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Do Robots Increase Wealth Dispersion?

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We document significant negative effects of exposure to increased automation at work on household wealth accumulation. Beyond the income and savings channels, we uncover a novel mechanism contributing to the negative wealth effects of automation that arises through the endogenous optimal portfolio decisions of households. We show that households rebalance their financial wealth away from the stock market in response to increased human capital risk induced by pervasive automation, thereby attaining lower wealth levels and relative positions in the wealth distribution. Our evidence suggests that the portfolio channel amplifies the inequality-enhancing effects of increased automation. (*JEL* D31, J24, E21, D1, G11)

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In recent years, we have witnessed an accelerated progress of digital technologies, including significant advancements in robotics and other related technologies. According to the International Federation of Robotics (IFR), the

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worldwide stock of industrial robots has almost tripled in the past decade, and is projected to grow at least at a similar rate over the next 10 years. The extent and rapidity of the progress in automation, including major leaps in artificial intelligence capabilities, raises several questions with important implications for individuals.[1]

In this paper we focus on the effects of increased automation on household wealth accumulation and on the underlying economic mechanisms, both empirically and theoretically. Our paper highlights an important mechanism driving the negative wealth effects of automation that arises from endogenous optimal portfolio decisions of households. In particular, we demonstrate that households endogenously rebalance their financial wealth away from the stock market due to increased human capital risk induced by automation, thereby attaining lower levels of wealth and relative positions in the wealth distribution.

In our empirical analysis, we focus on an industry-level measure of robot use to measure the increased importance of automation. Specifically, we consider the adoption of industrial robots, which are defined as reprogrammable and fully autonomous machines capable of being adapted to perform different tasks (Acemoglu and Restrepo 2020; Graetz and Michaels 2018; IFR 2017). We combine this industry-level measure of automation with an extensive individual-level panel data set from Sweden, which contains detailed wealth records and highly accurate information on the demographics and labor market outcomes of approximately 300,000 households from 1999 to 2007. We then study the effects of changes in exposure to robots in the workplace on financial behavior and wealth outcomes of households, including stock market participation and relative position in the wealth distribution.

The baseline empirical strategy relies on an instrumental variable (IV) approach that is estimated in a 2SLS fashion. Following a similar identification strategy as Autor, Dorn, and Hanson (2013), Bloom, Draca, and Van Reenen (2016), and Acemoglu and Restrepo (2020), we instrument for changes in robot density in Swedish industries using contemporaneous median changes in robot density across 11 other Western European countries. Our identification proceeds from the notion that the adoption of robots in the (non-Swedish) European countries represents the advances in the global technological frontier (Acemoglu and Restrepo 2020), which enables us to identify the exogenous variation in the use of robots in Swedish industries and to estimate its causal effects on household financial choices and outcomes. We assess the plausibility of the exclusion restriction in detail, and provide evidence that corroborates the validity of the instrument.

[1] A burgeoning literature focuses on the economic consequences of rapid automation, with a particular emphasis on its effects on the labor market. Recent evidence suggests that despite a positive impact on productivity (Graetz and Michaels 2018), automation and advances in production methods negatively affect the wages and employment opportunities of individual workers (Acemoglu and Restrepo 2020; Autor and Salomons 2018), and correlate with increases in labor income risk and wage inequality (Kogan et al. 2020).

We start our analysis by investigating the effects of exposure to the increased use of robots at work on net wealth levels and ranks. We provide strong evidence that increased automation has a significant negative impact on household wealth accumulation, even after accounting for a rich set of household characteristics, industry factors, and local economic conditions. In particular, a one-standard-deviation exogenous rise in exposure to robots at work reduces the rank of individuals within the corresponding birth cohort-year wealth distribution by 1.7 percentiles, on average.

We conduct numerous sensitivity checks to verify the robustness of our findings. For example, we use a difference-in-differences (DiD) type identification, which combines industrial variation in robot adoption intensity with household variation in exposure to the effects of robotization. To be more precise, we identify the effects of exposure to robotization from within industry variation by exploiting heterogeneity in the intersectoral transferability of human capital (acquired through formal education) of individuals working in the same industry. Consistent with our results from the base analysis, we observe a significant negative impact of robot adoption on the wealth accumulation of households even after the inclusion of industry fixed effects. Interestingly, there seems to be large response heterogeneity to the adoption of robots across employees in the same industry by the degree of the intersectoral transferability of their skills.

Having established a robust negative causal effect of robotization on household wealth accumulation, we next turn to the analysis of the underlying economic factors. Beyond the income and savings channels, our findings point to the existence of an additional and more nuanced mechanism, which we label as the *portfolio channel*. In particular, we first show that adoption of robots significantly increases the unemployment risk of exposed households. We then demonstrate that households facing increased background labor income risk, substantially reduce, or fully eliminate, their exposure to the stock market. For the latter, a one-standard-deviation exogenous rise in the robot density of the industry of employment leads to an 15% increase in the probability of a household exiting from the stock market. As households rebalance their financial portfolio away from the stock market, they forgo substantial equity returns up to 4.3% a year (Calvet, Campbell, and Sodini 2007) and therefore experience a substantial drop in the growth of their financial wealth and accumulate significantly less wealth relative to their incomes.

We scrutinize alternative mechanisms, including changes in labor income or in savings behavior. Our numerous empirical findings strongly suggest that the patterns we document in the wealth analysis are not a mere product of the income or savings effects, but are also driven by the portfolio channel. For the former, we document quantitatively similar effects of increased adoption of robots on household wealth accumulation when we explicitly control for household income growth in the analysis or exclude displaced workers from the sample. Furthermore, our results provide no empirical support for (changes in) household savings behavior as an operative channel.

Next, we study the effects of automation on the financial outcomes of households by level of education. While skill upgrading of jobs as a result of emerging technologies may favor some people, it can leave others behind, notably, those with lower human capital (Brynjolfsson and McAfee 2012; Autor 2015; Berg, Buffie, and Zanna 2018). Interestingly, we find that the negative effects of automation on stock market participation and wealth accumulation are only operative for less educated households and not among their better educated counterparts. Overall, our findings suggest that rapid automation can further widen the wealth gap between high- and low-skill individuals.

Building on our empirical findings, we develop and solve a life cycle model of consumption and portfolio choice with automation risk and endogenous stock market participation. Our model is similar to Gomes and Michaelides (2005) and Fagereng, Gottlieb, and Guiso (2017), but is extended by including a robotization shock to the labor income process. More precisely, both the level and the risk of the income process are functions of ex ante robot exposure and ex post robot shocks. We first calibrate the model to match the wealth accumulation of households with *high*, *medium*, and *low* robot exposure in the data. We show that the calibrated model replicates very well the asset allocations of these three groups. We then simulate the effects of a robot shock over the same time period as in the data. Crucially, we impose the same risk preferences and stock market participation costs for all households, so that changes in stock market participation and risky share are fully driven by the changing environment and the endogenous evolution of wealth in the simulations.

Finally, we conduct a counterfactual analysis, where we isolate the role of the portfolio channel in explaining the differences in wealth accumulations between the low and high robot exposure groups. We find that portfolio rebalancing in response to the robotization shock generates 15% of this difference, thus confirming that the portfolio channel is indeed an important mechanism driving differences in wealth accumulation, in line with our empirical findings.

Our paper complements a small but growing literature on the economic consequences of increased automation.[2] For example, Acemoglu and Restrepo (2020) find that penetration of industrial robots across U.S. local labor markets reduces aggregate employment and wages, while Graetz and Michaels (2018) document positive productivity effects of automation, which, however, reduce employment for low-skilled workers. We contribute to this literature

[2] See, for example, Bessen et al. (2019), Martinez (2019), Dauth et al. (2017), Aghion, Jones, and Jones (2018), Arntz, Gregory, and Zierahn (2016), Freeman (2015), Benzell et al. (2015), Hémous and Olsen (2022), Sachs and Kotlikoff (2012), and Sachs, Benzell, and LaGarda (2015).

along several dimensions. First, we provide the first direct evidence that the negative impact of robotization extend beyond the labor market to the dynamics of wealth accumulation. Second, the portfolio channel, as we document, amplifies the adverse effects of automation on household wealth accumulation and highlights an important economic mechanism through which automation affects household financial well-being. Specifically, we show that the endogenous portfolio responses of households to increased adoption of robots at work amplify the relation between labor market polarization and dispersion of wealth. Finally, our evidence on the negative labor market effects of robotization using detailed household micro data complements the findings of earlier studies.

In addition, our work links to the literature on the importance of uninsurable background risk for the demand of risky assets (Cocco, Gomes, and Maenhout 2005; Fagereng, Guiso, and Pistaferri 2017; Betermier et al. 2012). For example, Fagereng, Guiso, and Pistaferri (2017) conclude that households have a large marginal propensity to respond to earnings risk even though the authors observe relatively small responses in their analysis, which they attribute to a low level of earnings risk in their empirical setup. Our paper provides an empirical setting where the level of earnings risk is particularly high and, consistent with Fagereng, Guiso, and Pistaferri (2017), we estimate much larger economic responses, highlighting the importance of background labor income risk for household portfolio choice. Another key contribution of our paper to this literature is to identify an additional source of background risk, that is, the rapid adoption of robots in the workplace. As we both empirically and theoretically show in our paper, this risk is essential and is very likely to become increasingly so for household portfolio choice and wealth accumulation in the future, given the rapid progress in automation.

