0.00026	-0.00046
	(0.0007)	(0.0008)	(0.0006)	(0.0006)
Constant	-2.21683***	-2.21816***	1.00533***	1.00340***
	(0.1214)	(0.1208)	(0.0982)	(0.0973)
Observations	30375	30375	22125	22125
R^2	0.1581	0.1581	0.0536	0.0536
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table VI: Exposure to Robots and Financial Wealth

This table presents the coefficient estimates from the OLS and second-stage of the IV regressions for household financial wealth accumulation. In all specifications, measures of financil wealth is regressed on the changes in robot density between 1999 and 2007, initial observable household and contemporaneous industry characteristics and municipality dummies. In (1) and (3), OLS regressions are estimated, while we estimate an IV regression in (2) and (4) instrumenting for the change in robot density in Sweden using the median change in robot density across the (non-Swedish) 11 European countries. In all specifications, we account for potential spatial correlation across households within a municipality by clustering the standard errors at the municipality 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.

	Changes in Financial Wealth		Wealth-to-Income Ratio	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.02758***	-0.04680***	-0.01695***	-0.02698***
	(0.0075)	(0.0099)	(0.0045)	(0.0065)
Age	-0.01347	-0.01381	-0.04789***	-0.04808***
	(0.0249)	(0.0247)	(0.0159)	(0.0158)
Age squared	0.00023	0.00023	0.00097***	0.00097***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Male	0.37499***	0.37415***	-0.12373***	-0.12405***
	(0.0514)	(0.0512)	(0.0346)	(0.0344)
Married	0.12367***	0.12274***	-0.14464***	-0.14504***
	(0.0326)	(0.0324)	(0.0254)	(0.0252)
College and more	0.70377***	0.69486***	0.18282***	0.17802***
	(0.0476)	(0.0471)	(0.0371)	(0.0368)
High school	0.29350***	0.28913***	0.05408*	0.05175*
	(0.0425)	(0.0422)	(0.0291)	(0.0289)
Nbr of adults	-0.08304**	-0.08325**	-0.25239***	-0.25252***
	(0.0381)	(0.0379)	(0.0352)	(0.0349)
Nbr of children	-0.09889***	-0.09979***	-0.13548***	-0.13595***
	(0.0169)	(0.0167)	(0.0119)	(0.0118)
(IHS) Disposable Income	0.99564***	0.99939***	0.54586***	0.54749***
	(0.0496)	(0.0492)	(0.0815)	(0.0809)
Immigrant	0.00356	0.00745	0.08762**	0.08967***
	(0.0603)	(0.0600)	(0.0338)	(0.0336)
ΔNo of Employees (1993-98)	0.00300**	0.00415***	0.00453***	0.00513***
	(0.0015)	(0.0015)	(0.0013)	(0.0013)
$\Delta Chinese\_Import^{99\rightarrow 07}$	-0.01352***	-0.01505***	-0.00168	-0.00246
	(0.0049)	(0.0048)	(0.0042)	(0.0043)
ΔCapital Intensity	0.26109*	0.16290	-0.63089***	-0.68192***
	(0.1399)	(0.1377)	(0.1241)	(0.1243)
ΔICT Capital	0.30275***	0.26780***	0.28882***	0.27047***
	(0.0965)	(0.0997)	(0.0818)	(0.0810)
Initial Robot Density (1995)	-0.00601	-0.00116	-0.01187***	-0.00933***
	(0.0044)	(0.0051)	(0.0026)	(0.0028)
Financial Wealth in Logs (1999)	-0.66295***	-0.66324***		
	(0.0069)	(0.0068)		
(IHS) Net Wealth (1999)			0.03138***	0.03132***
			(0.0008)	(0.0008)
Constant	-5.18899***	-5.13122***	-5.64021***	-5.60684***
	(0.7767)	(0.7728)	(1.0282)	(1.0192)
Observations	30375	30375	29955	29955
R^2	0.5781	0.5780	0.0655	0.0652
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table VII: Distributional Effects of Robots