Finally, our findings on the importance of the portfolio channel for household wealth accumulation relate to the recent literature on the underlying factors of the observed wealth distribution (Benhabib, Bisin, and Zhu 2011; Gabaix et al. 2016; Hubmer, Krusell, and Smith 2016), and on the large heterogeneity in returns on wealth (Bach, Calvet, and Sodini 2020; Fagereng et al. 2020; Campbell, Ramadorai, and Ranish 2019).

1. Data and Empirical Specification

In this section, we first introduce the data sources and provide detailed information on our main variables of interest. We then discuss the econometric challenges in the empirical analysis and explain how we tackle them.

1.1 Data and sample construction

To measure household exposure to increased automation in the workplace, we use data provided by the IFR on the stock of industrial robots, disaggregated at the industry level. The IFR collects annual information on the total stock of robots and new robot installations, detailed at the two-digit or three-digit industry level since 1993 by surveying robot producers and suppliers in approximately 50 countries (Graetz and Michaels 2018; Acemoglu and Restrepo 2020; IFR 2017). For Sweden, the focus of our empirical investigation, we observe the total stock of robots for 14 industries on a yearly basis from 1993 to 2016. These industries include *agriculture, forestry, and fishing*; *mining and quarrying*; *manufacturing*; *utilities*; *construction*; and *education, research, and development*. For manufacturing, we have a more detailed industry breakdown at the three-digit level, which includes *food and beverages*; *textiles*; *wood and furniture*; *pharmaceuticals*; *rubber, plastic, and chemical products*; *basic metal and metal products*; *industrial machinery*; *electrical products and electronics*; and *automotive industries*.[3]

We then merge the industry-level robot data with the number of employees in each industry, which we collect from the *EU KLEMS* data set (Jäger 2016). Table 1 provides information on the use of industrial robots and the number of workers for the Swedish industries during the sample period (1999 to 2007). The automotive industry has the highest robot density, with 27.86 robots per thousand workers, followed by the basic metal and metal products industry with 11.35 robots per thousand workers as of 1999.

Next, we merge the data on the stock of robots with the LINDA (Longitudinal INdividual DAta for Sweden) database, which is provided by Statistics Sweden.[4] LINDA consists of an annual cross-sectional sample of around 300,000 individuals, or approximately 3% of the entire Swedish population, and their family members. The sampling procedure ensures that households in the panel are representative of the population as a whole, and that each annual cohort is cross-sectionally representative. The data contain highly accurate and detailed information on debt and asset holdings, as well as demographic characteristics of each sampled individual from 1999 to 2007.[5]

In our analysis, we use information at the household rather than at the individual level. To identify the head of a household, that is, the reference person, we follow the Canberra definition.[6] We then use the socioeconomic

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3 To minimize potential misclassification and measurement errors, we do not consider the number of robots that fall into the "Unspecified" category when calculating the robot exposure variable.

4 Since the IFR and Statistics Sweden use different industry classifications, we follow a similar matching procedure as in Graetz and Michaels (2018). Table O.A.1 in the Internet Appendix provides further details about the matching procedure.

5 The extensive financial and wealth information originates from the collection for wealth taxation, which was abolished in 2007. Even though wealth taxation in Sweden has a longer history, originally dating back to the early 1900s, we focus on the 1999-2007 period because of the availability of wealth information at the household level in the archives of our data provider *Statistics Sweden*, which is the Swedish government's statistical agency. Note that all wealth data at the household level prior to 1999 was unfortunately destroyed.

6 The Canberra definition of the reference person in a household applies the following rule in the order provided: "one of the partners in a registered or de facto marriage, with children; one of the partners in a registered or de facto marriage, without dependent children; a lone parent with dependent children; the person with the highest income; the eldest person" (Haliassos, Jansson, and Karabulut 2017).

Table 1
Use of industrial robots in the Swedish industries

Name of industry	No of obs	No of workers (1995)	No of robots (1999)	No of robots (2007)	Robot density (1999)	Robot density (2007)	ΔRobot density (1999–2007)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agriculture, forestry, fishing	1,215	46	0	1	0.000	0.022	0.022
Food and beverages; tobacco	1,699	69	96	416	1.391	6.029	4.637
Textiles	320	15	7	0	0.467	0.000	−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	0.000	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	1,249	1,943	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	2,424	3,089	27.862	35.505	7.643
Education/research/development	1,666	398	129	93	0.324	0.234	−0.090
Construction	5,372	187	39	49	0.209	0.2620	0.053
Electricity, gas, water supply	878	41	1	1	0.024	0.024	0.000
Mining and quarrying	296	10	0	0	0.000	0.000	0.000

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. See the Internet Appendix for detailed variable definitions.

characteristics of the household head when defining household controls, such as age, educational level, and work status. Asset and debt holdings, along with income, are aggregated at the household level.

When constructing the working sample, we adopt a conservative strategy to minimize potential misclassification and measurement errors. First, we only consider working age households between the ages of 22 and 60 (Autor, Dorn, and Hanson 2013). Second, we exclude households who are classified as student, housemaker, self-employed, or unemployed or retired, and consider only employed households in the initial period. Third, we focus on households who work in industries for which the IFR provides information on the number of robots.[7] Importantly, we require households to be employed only during the initial period, and allow them to endogenously switch industries, become unemployed, or move to another geographical location in subsequent years. Finally, we eliminate households with any missing information on labor market outcomes, asset holdings, or demographics. Overall, the final sample comprises 30,375 unique households who are observable in any given year during the 1999-2007 period. Panel A of Table 2 presents descriptive statistics on relevant household characteristics.

1.2 Variable definitions

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

$$\Delta Robot\_density_j^{99\rightarrow 07} = \frac{\text{No of robots}_j^{07}}{\text{No of workers}_j^{95}} - \frac{\text{No of robots}_j^{99}}{\text{No of workers}_j^{95}}. \tag{1}$$

Since our focus is on the impact of long-differences in exposure to robots on changes in household economic choices and outcomes, we consider changes in robot density in a given industry between 1999 and 2007. In the construction of this variable, we use the number of workers in 1995, rather than the contemporaneous values, as the baseline employment level to limit the potential simultaneity bias in employment and the adoption of robots (Acemoglu and Restrepo 2020).[8] Panel B of Table 2 provides information about this key variable. During the sample period, we observe on average an increase in the number of robots per 1,000 employees across Swedish industries with a mean (standard deviation) value of 2.69 (3.27).

[7] According to the employment numbers from the *EU KLEMS* database, the number of employees in the industries included in our analysis represents 55.5% of workers in the market economy and 35% of workers across all industries in Sweden. We verify our findings by considering households that work in industries for which the IFR does not provide any information about robot stock by setting robot adoption in those industries to zero.

[8] For instance, the employment level in an industry in the year of 1999 might be affected by the (planned) increase in robots between 1999 and 2007 in that specific industry. It is however much less likely that the employment level in an earlier period, as in 1995, reflects expectations of future labor market trends. Still, we verify the robustness of our findings using the 1999 values as the baseline employment level.

Table 2
Summary statistics for the final sample

	Observations	Mean	SD
	(1)	(2)	(3)
A. Household demographics and financial characteristics			
Age	30,375	38.8532	7.5261
Male	30,375	0.8699	0.3365
Married	30,375	0.5507	0.4974
College and more	30,375	0.2424	0.4286
High school	30,375	0.5581	0.4966
Number of adults	30,375	1.9267	0.6273
Number of children	30,375	1.4168	1.1490
Immigrant	30,375	0.0995	0.2994
Gross wealth (in SEK)	30,375	980,456.6	2,116,590
Net wealth (in SEK)	30,375	524,553.4	1,730,830
Financial wealth (in SEK)	30,375	225,593.9	863,549.6
Housing wealth (in SEK)	30,375	547,806.8	560,392.4
Debt (in SEK)	30,375	424,828.3	765,143
(IHS of) Disposable income	30,375	13.2065	0.4075
(IHS of) Labor income	30,375	12.7125	0.5225
B. Variables of interest			
$\Delta Robot\_density^{99\to07}$	30,375	2.6927	3.2744
$\Delta Robot\_density_{EU}^{99\to07}$	30,375	0.4225	0.5255
C. Dependent variables			
Stockholding status	30,375	0.7808	0.4137
Stock market exit	22,125	0.0819	0.2744
Change in risky share	30,375	−0.1630	0.4069
Unemployment risk	30,375	0.0423	0.2014
Change in earnings	30,375	0.1955	1.5471
Net wealth levels	30,375	10.1922	9.8281
Net wealth rank	30,375	52.9843	27.1651
Change in net wealth	30,375	0.1948	21.2564
Change in financial wealth	30,375	2.1391	3.7284
Wealth-to-income ratio	29,955	0.8728	1.8076
D. Industry characteristics			
ΔNo of employees (1993-98)	30,375	−1.6201	15.5676
$\Delta Chinese\_import^{99\to07}$	30,375	2.4709	4.4889
ΔCapital intensity	30,375	0.2019	0.1145
ΔICT capital	30,375	0.3863	0.1853
Initial robot density (1995)	30,375	4.3988	6.2528
$\Delta EU\_import^{99\to07}$	30,375	1.4765	2.1931
$Labor\_intensity$ (1999)	30,375	0.3001	0.1843
$\Delta Profits$	30,375	149.198	145.007

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 household control variables that are defined in 1999. *SEK* refers to values in Swedish kronor and *IHS* refers to the inverse hyperbolic sine transformation. Panel B reports summary statistics for the main variables of interest in our analysis, that are the changes in robot density in the Swedish and European industries, respectively. Panels C and D presents the descriptive statistics for the outcome variables defined at the household-level and industry-level controls, respectively. See the Internet Appendix for detailed variable definitions.