This table presents the coefficient estimates from the second-stage of the IV regressions for various household economic variables. In (1) and (2), the dependent variable is a dummy variable that equals to 1 if a household, who was not saving for retirement in 1999, starts to contribute to the private retirement accounts in 2007. In (3) and (4), the dependent variable is a dummy variable that equals to 1 if a household, who was saving for retirement in 1999, stops contributing to the private retirement accounts in 2007. The dependent variable is regressed on the changes in robot density between 1999 and 2007, initial observable household and contemporaneous industry characteristics and municipality dummies. In (1) and (3), an OLS regression is estimated, while we estimate an IV regression in (2) and (4) instrumenting for the change in robot density in Sweden 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, hence, our estimation model is equivalent to a fixed-effects regression. In all specifications, we account for potential spatial correlation across households within a municipality by clustering the standard errors at the municipality 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	
$\Delta Robot\_Density^{99\rightarrow07}$	-0.01727**	-0.01438*	0.00511***	0.00240*
	(0.0071)	(0.0083)	(0.0010)	(0.0014)
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow07}$	-1.00243***	-0.25920	0.00456***	-0.00238
	(0.1083)	(0.1827)	(0.0017)	(0.0038)
	Panel C. Financial Risk Taking			
	Financial Wealth-to-Income Ratio		Exit from the Stock Market	
$\Delta Robot\_Density^{99\rightarrow07}$	-0.03847***	-0.02735**	0.00429***	-0.00294
	(0.0072)	(0.0128)	(0.0014)	(0.0019)
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Appendix for Online Publication

“Do Robots Increase Wealth Dispersion?”

THOMAS JANSSON and YIGITCAN KARABULUT

February 14, 2019

Abstract

This Online Appendix includes tables 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

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: Exposure to Robots and Income Growth - Allowing for Transfers

	Change in Income (incl. transfers)	
	OLS Estimates	*IV Estimates*
	(1)	(2)
$\Delta Robot\_Density^{99\to07}$	-0.00268***	-0.00597***
	(0.0008)	(0.0012)
Age	-0.02660***	-0.02665***
	(0.0035)	(0.0034)
Age squared	0.00024***	0.00024***
	(0.0000)	(0.0000)
Male	0.09214***	0.09202***
	(0.0067)	(0.0066)
Married	0.04945***	0.04932***
	(0.0043)	(0.0043)
College and more	0.07745***	0.07593***
	(0.0065)	(0.0064)
High school	0.01697***	0.01621***
	(0.0049)	(0.0048)
Nbr of adults	-0.10769***	-0.10756***
	(0.0041)	(0.0041)
Nbr of children	0.03484***	0.03473***
	(0.0022)	(0.0022)
Immigrant	0.01007	0.01078*
	(0.0066)	(0.0065)
ΔNo of Employees (1993-98)	-0.00008	0.00011
	(0.0002)	(0.0002)
$\Delta Chinese\_Import^{99\to07}$	-0.00098*	-0.00125**
	(0.0005)	(0.0005)
ΔCapital Intensity	-0.02844	-0.04523*
	(0.0267)	(0.0270)
ΔIT Capital	0.05255***	0.04650***
	(0.0135)	(0.0135)
Initial Robot Density (1995)	-0.00103*	-0.00020
	(0.0006)	(0.0006)
Constant	1.12218***	1.13963***
	(0.0655)	(0.0653)
Observations	30375	30375
R-squared	0.1011	0.1007
Clustering	Muni	Muni
Municipality FEs	Yes	Yes

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

	Upward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*
	(1)	(2)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.00293**	-0.00450***
	(0.0012)	(0.0015)
Age	-0.02770***	-0.02774***
	(0.0039)	(0.0039)
Age squared	0.00039***	0.00039***
	(0.0001)	(0.0001)
Male	0.05088***	0.05082***
	(0.0075)	(0.0075)
Married	0.02148***	0.02141***
	(0.0071)	(0.0071)
College and more	0.14350***	0.14278***
	(0.0094)	(0.0093)
High school	0.04333***	0.04298***
	(0.0071)	(0.0070)
Nbr of adults	0.00578	0.00575
	(0.0065)	(0.0065)
Nbr of children	-0.00282	-0.00289
	(0.0028)	(0.0028)
(IHS) Disposable Income	0.16888***	0.16916***
	(0.0102)	(0.0101)
Immigrant	-0.05625***	-0.05594***
	(0.0093)	(0.0092)
Net wealth quartile II (1999)	-0.28859***	-0.28870***
	(0.0133)	(0.0132)
Net wealth quartile III (1999)	-0.39764***	-0.39775***
	(0.0163)	(0.0162)
Net wealth quartile IV (1999)	-0.52697***	-0.52739***
	(0.0133)	(0.0132)
ΔNo of Employees (1993-98)	-0.00029	-0.00019
	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.00234***	-0.00247***
	(0.0007)	(0.0007)
ΔCapital Intensity	-0.06369**	-0.07172**
	(0.0288)	(0.0295)
ΔIT Capital	0.06563***	0.06282***
	(0.0170)	(0.0169)
Initial Robot Density (1995)	-0.00043	-0.00004
	(0.0008)	(0.0008)
Constant	-1.12314***	-1.11815***
	(0.1412)	(0.1401)
Observations	30375	30375
R-squared	0.1813	0.1813
Clustering	Muni	Muni
Municipality FEs	Yes	Yes

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

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99 \rightarrow 07}$	-0.39444***	-0.71109***	0.00254**	0.00365**
	(0.0703)	(0.0877)	(0.0012)	(0.0015)
Age	-2.75724***	-2.76268***	0.02959***	0.02961***
	(0.2105)	(0.2079)	(0.0042)	(0.0042)
Age squared	0.03037***	0.03039***	-0.00035***	-0.00035***
	(0.0027)	(0.0027)	(0.0001)	(0.0001)
Male	2.16855***	2.15563***	-0.03545***	-0.03541***
	(0.4388)	(0.4362)	(0.0083)	(0.0083)
Married	1.62278***	1.60858***	-0.00828	-0.00823
	(0.3606)	(0.3578)	(0.0073)	(0.0072)
College and more	12.02502***	11.87052***	-0.10733***	-0.10679***
	(0.5281)	(0.5319)	(0.0097)	(0.0096)
High school	4.04676***	3.97187***	-0.02381***	-0.02355***
	(0.4090)	(0.4096)	(0.0077)	(0.0076)
Nbr of adults	-1.74984***	-1.75096***	-0.01323**	-0.01322**
	(0.3712)	(0.3672)	(0.0064)	(0.0064)
Nbr of children	-0.91285***	-0.92629***	0.00205	0.00210
	(0.1396)	(0.1382)	(0.0029)	(0.0029)
(IHS) Disposable Income	12.89260***	12.94288***	-0.12009***	-0.12026***
	(0.7406)	(0.7293)	(0.0116)	(0.0116)
Immigrant	-7.77204***	-7.70324***	-0.00865	-0.00889
	(0.5200)	(0.5174)	(0.0104)	(0.0104)
Homeowner	19.63302***	19.60465***	0.00715	0.00725
	(0.7222)	(0.7196)	(0.0108)	(0.0107)
ΔNo of Employees (1993-98)	0.10520***	0.12412***	0.00020	0.00014
	(0.0158)	(0.0161)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99 \rightarrow 07}$	-0.14144***	-0.16667***	0.00325***	0.00333***
	(0.0405)	(0.0407)	(0.0008)	(0.0008)
ΔCapital Intensity	-4.34611***	-5.96454***	0.14974***	0.15538***
	(1.6294)	(1.6706)	(0.0307)	(0.0316)
ΔIT Capital	8.98883***	8.40994***	-0.04829***	-0.04627**
	(0.9972)	(0.9591)	(0.0184)	(0.0183)
Initial Robot Density (1995)	-0.30866***	-0.22872***	-0.00038	-0.00066
	(0.0473)	(0.0476)	(0.0007)	(0.0008)
Constant	-72.49908***	-71.42324***	1.54161***	1.53786***
	(9.4857)	(9.3807)	(0.1553)	(0.1543)
Observations	30375	30375	30375	30375
R-squared	0.3078	0.3072	0.0644	0.0643
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