In our analysis we account for numerous industry characteristics in order to isolate the effects of increased robotization from other industry-wide factors and trends. First, previous literature shows that increased imports from China (and other low-wage countries) have a negative effect on employment, wages, and labor-force participation (Autor, Dorn, and Hanson 2013; Bloom, Draca, and Van Reenen 2016). Therefore, we follow Autor, Dorn, and Hanson (2013) and construct a variable for exposure to imports from China, which captures the increase in this exposure per thousand of employees between 1999 and 2007 in a given industry. Second, international trade competition, other than import exposure to China, can also affect the economic outcomes of Swedish households and the proliferation of robots in Swedish industries. We address this issue by accounting for median changes in import exposure to 11 developed Western European countries, which we use to construct the excluded instrument described in Section 1.3. Third, we control for whether a given industry is declining in terms of change in the nationwide employment levels between 1993 and 1998 to account for industry pre-trends (Acemoglu and Restrepo 2020). Fourth, we construct additional variables for changes in industry profitability between 1999 and 2007, as well as for initial labor intensity that is proxied by the labor-to-capital ratio of a given industry in 1999.[9] Lastly, we introduce control variables for changes in capital intensity and ICT capital in the regressions. As we discuss in Section 1.4, the increased use of robots is only weakly related to these industry-wide trends, and represents a distinct factor. Panel D of Table 2 provides summary statistics for the industry controls.

Finally, we use a rich set of household-level characteristics as additional controls in the empirical analysis. These include age and educational level of the household head, marital status, household size and adult-children composition, and (initial) household disposable income and net wealth. We provide detailed information about the variables employed in the empirical analysis in the Internet Appendix.

1.3 Empirical specification

We study the effects of changes in exposure to robots in the workplace on various household economic outcomes, accounting for a wide range of household characteristics, industry trends, and local economic conditions. The base model takes the following form:

$$\begin{aligned}\Delta Y_{ijk}^{99\rightarrow 07} = {} & \alpha \cdot \Delta Robot\_Density_{j}^{99\rightarrow 07} \\ & + \beta \cdot \Delta HH\_Controls_{i}^{99\rightarrow 07} + \gamma \cdot \Delta IND\_Controls_{j}^{99\rightarrow 07} + \delta_k + \epsilon_{ijk}\end{aligned} \tag{2}$$

where $\Delta Y_{ijk}^{99\rightarrow 07}$ represents the long-differences (i.e., changes between 1999 and 2007) in the economic and financial outcomes of interest for household i

9 Regarding the former variable, an industry with declining profitability may exhibit lower-income growth and, at the same time, higher automation growth to increase profits. For the latter variable, more labor intense, and potentially more profitable, industries (such as luxury goods or high-end fashion) could offer higher-income growth and less potential for the adoption of robots.

working in industry j and living in municipality k in 1999. In estimating the impact of exposure to robots, we control for numerous observed characteristics of the household ($\Delta HH\_Controls_i^{99\rightarrow 07}$) and several relevant industry controls ($\Delta IND\_Controls_j^{99\rightarrow 07}$), which we introduced and described in the previous section. The vector $\Delta HH\_Controls_i^{99\rightarrow 07}$ of household level controls includes changes in marital status, changes in level of education (distinguishing between college education, high school, and less than high school) of the household head, changes in the number of adults and in the number of children as well as fixed effects for deciles of household initial wealth and income in 1999. We further include regional fixed effects for the location of residence, defined at the municipality level and denoted as δ_k, to account for potential differences in regional economic conditions.[10] In addition, we control for the initial robot density of an industry (measured in the base year of 1995), which allows us to focus on the variation in changes in the adoption of robots across industries within a municipality.

Equation (2) is defined and estimated in first differences and is, therefore, equivalent to a fixed effects regression. The first-differencing addresses concerns arising from unobserved household characteristics that may otherwise contaminate estimation of the true effect of automation on household outcomes. Standard errors are double clustered by region and industry.

Even though we include a rich set of industry controls in the regressions, there may still be some unobserved industry-wide factors that can simultaneously affect changes in robot density and the economic outcomes of households working in that industry. For example, a rapid increase in unionization in some Swedish industries could lead to the increased adoption of robots as well as higher wages and improved job security for workers in those industries, which would yield a positive correlation without implying a causal link. This would pose a threat to our identification.

Our empirical strategy addresses this challenge by using an IV approach that is estimated in a 2SLS fashion. Following a similar identification strategy as in Autor, Dorn, and Hanson (2013), Bloom, Draca, and Van Reenen (2016), and Acemoglu and Restrepo (2020), we instrument for changes in robot density between 1999 and 2007 in the Swedish industries using contemporaneous median changes in the robot density across 11 other developed Western European countries.[11] Building on the same ideas as Acemoglu and Restrepo (2020), we use the adoption of robots in (non-Swedish) European industries to capture the advances of the global technological frontier, which is assumed to

[10] In Sweden, 290 municipalities are responsible for various tasks, such as social services or physical planning. Hence, municipality fixed effects account for latent regional characteristics and capture the direct effects of the location of households.

[11] The 11 other developed countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Portugal, and the United Kingdom. Note that the industry breakdown of robot stock for Austria, Belgium, the Netherlands, and Portugal is not available prior to 2004. Therefore, for these countries, we use the robot density from 2007 in the corresponding industries.

be positively correlated with the growth of robot density in Swedish industries but uncorrelated with the error term in the equations of interest.[12] Indeed, the first-stage regressions, presented in Table O.A.2, show a positive and statistically highly significant effect (p-value$<.01$) 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, does not suffer from a weak instrument problem. Overall, the IV strategy will identify the exogenous variation in robot adoption in Swedish industries induced by advances in the technological frontier of robotics, which allows us to isolate the effect of an exogenous increase in robotization on the economic outcomes of households.

1.4 Examination of the exclusion restriction

Since Sweden is a small open economy, and we focus on European countries for defining the technological frontier of robotics, one may worry about the validity of the exclusion restriction. For example, changes in robot adoption in European countries could be correlated with negative shocks to Swedish industries, contaminating the identification strategy. We tackle this concern in a number of ways.

First, as shown in Equation (2), we explicitly allow for a rich set of industry factors and trends in all regressions, which partially mitigates any concerns about omitted time-varying factors. Second, we examine the validity of the exclusion restriction by estimating pairwise correlations between the adoption of robots in European and Swedish industries and other industry-level trends in Sweden. Panel A of Table O.A.3 shows that the correlation coefficients are relatively weak, suggesting that robotization represents a distinct factor from other contemporaneous industry trends and other types of recent technologies (Tuzel and Zhang 2021). When we consider the relation between past income growth (i.e., 1995-1998) and the robotization rate between 1999 and 2007 in an industry, we observe a positive association. Similar conclusions follow when we consider early trends in industry-level employment growth, indicating that industries that experienced greater past income or employment growth tend to adopt more robots. These results provide strong support for the argument that confounding industry pre-trends, such as declining income growth or labor demand, are not likely to drive our results.

We also estimate a DiD type regression by exploiting our ability to observe household income from earlier time periods. Specifically, we first compute

[12] When defining the technological frontier of robotics, we could have considered a non-European country, such as the United States or Japan, which would have been potentially less susceptible to unobserved industry shocks. However, this is not feasible for at least two reasons. First, the U.S. is lagging behind European countries (including Sweden) in terms of robot adoption; therefore, U.S. industries would have not represented an appropriate technological frontier. Second, the robot stock data provided by the IFR for Japan were subject to significant reclassification; therefore, we are not able to use the industry-level robot adoption data for Japan in our analysis.

cumulative income growth at the household level for 1995-1998 (i.e., pre-period) and 1999-2007 (i.e., post-period). Then, we regress income growth on the interaction term between a post-period indicator and a high robotization dummy, which takes the value of one if change the industry's robot density is above the sample mean. Since we have two time periods in these regressions, we are able to introduce industry fixed effects and focus on within-industry changes. Panel B of Table O.A.3 shows that the DiD coefficient is negative and statistically highly significant, suggesting that increases in robot exposure are associated with a large drop in labor income growth.

Fourth, it is important to note that Sweden is not a part of the European Monetary Union, even though it has been a member of the European Union (EU) since 1995. Sweden has its own currency, a floating exchange rate regime, and an independent monetary policy, which makes Swedish industries less prone to EU-wide common shocks. Consistent with this argument, Söderström (2008) shows that Sweden-specific shocks represent a significantly more important source of Swedish business cycle fluctuations than foreign (i.e., European) shocks, and that country-specific shocks account for most of the variability in the Swedish economy. Further, we compute the gross value-added beta of Swedish industries with respect to European and U.S. industries.[13] We find that changes in labor productivity in Swedish industries are, on average, significantly less sensitive to labor productivity growth in corresponding European industries than in U.S. industries.

Finally, we verify our empirical findings from the IV regressions using an alternative identification strategy, which follows the spirit of a DiD type identification and allows us to control for any unobserved (including time-varying) industry factors and trends (see Section 2.2). Taken together, the numerous findings presented in this section provide strong support for the validity of the exclusion restriction.

2. The Effects of Robots on Household Wealth

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

2.1 Robots and household wealth accumulation

We first analyze the effects of automation on the accumulation of household net wealth, calculated by subtracting household debt from total household assets (i.e., the sum of all financial and real assets). Following Black et al. (2020)

[13] To compute industry betas, we obtain annual data on industry value-added for Sweden, the 11 developed Western European countries, and the U.S. from the EU KLEMS database for the period from 1970 to 2015. The industry betas are calculated as the slope coefficients from rolling regressions of value-added growth of Swedish industries on the value-added growth of U.S. and European countries using 25 years of data up to *t*.

and Epper et al. (2020), we use the percentile rank of a household within the corresponding birth cohort-year distribution of net wealth as the preferred measure.[14] By definition, this variable accounts for life cycle differences across households, and also can be defined for zero or negative values of net wealth, which is, for example, not feasible with a log transformation.

Column 1 of Table 3 reports estimates of the effect of exposure to increased automation on the relative position of households in the wealth distribution. The regression estimates imply a negative and statistically highly significant effect of robotization on the percentile wealth rank of households at the end of the observation period (t-stat. = −2.05), even after accounting for a rich set of household characteristics, industry factors, and local economic conditions. To give an idea of the magnitude of the estimated effect, we can say that a one-standard-deviation increase in robot density in an industry reduces the rank of individuals in the wealth distribution by 1.71 percentiles, on average. To put this into context, we could say this corresponds to approximately one-third of the impact of attending college, which is quite considerable. We recognize that using net wealth rank as a dependent variable may mask some potential rank-preserving shifts in household wealth, which we address by using (the inverse hyperbolic sine of) net wealth as an alternative outcome variable (Chen 2013). Reassuringly, as reported in Column 2 of Table 3, we find statistically significant and economically sizeable effects of robot adoption also on the level of net wealth (t-stat. = −2.83).[15]

Next, we focus on the wealth mobility effects of robots. More specifically, we use changes in the net wealth rank of a household within the corresponding birth cohort distribution between 1999 and 2007.[16] The results in column 3 of Table 3 show that households that are more exposed to industrial robots at work experience a significantly larger drop in the wealth distribution. The IV estimate in column 3 of –0.487 indicates that a one-standard-deviation exogenous rise in robot use leads to a 1.60 percentile decline in the change in net wealth rank of the exposed households on average (t-stat. =−2.01). Taken

[14] We define 12 birth cohorts, whereby each consists of 5-year intervals from 1923 to 1983. When computing the net wealth rank of households, we no longer restrict our attention to the households in the final sample, but rather consider all households in the LINDA data set in order to more accurately identify households' relative position in the entire wealth distribution. As shown by Acemoglu and Restrepo (2020), increased automation can generate externalities even for individuals who are not directly exposed to robotization in their industry of employment. Thus, considering all households in the LINDA database (with nonmissing wealth information) when constructing the wealth rank variable partly allows us to take into account the general equilibrium spillover effects of automation on the wealth distribution. In untabulated results, we find similar results when only considering households in our final sample.

[15] Since we use the inverse hyperbolic sine of net wealth as the outcome variable, the coefficient estimates in these regressions can be interpreted as a semielasticity. Hence, a coefficient of 0.167 would imply that an increase by one robot per 1,000 employees in the industry of employment would decrease the net wealth of exposed households by 16.7%, on average.

[16] This measure enables us to assess the intracohort mobility of households over time, and provides insights about the impact of robots on the dynamics of household wealth net of any life cycle effects (Quadrini 2000).

Table 3
Exposure to robots and household net wealth

	Net wealth rank	Net wealth level	Change in net wealth rank
	(1)	(2)	(3)
Δ*Robot_density*$^{99\rightarrow07}$	−0.52219**	−0.16755***	−0.48734**
	(0.2547)	(0.0593)	(0.2419)
ΔMarried	1.02538*	−0.01232	0.92092*
	(0.5690)	(0.1950)	(0.5588)
ΔCollege	−4.95333***	−3.09470***	−4.87931***
	(0.8593)	(0.4227)	(0.8428)
ΔHigh school	−3.76020***	−2.53362***	−3.68515***
	(1.0332)	(0.3997)	(0.9225)
ΔNumber of adults	1.47095***	−0.17384**	1.43479***
	(0.1483)	(0.0746)	(0.1403)
ΔNumber of children	1.28079***	−0.32836***	1.27862***
	(0.1379)	(0.0655)	(0.1373)
ΔNo of employees (1993-98)	0.04125	−0.02617*	0.03374
	(0.0767)	(0.0151)	(0.0734)
Δ*Chinese_import*$^{99\rightarrow07}$	−0.13497	−0.00021	−0.11972
	(0.0883)	(0.0177)	(0.0850)
ΔCapital intensity	−6.23526	0.55681	−6.16855
	(6.1636)	(1.3816)	(5.8721)
ΔICT capital	4.43708	0.39071	4.26663
	(2.9112)	(0.5576)	(2.7586)
Initial robot density (1995)	−0.02137	0.05307*	−0.01616
	(0.1062)	(0.0309)	(0.0995)
Δ*EU_import*$^{99\rightarrow07}$	0.10625	0.09567***	0.12629
	(0.1194)	(0.0233)	(0.1153)
Labor_intensity (1999)	2.10066	−1.20881	2.32083
	(3.5561)	(0.9082)	(3.3934)
Δ*Profits*	−0.00181	0.00040	−0.00148
	(0.0029)	(0.0007)	(0.0028)
Constant	24.57797***	−2.80256***	18.42697***
	(2.7113)	(0.9433)	(2.6475)
Observations	30,375	30,375	30,375
R-squared	.5793	.2557	.3167
Income deciles (1999)	Yes	Yes	Yes
Wealth deciles (1999)	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, fixed effects for deciles of household initial wealth and income in 1999, contemporaneous industry characteristics, and municipality dummies. In column 1, we focus on the wealth rank of households within their birth cohort-year distributions. In column 2, the dependent variable is the inverse hyperbolic sine of net wealth. In column 3, the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. We estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model is defined and estimated in first differences. Standard errors are double clustered by municipality and industry. See the Internet Appendix for detailed variable definitions. $*p<.1; **p<.05; ***p<.01$.

together, our empirical analysis yields strong evidence for the negative effects of pervasive automation on wealth accumulation.

2.2 Intersectoral transferability of human capital and robots

The identification strategy used so far in the analysis is standard in the literature (Autor, Dorn, and Hanson 2013; Acemoglu and Restrepo 2020). However, a potential concern is that any unobserved shock in Swedish industries may be correlated with industry shocks in the other European countries that we use to construct the excluded instrument. While it is not possible to test the validity of the exclusion restriction explicitly, the evidence and corresponding discussion presented in Section 1.4 suggest that confounding industry factors are unlikely to drive our results. In this section, we examine the robustness of our findings by using an alternative identification strategy.

We rely on a DiD type design, which combines industrial variation in robot adoption intensity with household variation in exposure to the effects of automation. To be more precise, we identify the effects of exposure to robotization from within industry variation by exploiting heterogeneity in the intersectoral transferability of the human capital (acquired through formal education) of individuals working in the same industry. The importance of general and specific human capital for job mobility and determination of earnings has been the focus of a rich body of literature (Becker 1962; Altonji and Shakotko 1987; Topel 1991; Neal 1995; Parent 2000). Motivated by these studies, we argue that individuals with more industry-specific human capital are more adversely affected by the increased use of robots in their industry of occupation, mainly because of the higher moving frictions they face (Artuç, Chaudhuri, and McLaren 2010; Traiberman 2019) compared to their peers who are better suited to reallocate.

To measure the transferability of human capital empirically, we focus on educational level and major of study. For the former, we use two broad groups for higher and lower levels of education based on college attendance. For the latter, we use the three-digit SUN 2000 categorization of educational majors.[17] We intersect, wherever possible, educational level and orientation to define a total of 139 unique education major-level categories in our sample. We then compute the distribution of individuals within each category over their (two-digit) industry of employment, and construct a Herfindahl-Hirschman index (HHI) of industry specialization for each major-level group. A higher (lower) HHI implies lower (higher) levels of intersectoral transferability of human capital. We note that educational majors, such as medicine and dentistry, have very low intersectoral transferability, while majors including engineering and business administration have very high transferability (see Table O.A.4). Importantly, the formal tests tabulated in Table O.A.5 confirm our prior that individuals with more industry-specific human capital are significantly less likely to switch industries, during both the observation period and an earlier period.[18]

[17] In the Swedish education system, students are required to choose a major in high school, which allows us to construct our human capital measure for high school graduates as well. The SUN 2000 classification of Statistics Sweden is similar to that of the International Standard Classification of Education 1997 (ISCED-97), and the three-digit category consists of 117 different educational orientations. Our final sample comprises a total of 93 unique education majors across all households, and this figure accounts for 53 for high school graduates.

[18] Our focus on the orientation and level of education rather than on occupational experience, as in Kambourov and Manovskii (2009), or tasks performed in occupations, as in Gathmann and Schönberg (2010),

To identify individuals with higher industry-specific human capital, we define the indicator variable $Low\_transfer_{ij}$, which equals one if the HHI of household i's educational major is above the median HHI across individuals working in industry j, and zero otherwise.[19] We then estimate (within-industry) regressions of the following form where we interact the changes in robot density in the Swedish industries between 1999 and 2007 and the (household-level) indicator variable for having less transferable human capital:

$$\Delta Y_{ijk}^{99\rightarrow 07} = \beta_1 \cdot \Delta Robot\_density_j^{99\rightarrow 07} \times Low\_transfer_{ij} + \beta_2 \cdot Low\_transfer_{ij} + \theta \cdot \Delta HH\_controls_{ijk}^{99\rightarrow 07} + \delta_j + \delta_k + \epsilon_{ijk}. \quad (3)$$

Note that industry fixed effects, denoted as δ_j, subsume the direct effect of robotization and control for all sources of variation in differential industry factors and trends. Put differently, this approach allows us to capture and rule out the effects of any unobserved (including time-varying) industry characteristics, which may be correlated with increases in robot use and the wealth outcomes of households working in that industry.