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

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.44383***	-0.79439***	0.00254**	0.00359**
	(0.0752)	(0.0953)	(0.0012)	(0.0015)
Age	-2.21194***	-2.21885***	0.02995***	0.02997***
	(0.2313)	(0.2283)	(0.0042)	(0.0042)
Age squared	0.02460***	0.02463***	-0.00036***	-0.00036***
	(0.0030)	(0.0030)	(0.0001)	(0.0001)
Male	3.22733***	3.21132***	-0.03492***	-0.03487***
	(0.4592)	(0.4574)	(0.0082)	(0.0082)
Married	2.52042***	2.50322***	-0.00750	-0.00745
	(0.4146)	(0.4115)	(0.0072)	(0.0071)
College and more	12.67147***	12.49946***	-0.10851***	-0.10800***
	(0.6096)	(0.6117)	(0.0097)	(0.0096)
High school	4.55422***	4.47054***	-0.02440***	-0.02415***
	(0.4172)	(0.4168)	(0.0077)	(0.0077)
Nbr of adults	-1.07088**	-1.07322***	-0.01287**	-0.01286**
	(0.4148)	(0.4106)	(0.0064)	(0.0063)
Nbr of children	-0.42370**	-0.43932***	0.00154	0.00159
	(0.1641)	(0.1624)	(0.0029)	(0.0029)
(IHS) Disposable Income	16.89054***	16.94013***	-0.12275***	-0.12290***
	(0.8032)	(0.7908)	(0.0113)	(0.0113)
Immigrant	-10.78501***	-10.70422***	-0.00694	-0.00718
	(0.5472)	(0.5429)	(0.0107)	(0.0106)
Risk exposure (1999)	4.11730***	4.10907***	0.02291***	0.02293***
	(0.4513)	(0.4502)	(0.0074)	(0.0073)
ΔNo of Employees (1993-98)	0.10277***	0.12372***	0.00021	0.00015
	(0.0167)	(0.0171)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\rightarrow 07}$	-0.15279***	-0.18070***	0.00320***	0.00329***
	(0.0424)	(0.0427)	(0.0008)	(0.0008)
ΔCapital Intensity	-3.33717*	-5.13070***	0.14775***	0.15310***
	(1.7415)	(1.8053)	(0.0305)	(0.0315)
ΔIT Capital	9.70795***	9.06578***	-0.04784***	-0.04592**
	(0.9983)	(0.9604)	(0.0184)	(0.0183)
Initial Robot Density (1995)	-0.30949***	-0.22097***	-0.00039	-0.00066
	(0.0532)	(0.0527)	(0.0007)	(0.0008)
Constant	-130.60356***	-129.32241***	1.56051***	1.55668***
	(10.0987)	(9.9737)	(0.1537)	(0.1528)
Observations	30375	30375	30375	30375
R-squared	0.2369	0.2361	0.0647	0.0646
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

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

	Changes in Household Debt (1999-2007)			
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\to07}$	-0.00191	-0.00191	-0.00471	-0.00471
	(0.0124)	(0.0105)	(0.0092)	(0.0085)
Age	-0.42759***	-0.42759***	-0.21089***	-0.21089***
	(0.0409)	(0.0390)	(0.0312)	(0.0291)
Age squared	0.00431***	0.00431***	0.00155***	0.00155***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Male	0.12304	0.12304	0.34546***	0.34546***
	(0.0949)	(0.0757)	(0.0739)	(0.0609)
Married	-0.10868**	-0.10868**	0.13364***	0.13364***
	(0.0511)	(0.0530)	(0.0406)	(0.0400)
College and more	0.47686***	0.47686***	0.24851***	0.24851***
	(0.0808)	(0.0740)	(0.0522)	(0.0560)
High school	0.04155	0.04155	0.10292**	0.10292**
	(0.0575)	(0.0541)	(0.0500)	(0.0458)
Nbr of adults	0.03720	0.03720	0.29704***	0.29704***
	(0.0522)	(0.0503)	(0.0404)	(0.0401)
Nbr of children	-0.03084	-0.03084	0.21485***	0.21485***
	(0.0244)	(0.0225)	(0.0194)	(0.0184)
(IHS) Disposable Income	-0.72904***	-0.72904***	0.61667***	0.61667***
	(0.0998)	(0.0998)	(0.1086)	(0.0850)
Immigrant	0.37300***	0.37300***	-0.19504***	-0.19504***
	(0.0804)	(0.0915)	(0.0646)	(0.0740)
ΔNo of Employees (1993-98)	-0.00286	-0.00286	-0.00268	-0.00268
	(0.0029)	(0.0022)	(0.0020)	(0.0018)
$\Delta Chinese\_Import^{99\to07}$	-0.00410	-0.00410	-0.00442	-0.00442
	(0.0072)	(0.0060)	(0.0051)	(0.0046)
ΔCapital Intensity	-0.53097**	-0.53097**	-0.18900	-0.18900
	(0.2422)	(0.2230)	(0.1855)	(0.1739)
ΔIT Capital	0.24082	0.24082	0.18206	0.18206
	(0.1495)	(0.1555)	(0.1303)	(0.1240)
Initial Robot Density (1995)	0.00047	0.00047	0.00106	0.00106
	(0.0061)	(0.0055)	(0.0056)	(0.0048)
Household Debt in Logs (1999)			-0.60806***	-0.60806***
			(0.0108)	(0.0091)
Constant	20.35497***	20.35497***	3.89887***	3.89887***
	(1.5248)	(1.4380)	(1.4419)	(1.2171)
Observations	30375	30375	30375	30375
R-squared	0.0759	0.0759	0.4049	0.4049
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

Table O.A.7: Exposure to Robots and Household Net Wealth - Controlling for Income Growth

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\rightarrow07}$	-0.43786***	-0.77112***	0.00244**	0.00345**
	(0.0755)	(0.0964)	(0.0012)	(0.0015)
Age	-2.25541***	-2.26185***	0.02989***	0.02991***
	(0.2332)	(0.2302)	(0.0042)	(0.0042)
Age squared	0.02537***	0.02540***	-0.00036***	-0.00036***
	(0.0030)	(0.0030)	(0.0001)	(0.0001)
Male	2.83914***	2.82610***	-0.03180***	-0.03176***
	(0.4649)	(0.4629)	(0.0083)	(0.0082)
Married	2.32813***	2.31258***	-0.00702	-0.00697
	(0.4114)	(0.4085)	(0.0072)	(0.0072)
College and more	12.63206***	12.46989***	-0.10414***	-0.10365***
	(0.6214)	(0.6243)	(0.0097)	(0.0097)
High school	4.56213***	4.48314***	-0.02229***	-0.02204***
	(0.4169)	(0.4167)	(0.0077)	(0.0077)
Nbr of adults	-1.20851***	-1.21001***	-0.01193*	-0.01192*
	(0.4143)	(0.4102)	(0.0064)	(0.0064)
Nbr of children	-0.45333***	-0.46747***	0.00375	0.00380
	(0.1670)	(0.1655)	(0.0029)	(0.0029)
(IHS) Disposable Income	17.64789***	17.69373***	-0.11802***	-0.11816***
	(0.8230)	(0.8103)	(0.0114)	(0.0113)
Immigrant	-11.05198***	-10.97578***	-0.01244	-0.01267
	(0.5605)	(0.5574)	(0.0105)	(0.0104)
Income Growth (1999 - 2007)	1.05096***	1.04476***	-0.00960***	-0.00958***
	(0.0893)	(0.0887)	(0.0020)	(0.0020)
ΔNo of Employees (1993-98)	0.10169***	0.12160***	0.00020	0.00014
	(0.0168)	(0.0172)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\rightarrow07}$	-0.13646***	-0.16306***	0.00316***	0.00324***
	(0.0424)	(0.0429)	(0.0008)	(0.0008)
ΔCapital Intensity	-2.85370	-4.55955**	0.14999***	0.15519***
	(1.7362)	(1.8041)	(0.0306)	(0.0316)
ΔIT Capital	9.51263***	8.90324***	-0.04660**	-0.04474**
	(0.9782)	(0.9425)	(0.0184)	(0.0184)
Initial Robot Density (1995)	-0.30692***	-0.22279***	-0.00038	-0.00064
	(0.0529)	(0.0523)	(0.0007)	(0.0008)
Constant	-137.68344***	-136.45469***	1.51196***	1.50821***
	(10.1443)	(10.0303)	(0.1537)	(0.1528)
Observations	30375	30375	30375	30375
R-squared	0.2366	0.2359	0.0652	0.0651
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

Table O.A.8: Exposure to Robots and Household Net Wealth - Controlling for Household Saving Rate in 1999

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\to07}$	-0.37517***	-0.66804***	0.00483***	0.00671***
	(0.0737)	(0.0958)	(0.0014)	(0.0018)
Age	-1.92988***	-1.94054***	0.01980***	0.01987***
	(0.2280)	(0.2263)	(0.0049)	(0.0048)
Age squared	0.01931***	0.01939***	-0.00030***	-0.00030***
	(0.0029)	(0.0028)	(0.0001)	(0.0001)
Male	2.66917***	2.65710***	-0.03225***	-0.03217***
	(0.4601)	(0.4574)	(0.0101)	(0.0100)
Married	1.92899***	1.92371***	-0.01524*	-0.01521*
	(0.3579)	(0.3549)	(0.0078)	(0.0078)
College and more	10.46690***	10.32903***	-0.11366***	-0.11277***
	(0.5349)	(0.5321)	(0.0111)	(0.0111)
High school	3.65475***	3.57977***	-0.03190***	-0.03142***
	(0.4271)	(0.4250)	(0.0088)	(0.0087)
Nbr of adults	-0.14505	-0.15380	-0.00768	-0.00762
	(0.3458)	(0.3432)	(0.0074)	(0.0074)
Nbr of children	0.16129	0.14697	0.00056	0.00066
	(0.1628)	(0.1615)	(0.0033)	(0.0033)
(IHS) Disposable Income	13.39191***	13.46160***	-0.09294***	-0.09339***
	(0.6544)	(0.6473)	(0.0130)	(0.0129)
Immigrant	-7.13208***	-7.08506***	0.02204*	0.02174*
	(0.5724)	(0.5685)	(0.0126)	(0.0126)
Saving rate (1999)	-0.25830**	-0.25519**	-0.05262***	-0.05264***
	(0.1151)	(0.1143)	(0.0023)	(0.0022)
ΔNo of Employees (1993-98)	0.09338***	0.10918***	-0.00078**	-0.00088***
	(0.0173)	(0.0180)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\to07}$	-0.18195***	-0.20239***	0.00344***	0.00357***
	(0.0438)	(0.0440)	(0.0010)	(0.0010)
ΔCapital Intensity	-9.30398***	-10.62448***	0.16717***	0.17566***
	(1.8112)	(1.8553)	(0.0330)	(0.0336)
ΔIT Capital	9.63583***	9.04853***	-0.08014***	-0.07636***
	(1.1653)	(1.1468)	(0.0211)	(0.0208)
Robot Density (1995)	-0.30712***	-0.22986***	0.00197**	0.00147*
	(0.0445)	(0.0447)	(0.0008)	(0.0009)
Constant	-74.07100***	-73.31138***	1.53527***	1.53039***
	(10.4745)	(10.3418)	(0.1923)	(0.1907)
Observations	20933	20933	20933	20933
R-squared	0.2299	0.2292	0.1366	0.1366
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