Table 4 reports the regression estimates. Consistent with our results from the base analysis, we observe a negative and significant effect of robot adoption on wealth accumulation of households even after the inclusion of industry fixed effects. As presented in column 2 of panel A, a one-standard-deviation increase in the robot density of a given industry reduces the net wealth rank of individuals with more industry-specific human capital by 1.17 percentiles (t-stat. $=-2.74$), on average, compared to those with less industry-specific human capital working in the same industry. Hence, there appears to be large response heterogeneity to the adoption of robots across employees in the same industry by the degree of the intersectoral transferability of their skills.[20] These results are robust to controlling for changes in household characteristics over the sample period and for municipality fixed effects.

To address the concern that educational choices may partially reflect expectations of future labor market trends, such as the increased use of robots,

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is motivated by two reasons. First, formal education represents one of most important sources of human capital. Second, the choice of educational major, and hence, the intersectoral transferability of human capital, is likely to be exogenous to current advances in automation, since educational choices were made many years in the past.

19 In principle, we intend to compare individuals with similar (financial and demographic) characteristics working in the same industry, some of whom are more affected by increased automation, and some of whom are not or less affected. As shown in Figures O.A.1 and O.A.2, the distributions of household income and net wealth across both groups are very similar, suggesting that we have a sample of fairly balanced treatment and control households.

20 The magnitudes of the coefficient estimates from the DiD analysis require a nuanced interpretation. Since, by construction, the treatment and control groups in the DiD design are of equal size, the mean of the treatment effects in each of the two skill subgroups (i.e., -1.17) should correspond to the population average treatment effect that we document in the IV regressions (i.e., -1.71) presented in Section 2.1. Solving the exactly identified system of two equations and two unknowns implies that a one-standard-deviation increase in the robot density of a given industry reduces the net wealth rank of individuals with more industry-specific human capital by 2.295 percentiles, on average. For individuals with less industry-specific human capital, the corresponding effect would be 1.12 percentiles.

Table 4
Intersectoral transferability of human capital and robots

A. Full sample

	Net wealth rank		Net wealth levels		Change in net wealth rank	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_density^{99\rightarrow 07}$ x $Low\_transfer$	−0.47452***	−0.35786**	−0.10826***	−0.07309***	−0.22567**	−0.18085***
	(0.1683)	(0.1305)	(0.0296)	(0.0259)	(0.0917)	(0.0652)
Observations	30,375	30,375	30,375	30,375	30,375	30,375
R-squared	.0483	.1444	.0158	.0489	.0074	.0579
Household controls	No	Yes	No	Yes	No	Yes
Municipality FE	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

B. Households with above-median age

	Net wealth rank		Net wealth levels		Change in net wealth rank	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Robot\_density^{99\rightarrow 07}$ x $Low\_transfer$	−0.58128***	−0.38587**	−0.17970***	−0.13403***	−0.29302***	−0.23135***
	(0.2091)	(0.1629)	(0.0382)	(0.0355)	(0.0686)	(0.0610)
Observations	15,320	15,320	15,320	15,320	15,320	15,320
R-squared	.0644	.1802	.0205	.0600	.0091	.0767
Household controls	No	Yes	No	Yes	No	Yes
Municipality FE	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents coefficient estimates from difference-in-differences type regressions. Wealth measures are regressed on the interaction term between changes in robot density between 1999 and 2007, (household-level) indicator variable for having a lower portable human capital, changes in observable household characteristics between 1999 and 2007, and industry fixed effects. Note that industry fixed effects subsume the direct effect of robotization and control for all sources of variation in differential industry trends and changes. In all specifications, the standard errors are clustered at the industry-treatment level. See the Internet Appendix for detailed variable definitions. $*p<.1$; $**p<.05$; $***p<.01$.

we conduct a sensitivity analysis where we restrict our sample to households who are older than 39 years old (i.e., the sample median age) and thereby rendering their educational major choices far in the past when concerns over robotization had not yet gained much prominence. The results of this validation exercise are presented in panel B of Table 4. Reassuringly, we document similar findings. If anything, the effects increase slightly for this subsample. Taken together, the empirical results presented in this section imply that our findings on the adverse effects of automation on household wealth accumulation are not simply an artifact of unobserved industry factors.

2.3 Additional robustness and sensitivity analysis

In this section, we perform several additional empirical tests to ensure the robustness of our findings. We present these results in the Internet Appendix.

First, individuals may anticipate the increased future use of robots and therefore sort themselves into industries that have a lower potential for robot adoption. We tackle this concern by focusing on a subset of households that were employed in the same industry since at least 1995, that is, when concerns over automation had not yet gained much prominence. Table O.A.6 shows that our findings are robust to constructing our exposure variable based on industry of employment from the prior decade.

Second, the results in Table O.A.7 show that the negative impact of robots on household wealth accumulation remains almost identical when accounting for initial differences in homeownership status.

Third, one can argue that observed variation in household wealth accumulation is induced by differences in risk preferences. Table O.A.8 repeats the wealth analysis controlling for initial risk exposure, which is measured by the share of financial wealth invested in risky assets in 1999 (Fagereng et al. 2020). We again obtain similar results.

Fourth, in a recent paper, Barrot et al. (2022) show that households in regions where manufacturing industries are more exposed to import competition significantly lever up to smooth their consumption. We examine this explanation by regressing changes in household debt on the industry-level changes in robot density and other household and industry controls. As presented in Table O.A.9, we find no significant effect of increased robotization on household debt, suggesting that automation affects household wealth accumulation by influencing the asset side of household balance sheets.

Fifth, we verify our results excluding individuals working in the automotive industry, which historically has the highest robot density. The results, tabulated in Table O.A.10, are consistent with the baseline regressions.

Sixth, we reestimate our base analysis using the full set of industries available in the data set to alleviate any concerns of sample selection bias.[21] The results in Table O.A.11 are qualitatively similar, though smaller in magnitude, to what we observe in our base specification.

Seventh, as presented in Table O.A.12, we find qualitatively and quantitatively similar results when we eliminate individuals working in the rubber and plastics industry, which experienced the largest growth in robot use in Sweden during the sample period.

Eighth, in the base regressions we account for potential differences in regional economic conditions by the introduction of municipality fixed effects based on the location of residence. One may worry that the municipality of residence and the municipality of employment may not necessarily correspond to the same region if there are many commuters in our sample. The regression results, presented in Table O.A.13, show that our results are robust to the exclusion of commuters from the sample.[22]

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21 Specifically, we consider households employed in industries for which the IFR does not provide any information about robot stock by setting the robot adoption rate to zero, which increases the sample size to 82,424 households.

22 Even though our data set is very rich along many dimensions, we have no information about the municipality of employment. To address this issue, we take an indirect approach and exploit information about the commuting costs of households to identify the commuters in the sample. Specifically, in Sweden, all employees are allowed to deduct commuting costs if they are above a certain threshold from their labor income in order to reduce income taxes. Hence, we define households who have high traveling costs to work and deduct those costs from their income in the tax form as commuters (that equals to approximately one-third of the sample). Our conjecture is that these households are the most likely ones to live in one municipality and work in another.

Ninth, we conduct additional robustness checks to ensure that the statistical inference in our base analysis is not sensitive to potential downward biases in standard errors. These tests include: (1) using bootstrap techniques, specifically the wild bootstrap procedure of Cameron, Gelbach, and Miller (2008), to deal with issues arising from having too few clusters; (2) clustering at different levels of industry; and (3) conducting a placebo experiment.[23] As reported in Table O.A.14, we obtain similar results.

Tenth, when we use the number of workers in an industry in 1999 in lieu of the 1995 values as the baseline employment level when measuring the changes in robot density in a given industry, the economic magnitude and statistical significance of our main effect increase as compared to our base result (see Table O.A.15).

Finally, Table O.A.16 shows that our findings are robust to controlling for additional life cycle controls and preference shifters.[24]

3. Understanding the Mechanism

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

3.1 Robots and labor market outcomes

Since recent empirical literature documents a significant negative effect of increased use of robots in the workplace on wages and employment prospects for individuals (Acemoglu and Restrepo 2020; Graetz and Michaels 2018), we start our analysis by estimating the effects of robotization on labor market outcomes.

First, we investigate the effects of increased automation on changes in household income, which is defined as the log differences in earnings (net of any transfers or capitals gains) between 1999 and 2007. Consistent with existing evidence, we document that individuals working in industries with a higher rate of robot adoption, on average, experience lower income growth, as presented in column 1 in panel A of Table 5. Interestingly, when we also include received transfers, such as unemployment benefits and social welfare payments, in the income definition, we note that the effect of robot adoption in fact turns out to be statistically insignificant, as tabulated in Table O.A.17 in the Internet Appendix.

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23 In the placebo experiment, we randomly assign different industry-level robot exposure to households. For example, households working in the automotive industry are randomly allocated to a different industry. We construct 1,000 placebo samples and rerun our analysis in Table 3 on these placebo samples. Figure O.A.3 in the Internet Appendix shows that the *t*-statistics on our placebo samples are centered on zero, suggesting that the documented effects are not a mere result of some spurious correlations with omitted factors.