Table O.A.9: Exposure to Robots and Household Net Wealth - Controlling for Initial Wealth Quartiles

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99\to07}$	-0.20653***	-0.32478***	0.00449***	0.00708***
	(0.0496)	(0.0636)	(0.0012)	(0.0015)
Age	-2.22034***	-2.22294***	0.02851***	0.02857***
	(0.1782)	(0.1767)	(0.0040)	(0.0040)
Age squared	0.01732***	0.01733***	-0.00040***	-0.00040***
	(0.0023)	(0.0023)	(0.0001)	(0.0001)
Male	1.93656***	1.93167***	-0.04598***	-0.04587***
	(0.3568)	(0.3540)	(0.0077)	(0.0077)
Married	0.79514***	0.79012***	-0.02249***	-0.02238***
	(0.2726)	(0.2709)	(0.0071)	(0.0071)
College and more	7.25287***	7.19816***	-0.14675***	-0.14556***
	(0.4485)	(0.4454)	(0.0097)	(0.0097)
High school	2.34184***	2.31489***	-0.04419***	-0.04360***
	(0.3067)	(0.3049)	(0.0072)	(0.0072)
Nbr of adults	-0.19703	-0.19863	-0.00417	-0.00414
	(0.2417)	(0.2395)	(0.0064)	(0.0063)
Nbr of children	-0.32738***	-0.33272***	0.00191	0.00203
	(0.1088)	(0.1078)	(0.0028)	(0.0028)
(IHS) Disposable Income	9.09334***	9.11473***	-0.17855***	-0.17902***
	(0.5211)	(0.5155)	(0.0119)	(0.0118)
Immigrant	-4.37404***	-4.35017***	0.06035***	0.05983***
	(0.3862)	(0.3831)	(0.0100)	(0.0099)
Wealth Quartile II (1999)	13.23806***	13.23006***	0.29230***	0.29248***
	(0.3355)	(0.3329)	(0.0133)	(0.0132)
Wealth Quartile III (1999)	29.60435***	29.59584***	0.39496***	0.39514***
	(0.4061)	(0.4028)	(0.0167)	(0.0166)
Wealth Quartile IV (1999)	50.08486***	50.05290***	0.45317***	0.45387***
	(0.5743)	(0.5677)	(0.0133)	(0.0132)
ΔNo of Employees (1993-98)	0.02769**	0.03481***	-0.00027	-0.00042
	(0.0119)	(0.0118)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99\to07}$	-0.12677***	-0.13620***	0.00299***	0.00320***
	(0.0297)	(0.0296)	(0.0007)	(0.0008)
ΔCapital Intensity	-1.84733	-2.45467**	0.12669***	0.13999***
	(1.1811)	(1.2264)	(0.0291)	(0.0299)
ΔIT Capital	4.18632***	3.97380***	-0.08529***	-0.08063***
	(0.7741)	(0.7640)	(0.0173)	(0.0171)
Initial Robot Density (1995)	-0.08092**	-0.05126	0.00116	0.00051
	(0.0326)	(0.0355)	(0.0008)	(0.0008)
Constant	-32.16498***	-31.78803***	2.18566***	2.17741***
	(6.7957)	(6.7368)	(0.1569)	(0.1556)
Observations	30375	30375	30375	30375
R-squared	0.5624	0.5623	0.1693	0.1692
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

Table O.A.10: Exposure to Robots and Household Net Wealth - Controlling for Initial Wealth in Levels

	Net Wealth Rank (2007)		Downward Mobility (1999-2007)	
	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
$\Delta Robot\_Density^{99 \to 07}$	-0.28598***	-0.53625***	0.00452***	0.00676***
	(0.0590)	(0.0760)	(0.0012)	(0.0015)
Age	-2.43016***	-2.43482***	0.02745***	0.02749***
	(0.1901)	(0.1882)	(0.0040)	(0.0040)
Age squared	0.02302***	0.02304***	-0.00038***	-0.00038***
	(0.0025)	(0.0024)	(0.0001)	(0.0001)
Male	2.30494***	2.29462***	-0.04617***	-0.04608***
	(0.3641)	(0.3625)	(0.0078)	(0.0077)
Married	1.52273***	1.51167***	-0.01929***	-0.01919***
	(0.3227)	(0.3206)	(0.0071)	(0.0071)
College and more	10.23673***	10.11684***	-0.14061***	-0.13954***
	(0.4670)	(0.4668)	(0.0095)	(0.0094)
High school	3.00960***	2.95170***	-0.04460***	-0.04408***
	(0.3458)	(0.3448)	(0.0071)	(0.0071)
Nbr of adults	-0.44063	-0.44304	-0.00490	-0.00488
	(0.3073)	(0.3040)	(0.0062)	(0.0062)
Nbr of children	-0.34475***	-0.35602***	0.00162	0.00172
	(0.1275)	(0.1266)	(0.0028)	(0.0028)
(IHS) Disposable Income	13.10548***	13.14517***	-0.17517***	-0.17553***
	(0.6275)	(0.6191)	(0.0112)	(0.0111)
Immigrant	-5.78479***	-5.73296***	0.05884***	0.05837***
	(0.3957)	(0.3939)	(0.0104)	(0.0103)
(IHS) Net Wealth (1999)	1.15618***	1.15481***	0.01435***	0.01437***
	(0.0153)	(0.0152)	(0.0005)	(0.0005)
ΔNo of Employees (1993-98)	0.07358***	0.08856***	-0.00014	-0.00028
	(0.0137)	(0.0138)	(0.0003)	(0.0003)
$\Delta Chinese\_Import^{99 \to 07}$	-0.16532***	-0.18522***	0.00300***	0.00318***
	(0.0340)	(0.0340)	(0.0008)	(0.0008)
ΔCapital Intensity	-5.38992***	-6.66709***	0.11916***	0.13058***
	(1.4106)	(1.4478)	(0.0285)	(0.0295)
ΔIT Capital	7.24189***	6.78670***	-0.07820***	-0.07413***
	(0.9029)	(0.8805)	(0.0174)	(0.0172)
Initial Robot Density (1995)	-0.22577***	-0.16272***	0.00063	0.00006
	(0.0390)	(0.0399)	(0.0008)	(0.0008)
Constant	-72.48685***	-71.63999***	2.33484***	2.32727***
	(8.2177)	(8.1287)	(0.1463)	(0.1452)
Observations	30375	30375	30375	30375
R-squared	0.4529	0.4525	0.1646	0.1645
Clustering	Muni	Muni	Muni	Muni
Municipality Fes	Yes	Yes	Yes	Yes

Table O.A.11: Exposure to Robots and Household Economic Behavior - Excluding the Automative Industry

	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
	Panel A. Labor Market			
	Change in Earnings		Transition into Unemployment	
$\Delta Robot\_Density^{99\to 07}$	-0.00950*	-0.02148***	0.00175***	0.00426***
	(0.0049)	(0.0064)	(0.0007)	(0.0009)
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\to 07}$	-0.48822***	-0.97492***	0.00247**	0.00369**
	(0.0755)	(0.0908)	(0.0012)	(0.0015)
	Panel C. Financial Risk Taking			
	Exit from the Stock Market		Wealth-to-Income Ratio	
$\Delta Robot\_Density^{99\to 07}$	0.00244***	0.00406***	-0.02145***	-0.03651***
	(0.0009)	(0.0011)	(0.0048)	(0.0068)
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