24 Following Brunnermeier and Nagel (2008), we use age and age squared, and their interactions with education variables; gender and its interaction with age and age squared; household size; changes in household size; log disposable income in 1995; a dummy variable for being unemployed in any year from 1999 to 2007; (percentage)

Table 5
Exposure to robots and labor market outcomes

A. Base model

	Change in earnings	Unemployment risk
	(1)	(2)
$\Delta Robot\_density^{99\rightarrow07}$	−0.01715*	0.00422**
	(0.0100)	(0.0020)
Observations	30,375	30,375
R-squared	.0396	.0241
Industry controls	Yes	Yes
Household controls	Yes	Yes
Wealth deciles (1999)	No	No
Income deciles (1999)	No	No
Municipality FE	Yes	Yes

B. Base model + Initial income and wealth controls

	Change in earnings	Unemployment risk
	(1)	(2)
$\Delta Robot\_density^{99\rightarrow07}$	−0.02023*	0.00447**
	(0.0117)	(0.0020)
Observations	30,375	30,375
R-squared	.0662	.0400
Industry controls	Yes	Yes
Household controls	Yes	Yes
Wealth deciles (1999)	Yes	Yes
Income deciles (1999)	Yes	Yes
Municipality FE	Yes	Yes

This table presents coefficient estimates from the second-stage of the IV regressions for labor market outcomes. In all specifications, labor market measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, contemporaneous industry characteristics, and municipality dummies. In column 1, we focus on the log changes in household earnings between 1999 and 2007. In column 2, the dependent variable is an indicator variable that takes the value of one if a household is unemployed in 2007 conditional on being employed in 1999. In panel B, we account for fixed effects for deciles of household initial wealth and income in addition to industry and household controls. We estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model is defined and estimated in first differences. Standard errors are double clustered by municipality and industry. See the Internet Appendix for detailed variable definitions. $*p<.1; **p<.05; ***p<.01$.

Second, we turn to the impact of automation on unemployment risk. It represents one of the most important sources of background risk, a risk that is nontradable and not fully insurable due to market illiquidity or incompleteness (Kimball 1993; Aiyagari 1994; Fagereng, Guiso, and Pistaferri 2017). Our dependent variable is an indicator variable that takes the value of one if a given household was employed in 1999 but became unemployed in 2007. In other words, we estimate the transition probability from employment to unemployment during the observation period. Unemployment status is defined at the household level using information about whether the household head received any unemployment benefits in a given year.

change in income between 1995 and 1997; change in income between 1997 and 1999; and a set of indicator variables for homeownership, business ownership, and positive labor income in 1999 and 2007.

The regression estimates in column 2 of Table 5 indicate that, ceteris paribus, a one-standard-deviation increase in robot density increases the probability of becoming unemployed by 1.4 percentage points, on average. The effect is statistically significant (t-stat. = 2.11) and meaningful in economic terms. Our estimates put this into context by implying a 32% increase in the unemployment probability, as the unconditional unemployment rate in our sample equals 4.2%. As presented in panel B of Table 5, we obtain similar results when we in addition control for differences in initial levels of income and wealth. In summary, we establish negative and significant effects of robot adoption on labor market outcomes, particularly on the unemployment risk of households.[25]

3.2 Robots, financial risk-taking, and financial wealth

Next, we examine whether increased automation affects wealth accumulation through its effects on household financial risk-taking and investment choices, which we label as the *portfolio channel*.

How can the increased use of robots affect the financial behavior of households? The rapid adoption of robots in the workplace results in individuals facing higher background labor income risk, as shown by our labor market analysis in Section 3.1. The theory argues that increased background risk reduces the willingness of investors to take other types of risk, such as holding risky financial assets.[26] As returns on wealth are directly affected by the willingness of households to take financial risk (Ameriks, Caplin, and Leahy 2003), reducing or completely eliminating exposure to the stock market (in response to increased human capital risk) would lead to accumulation of less wealth over time.[27]

Panel A of Table 6 reports the empirical results of the financial risk-taking analysis. In column 1, the dependent variable is an indicator variable on whether the household invests in the stock market in 2007, either directly or indirectly through mutual funds excluding investments through retirement accounts.[28] After controlling for other well-known predictors of stockholding, we find that increased exposure to robots in an industry significantly reduces

25 The positive contribution of robot adoption to jobloss risk is consistent with Kogan et al. (2020), who document that advances in production methods are associated with substantial increases in labor income risk of individual workers. Still, we acknowledge that our analysis is silent on the general equilibrium spillover effects of automation on wages and employment in other sectors, as our analysis focuses on households that are directly exposed to robots at work. Hence, the displacement effect of robots may be partly offset by their reinstatement effect (Acemoglu and Restrepo 2019), which would, in turn, mitigate the adverse effects of automation on overall employment.

26 Cocco, Gomes, and Maenhout (2005) build and simulate a life cycle model of consumption and portfolio choice with nontradable labor income, showing 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 the annual consumption of investors.

27 In Section 4, we formalize these ideas by developing and solving a life cycle model of consumption and portfolio choice with endogenous stock market participation and automation risk.

28 Since the wealth data were collected to assess wealth taxes, stockholding under the mandatory first pillar of social security and in tax-deferred retirement accounts is not included in our data because they were not part of

Table 6
Exposure to robots and financial risk-taking and financial wealth

A. Financial risk-taking

	Stockholding status	Stock market exit	Change in risky share
	(1)	(2)	(3)
$\Delta Robot\_density^{99\to07}$	−0.00517**	0.00384**	−0.00402**
	(0.0024)	(0.0018)	(0.0018)
Observations	30,375	22,125	22,125
R-squared	.1698	.0715	.0800
Industry controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Wealth deciles (1999)	Yes	Yes	Yes
Income deciles (1999)	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

B. Financial wealth outcomes

	Change in fin. wealth	Wealth-to-income ratio
	(1)	(2)
$\Delta Robot\_density^{99\to07}$	−0.04645**	−0.01551*
	(0.0232)	(0.0084)
Observations	30,375	29,955
R-squared	0.5968	0.1881
Industry controls	Yes	Yes
Household controls	Yes	Yes
Wealth deciles (1999)	Yes	Yes
Income deciles (1999)	Yes	Yes
Municipality FE	Yes	Yes

This table presents coefficient estimates from the second-stage of the IV regressions for household risk-taking and financial wealth. In all specifications, outcome variables are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, fixed effects for deciles of household initial wealth and income in 1999, contemporaneous industry characteristics, and municipality dummies. In column 1 of panel A, we focus on stockholding status of households in 2007. In column 2 of panel A, the dependent variable is an indicator variable that takes the value of one if a stockholder household in 1999 exits the stock market as of 2007, and zero otherwise. In column 3 of panel A, the dependent variable is the changes in risky share between 1999 and 2007. In Panel B, we consider the changes in financial wealth between 1999 and 2007 and financial-wealth-to-income ratio in 2007 in columns 1 and 2, respectively. We estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model is defined and estimated in first differences. Standard errors are double clustered by municipality and industry. See the Internet Appendix for detailed variable definitions. $*p<.1; **p<.05; ***p<.01$.

the probability of households in that industry owning stocks (t-stat. = −2.15). In terms of economic magnitude, ceteris paribus, a one-standard-deviation increase in robot density lowers the likelihood of stockownership by approximately 1.7 percentage points, on average.

Next, we consider changes in household risk-taking. In column 2, we focus on stock market exits using an indicator variable for whether the household participated in the stock market in 1999 but liquidated its investments by 2007. In column 3, we use changes in risky share, which is defined as differences in

the tax base. Note that defined-contribution retirement wealth was still very limited in Sweden during the sample period.

the ratio of direct and indirect stock holdings to total household financial assets between 1999 and 2007.

Our results in columns 2 and 3 show that higher exposure to robotization significantly increases the probability of exiting the stock market and decreases the share of financial wealth invested in stocks. The estimated effects are economically highly meaningful. For example, the IV estimate in column 2 indicates that a one-standard-deviation exogenous rise in robot use increases the probability of exiting the stock market by approximately 1.25 percentage points.[29] This estimate implies a 15% increase in the exit probability, as the stock market exit rate in our sample equals 8.2%. Similar conclusions follow from the portfolio risky share analysis. To put these results into context, Betermier et al. (2012) report that an increase in wage volatility by 3% leads to an active decrease in the share of risky assets by 1%, and Fagereng, Guiso, and Pistaferri (2017) find that a one-standard-deviation increase in wage risk reduces the risky assets share by only 0.12 percentage points. Therefore, we conclude that this specific form of background risk, that is, automation risk, is essential and given the rapid recent progress in automation, it is likely to become increasingly important for the portfolio choice and wealth accumulation of households.[30]

In additional tests presented in Table O.A.19, we analyze the effects of robotization on the housing tenure decisions of households. Consistent with the financial risk-taking results, we find that increased exposure to robots in the workplace significantly increases (decreases) the probability of households selling (buying) a house during the sample period, suggesting that the effects of increased automation extend beyond financial assets to the real assets of households.

Thus far, we have stressed the importance of labor income risk when interpreting the results of the financial risk-taking regressions. However, expected changes in human capital also affect household risk-taking behavior (Calvet and Sodini 2014). To address this channel, we follow Mian and Sufi (2011) and proxy for income expectations using realized household-level income growth between 1999 and 2007. Panel A of Table O.A.20 shows that the exposure to robot variable retains its economic and statistical significance, even after controlling for household income expectations.[31]

[29] In Table O.A.18, we estimate the impact of increased exposure to robots in the workplace on stock market entry, and find no effect of robots on the probability of entering the stock market.

[30] It is also important to note that our focus in on the impact of (changing) income risk expectations on portfolio choice, as opposed to ("only actual") income shock realizations. By comparison, Basten, Fagereng, and Telle (2016) study the impact of unemployment shocks on portfolio allocation, and estimate a reduction in risky share of about 0.5%. This estimate is in fact similar to the one that we document (i.e., a reduction of 0.4%) even though we focus on the total population of households that has experienced an increase in their unemployment probability and not only those that actually became unemployed.

[31] As noted by Aladangady (2017), household expectations are likely to be correlated with their realized income growth, even though households do not have perfect foresight. For robustness purposes, we instead use past

Finally, we investigate whether increased automation contributes to differences in the accumulation of financial wealth across households. The results in panel B of Table 6 show that households working in industries with a higher rate of robot adoption experience a substantial drop in their financial wealth growth and accumulate less financial wealth relative to their income. Taken together, the findings presented in this section provide strong empirical support for our proposed mechanism that households that are more exposed to increased automation attain lower levels of financial wealth because they reduce, or fully eliminate, their stock market exposure in response to increases in their human capital risk.

3.3 The relative importance of different mechanisms

The results in the previous section provide strong evidence for the portfolio channel as an important mechanism through which exposure to automation affects household wealth accumulation. In this section, we discuss other potential explanations, including the direct impact of changes in labor income and changes in household savings behavior – and how we address them. Our intention is not to play down the importance of these other mechanisms, but rather to highlight that the portfolio channel is also operative and that it amplifies the adverse effects of increased automation on household financial well-being.

A powerful mechanism for the lower wealth levels of automation-exposed households is the income channel. The analysis in Section 3.1 shows a negative impact of robots on income growth. To scrutinize this channel, we would in principle like to estimate the wealth regressions by including both changes in robotization and realized income growth of households on the right-hand side of the model. Since realized income growth is endogenous to the increased use of robots in the industry of employment over the same period, such a model could lead to biased estimates. Therefore, we follow Zeldes (1989) and Shea (1995) and use past realized household-level income growth as an instrument. Specifically, we augment our base model by including realized income growth between 1995 and 1998 as an additional regressor. This corresponds to the reduced form of an IV regression, where we instrument current income growth by lagged income growth. Our findings in panel A of Table 7 indicate that exposure to the robot variable remains significant with a negative sign.[32] In addition, we find significantly negative and economically comparable effects of automation on household wealth accumulation in two subsamples, split by the median value of realized income growth between 1999 and 2007. Finally, to mitigate concerns that our wealth findings are entirely driven by displaced

income growth between 1995 and 1998, if households are more likely to form expectations based on past realizations, and obtain similar results.

32 We obtain similar results when we replace the income deciles in 1999 with average disposable income over 1995-1998 (see Table O.A.21).

Table 7
Exposure to robots and household net wealth: Addressing household income and savings channels

A. Wealth regressions controlling for past income growth

	Net wealth rank	Net wealth level	Change in net wealth rank
	(1)	(2)	(3)
$\Delta Robot\_density^{99\to07}$	−0.57877**	−0.19813***	−0.54185**
	(0.2573)	(0.0657)	(0.2438)
$\Delta Income^{95\to98}$	−0.17596	−0.13081	−0.21712
	(0.2739)	(0.1462)	(0.2702)
Observations	26,103	26,103	26,103
R-squared	.5972	.2632	.3027
Industry controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Wealth deciles (1999)	Yes	Yes	Yes
Income deciles (1999)	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

B. Wealth regressions controlling for active savings rates

	Net wealth rank	Net wealth level	Change in net wealth rank
	(1)	(2)	(3)
$\Delta Robot\_density^{99\to07}$	−0.51367**	−0.16584***	−0.47910**
	(0.2492)	(0.0581)	(0.2366)
Active savings rate (2000)	5.87378***	1.23525***	5.66322***
	(0.3217)	(0.1231)	(0.2978)
Observations	30,374	30,374	30,374
R-squared	.5843	.2574	.3244
Industry controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Wealth deciles (1999)	Yes	Yes	Yes
Income deciles (1999)	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

This table presents coefficient estimates from the second-stage of the IV regressions for household net wealth. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, fixed effects for deciles of household initial wealth and income in 1999, contemporaneous industry characteristics, and municipality dummies. In column 1, we focus on the wealth rank of households within their birth cohort-year distributions. In column 2, the dependent variable is the inverse hyperbolic sine of net wealth. In column 3, the dependent variable is the change in the net wealth rank of a household within her birth cohort distribution between 1999 and 2007. In panel A, we include realized income growth between 1995 and 1998 as an additional regressor in the regressions (that corresponds to the reduced form of an IV regression where we instrument current income growth by lagged income growth). In panel B, we include (initial) active savings rate as an additional control. We estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model is defined and estimated in first differences. Standard errors are double clustered by municipality and industry. See the Internet Appendix for detailed variable definitions. $*p<.1; **p<.05; ***p<.01$.

workers, we exclude households that become unemployed from the sample and repeat the estimation. Table O.A.22 shows that the coefficient for exposure to the robot variable declines but retains its economic and statistical significance.

Further, we recognize that heterogeneity in savings behavior can contribute to observed differences in wealth accumulation (De Nardi and Fella 2017; Meeuwis 2020). We address this alternative explanation in a number of ways. First, we compute the (initial) active savings rate of each household and include it as a control variable in the wealth regressions. The results, tabulated in panel

B of Table 7, show that the exposure to robots variable still exhibits a negative significant effect when accounting for heterogeneity in savings behavior across households.[33] Next, we consider the direct effects of increased automation on household savings behavior. The regression estimates in Table O.A.24 show no significant effect of robot exposure on the savings rates of households, suggesting that savings behavior is not an operative channel.

Finally, we perform a causal mediation analysis to estimate the share of the effect of increased automation on household wealth accumulation that runs through realized income growth. In principle, the mediation analysis allows to disentangle the average causal effect of a treatment variable (*automation growth*) on an outcome variable (*changes in net wealth*) running through an observed intermediate outcome (*realized income growth*), that is, indirect effects, and through other mechanisms (*portfolio channel*), that is, direct effects (Imai, Keele, and Yamamoto 2010; Imai et al. 2011; Heckman and Pinto 2015).[34] Based on the parameter estimates presented in columns 1 and 2 in Table O.A.25, we note that income growth as a mediator explains approximately two-thirds of the total effect of increased exposure to robots at work on household wealth accumulation.

Overall, our numerous findings presented in this section confirm a significant negative effect of robots on wealth accumulation that is not explained by a direct income effect or by differences in savings. Hence, the portfolio channel seems to represent an additional important and a relevant wealth accumulation factor.

3.4 The distributional effects of robots

While skill upgrading of jobs as a result of emerging technologies may favor some people, it could also leave others behind. In fact, Acemoglu and Restrepo (2022) show that middle-aged workers who perform blue-collar tasks are more likely to be replaced by industrial robots relative to older workers who are specialized in nonproduction services. Thus, we next study the distributional effects of automation by analyzing its impact on the economic outcomes of households by skill level. In line with Card and Lemieux (2001) and Acemoglu, Autor, and Lyle (2004), we argue that level of educational attainment is a good proxy for skill level, with less educated (i.e., high school or less) households more likely to perform blue-collar tasks.[35]

As shown in Table 8, an interesting pattern emerges when we analyze the effects of robot adoption by education level. Increased exposure to robots

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33 We verify this finding using the initial total savings rate instead of the active savings rates, as shown in Table O.A.23. We refer the reader to Section A of the Internet Appendix for a detailed description of how we use detailed household portfolio data to compute the savings rates.

34 We use the identification framework of Pinto et al. (2019) that enables, given some assumptions, such a decomposition in IV settings where both treatment and intermediate outcomes are endogenous. A novel property of their identification framework is that it requires a single instrument for identification, whereas earlier methods

Table 8
Distributional effects of robots

A. Labor market outcomes

	Less-educated	*Better-educated*	*Less-educated*	*Better-educated*
	Change in earnings		Unemployment risk	
	(1)	(2)	(3)	(4)
$\Delta Robot\_density^{99\rightarrow07}$	−0.01296	−0.01475	0.00441**	0.00265
	(0.0098)	(0.0100)	(0.0020)	(0.0018)
Observations	23,011	7,364	23,011	7,364

B. Wealth outcomes

	Less-educated	*Better-educated*	*Less-educated*	*Better-educated*
	Net wealth levels		Change in net wealth (in SEK)	
	(1)	(2)	(3)	(4)
$\Delta Robot\_density^{99\rightarrow07}$	−0.14592**	−0.06684	−45622.63313*	−21429.06049
	(0.0605)	(0.0489)	(26714.3725)	(20720.7180)
Observations	23,011	7,364	23,011	7,364

C. Financial risk-taking

	Less-educated	*Better-educated*	*Less-educated*	*Better-educated*
	Change in risky share		Stock market exit	
	(1)	(2)	(3)	(4)
$\Delta Robot\_density^{99\rightarrow07}$	−0.00464***	0.00148	0.00487**	−0.00344***
	(0.0018)	(0.0025)	(0.0020)	(0.0009)
Observations	16,091	6,034	16,091	6,034
Industry controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Wealth deciles (1999)	Yes	Yes	Yes	Yes
Income deciles (1999)	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes

This table presents coefficient estimates from the second-stage of the IV regressions for various household economic variables. In all specifications, wealth measures are regressed on changes in robot density between 1999 and 2007, changes in observable household variables, fixed effects for deciles of household initial wealth and income in 1999, contemporaneous industry characteristics, and municipality dummies. We use level of education of household head to identify low- and high-skill households, which we proxy by being a high-school graduate or less, and attending to college or more, respectively. Panels A and B report labor market and wealth outcomes of households, respectively. Panel C presents the results of the financial risk-taking analysis. We estimate IV regressions instrumenting for the change in robot density in Swedish industries using the median change in robot density across the (non-Swedish) 11 European countries. Note that our base model is defined and estimated in first differences. Standard errors are double clustered by municipality and industry. See the Internet Appendix for detailed variable definitions. $*p<.1$; $**p<.05$; $***p<.01$.

increases the unemployment risk and significantly decreases the financial risk-taking of the less educated households, whereas we find no such effects for the

require separate instruments for treatment and mediator. We provide details about the estimation procedure in Section B of the Internet Appendix.