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

	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
	Panel A. Labor Market			
	Change in Earnings		Transition into Unemployment	
$\Delta Robot\_Density^{99\to07}$	-0.01875***	-0.02576***	0.00438***	0.00755***
	(0.0072)	(0.0088)	(0.0010)	(0.0013)
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\to07}$	-0.79471***	-1.14770***	0.00257	0.00421*
	(0.1083)	(0.1373)	(0.0018)	(0.0023)
	Panel C. Financial Risk Taking			
	Exit from the Stock Market		Wealth-to-Income Ratio	
$\Delta Robot\_Density^{99\to07}$	0.00434***	0.00444**	-0.02345***	-0.04220***
	(0.0014)	(0.0018)	(0.0078)	(0.0102)
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.13: Exposure to Robots and Household Economic Behavior - Sorting of Households

	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
	Panel A. Labor Market			
	Change in Earnings		Transition into Unemployment	
$\Delta Robot\_Density^{99\to07}$	-0.00778	-0.01796*	0.00145*	0.00519***
	(0.0071)	(0.0098)	(0.0008)	(0.0010)
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\to07}$	-0.37680***	-0.69265***	0.00274*	0.00415**
	(0.0850)	(0.1099)	(0.0015)	(0.0019)
	Panel C. Financial Risk Taking			
	Exit from the Stock Market		Wealth-to-Income Ratio	
$\Delta Robot\_Density^{99\to07}$	0.00258**	0.00322**	-0.01418**	-0.02485***
	(0.0011)	(0.0015)	(0.0059)	(0.0083)
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes

Table O.A.14: Exposure to Robots and Household Economic Behavior - Controlling for Unobserved Household Heterogeneity

	IV Estimates	*IV Estimates*
	(1)	(2)
	Panel A. Labor Market	
	Change in Earnings	Transition into Unemployment
$\Delta Robot\_Density^{99\rightarrow07}$	-0.01975***	0.00532***
	(0.0065)	(0.0009)
	Panel B. Household Wealth	
	Percentile Net Wealth Rank	Downward Mobility
$\Delta Robot\_Density^{99\rightarrow07}$	-0.93156***	0.00458***
	(0.1024)	(0.0016)
	Panel C. Financial Risk Taking	
	Exit from the Stock Market	Wealth-to-Income Ratio
$\Delta Robot\_Density^{99\rightarrow07}$	0.00394***	-0.04238***
	(0.0012)	(0.0066)
Household Controls	Yes	Yes
Industry Controls	Yes	Yes
Clustering	Muni	Muni
Municipality FEs	Yes	Yes

Table O.A.15: Exposure to Robots and Household Economic Behavior - Alternative Technological Frontier

	IV Estimates	IV Estimates
	(1)	(2)
	Panel A. Labor Market	
	Change in Earnings	Transition into Unemployment
$\Delta Robot\_Density^{99\rightarrow07}$	-0.01039	0.00278***
	(0.0071)	(0.0008)
	Panel B. Household Wealth	
	Percentile Net Wealth Rank	Downward Mobility
$\Delta Robot\_Density^{99\rightarrow07}$	-0.60368***	0.00405**
	(0.1105)	(0.0016)
	Panel C. Financial Risk Taking	
	Exit from the Stock Market	Wealth-to-Income Ratio
$\Delta Robot\_Density^{99\rightarrow07}$	0.00158	-0.03565***
	(0.0012)	(0.0063)
Household Controls	Yes	Yes
Industry Controls	Yes	Yes
Clustering	Muni	Muni
Municipality FEs	Yes	Yes

Table O.A.16: Exposure to Robots and Household Economic Behavior - Correcting the SEs at the Muni-Industry Level

	OLS Estimates	*IV Estimates*	*OLS Estimates*	*IV Estimates*
	(1)	(2)	(3)	(4)
	Panel A. Labor Market			
	Change in Earnings		Transition into Unemployment	
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.00859*	-0.01665**	0.00189***	0.00471***
	(0.0046)	(0.0065)	(0.0006)	(0.0008)
	Panel B. Household Wealth			
	Percentile Net Wealth Rank		Downward Mobility	
$\Delta Robot\_Density^{99\rightarrow 07}$	-0.44696***	-0.78879***	0.00252**	0.00362**
	(0.0738)	(0.0978)	(0.0012)	(0.0016)
	Panel C. Financial Risk Taking			
	Exit from the Stock Market		Wealth-to-Income Ratio	
$\Delta Robot\_Density^{99\rightarrow 07}$	0.00208**	0.00285***	-0.02126***	-0.03375***
	(0.0009)	(0.0011)	(0.0044)	(0.0066)
Household Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Clustering	Muni	Muni	Muni	Muni
Municipality FEs	Yes	Yes	Yes	Yes