35 It is worth mentioning that the median net wealth rank in our data at the start (end) of the sample period accounts for 51 (49) and 67 (71) for low- and high-educated households, respectively. Hence, splitting the sample by education level allows us to draw conclusions about the effects of automation on the dispersion of wealth among high- and low-wealth households, while using an arguably less endogenous variable (i.e., level of education) than, for example, the initial level of wealth.

better educated. Similarly, we find a strong significant negative effect on the wealth accumulation of less educated households but no significant effect in the better educated subsample. For instance, a one-standard-deviation increase in robot density in the industry of employment leads to an approximately US$ 23,100 lower increase in net wealth levels over the sample period for the less educated, on average.[36] Since the median net wealth in that group is around US$ 100,000, the effect is indeed quantitatively important. Taken together, the increased adoption of robots displays – partly through the portfolio channel – asymmetric effects on the wealth accumulation of households across different segments of the population.

4. Life Cycle Model

In this section, we develop a life cycle model to provide an alternative quantification of the importance of the portfolio channel. We consider a standard life cycle portfolio choice model (as in, e.g., Gomes and Michaelides 2005, Fagereng, Gottlieb, and Guiso 2017, Catherine 2022), augmented to include a robotization shock to the labor income process. We solve the model for both pre- and post-robotization shock scenarios. We then simulate the model under the prerobotization conditions, to replicate the behavior in the year 1999 of the data. From that starting point, we introduce the robotization shock, and simulate the behavior of the agents for another 8 years, to match the sample period in our empirical analysis.

4.1 Model setup

Households have a finite horizon, divided into two periods: working-life and retirement. Before retirement, they earn labor income subject to undiversifiable shocks, and after retirement, they receive a fixed pension. They can invest their savings in both a riskless and risky asset, but investments in the risky asset face (per-period) participation costs.

In the empirical analysis, robotization is a continuous variable. In the model, we capture this by having three groups of households working in industries with different levels of exposure to robot risk: *low*, *medium*, and *high*. We will refer to those using the notation $\Omega = L, M$, and H, respectively. Importantly, stock market participation costs are the same for all groups such that, entry and exit decisions are fully determined by the endogenous outcome of the simulations. Likewise, all agents have the same risk aversion parameter, so that their demand for risky assets would be identical in a frictionless model.

4.1.1 Preferences. Households have Epstein-Zin utility functions (Epstein and Zin 1989) defined over the consumption of a single, nondurable

[36] The Swedish krona (SEK) traded at US$ 0.155 at the end of 2007.

good (C_t):

$$V_t = \left\{ (1-\beta)(C_t)^{1-1/\psi} + \beta E_t \left[\pi_t^s \left[V_{t+1}^{1-\gamma} \right] \right]^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}, \tag{4}$$

where γ is the coefficient of relative-risk aversion, ψ is the elasticity of intertemporal substitution, β is the subjective discount factor, and π_t^s is the conditional survival probability from age t to age $t+1$.[37] The conditional survival probabilities are a function of income, as will be described below.

4.1.2 Labor income process and retirement income. Labor income during working life is subject to both permanent shocks and transitory shocks as in Carroll (1997), Gourinchas and Parker (2002), Cocco, Gomes, and Maenhout (2005), or Gomes and Michaelides (2005), among others. However, we augment the stochastic process in these papers by considering a separate unemployment state (U_t). Crucially, all parameters of the income process are functions of robot exposure in the industry (Ω).

Each year households suffer an unemployment spell with probability $\pi^u(\Omega)$ in which case their income is given by $\lambda^u(\Omega)$. With probability $1-\pi^u(\Omega)$, households are employed and their labor income is given by the standard permanent and transitory combination:

$$ln(Y_t) = f(t,\theta;\Omega) + p_t + u_t, \tag{5}$$

$$p_t = p_{t-1} + z_t, \; z_t \tilde{} N(\mu_Z, \sigma_z^2(\Omega)), \tag{6}$$

$$u_t \tilde{} N(0, \sigma_u^2(\Omega)), \tag{7}$$

where $f(t,\theta;\Omega)$ is a deterministic function of age and other household characteristics (θ), as described in the Internet Appendix.

The common assumption in the literature is that $\mu_Z = 0$ (see Carroll (1997); Gourinchas and Parker (2002); Cocco, Gomes, and Maenhout (2005); Fagereng, Gottlieb, and Guiso (2017), among others). We extend this by allowing unemployment spells to be associated with a reduction in permanent income, as documented by Braxton, Herkenhoff, Rothbaum, and Schmidt (2021), for example.[38] More precisely, we set $\mu_Z = 0$ if the households was employed at $t-1$, and $\mu_Z = z_{low} < 0$ if the household was unemployed at $t-1$.

Households retire at age K, and, as standard in the literature, retirement income is a deterministic function of income in the last year of working life:[39]

$$Y_t = \lambda^R(\Omega) Y_K, \; t > K, \tag{8}$$

where λ^R is the retirement replacement ratio.

37 The conditional survival probability is equal to zero at a predetermined maximum age, which we calibrate to 100.

38 See Bagliano, Fugazza, and Nicodano (2019) for an alternative formulation, capturing the same mechanism.

39 In most life cycle models retirement income is a fraction of (last-year's) permanent income only. Since the level of income is already a state variable in our model, we are able to generalize that formulation.

4.1.3 Financial assets, participation costs, and budget constraints. Households can invest in a riskless one-period bond, and in an aggregate stock market index. Households who invest in the stock market face per-period costs of participation (F), as in Fagereng, Gottlieb, and Guiso (2017).

Letting W_t and α_t denote, respectively, wealth and the risky share at time t, the household's budget constraint is

$$W_{t+1} = (\alpha_t R_{t+1} + (1-\alpha_t)R_f)(W_t - C_t - F I_t^{\alpha>0}) + Y_{t+1}, \tag{9}$$

where $I^{\alpha>0}$ is a dummy variable that is equal to 1 if the household has positive stock holdings this year. The return on the riskless bond (R_f) is constant. Following Fagereng, Gottlieb, and Guiso (2017), the return on the stock market follows a normal distribution augmented to include both a tail event (with probability π_R) and idiosyncratic volatility:

$$R_{t+1} \sim \begin{cases} N(\mu_r, \sigma_{rm}^2 + \sigma_{ri}^2) & \text{with probability } 1-\pi_R \\ R_{low} & \text{with probability } \pi_R, \end{cases}$$

where the idiosyncratic volatility term (σ_{ri}) captures the underdiversification of individual portfolios (see, e.g., Calvet, Campbell, and Sodini 2007; Fagereng, Gottlieb, and Guiso 2017; Bach, Calvet, and Sodini 2020).

4.1.4 Survival probabilities. We capture the empirical correlation between survival probabilities and income, as described in the calibration section. In the model, life expectancy is a function of permanent income, instead of total income, to avoid large jumps in survival probability associated with unemployment spells. Since we have a correlation between unemployment and future permanent income (as discussed above), the unemployment spells still lead to a decrease in survival probabilities going forward, but in a smoother manner.

4.1.5 Model solution, simulations, and counterfactuals. The model has four state variables: wealth (W_t), income (Y_t), age (age), and an indicator for lagged unemployment ($I^{U_{t-1}}$).[40] In addition, we have to solve for the three types of agents ($\Omega = L, M$ and H), and both the environment with and without the robotization shock (denoted as RS and NRS, respectively). The solutions are obtained using standard numerical methods, as described in Section C.1 of the Internet Appendix, to yield the two decision rules: consumption/savings and share of wealth invested in the risky asset:[41]

$$C_t = C(W_t, Y_t, I^{U_{t-1}}, age; \Omega, RS/NRS), \tag{10}$$

$$\alpha_t = \alpha(W_t, Y_t, I^{U_{t-1}}, age; \Omega, RS/NRS). \tag{11}$$

[40] The lagged unemployment indicator is a required state variable because of the correlation between current unemployment and future permanent labor income.

[41] The participation decision is a by-product of the portfolio rule, since we "only" have per-period participation costs.

In the simulations, we first simulate an economy using the prerobotization decision rules and the corresponding data-generating processes, capturing the year 1999 in the data. Then, we introduce the robotization shock. More precisely starting from the pre-robotization equilibrium, we simulate the model using the post-robotization policy functions and associated data-generating processes. Consistent with the empirical analysis, we simulate this economy for 8 years, as will be discussed in more detail below. Furthermore, we feed into the simulations the actual realized asset returns during this period. We assume that robotization is an unexpected shock. The alternative would require making assumptions about household's subjective expectations of the shock, which would introduce an additional free parameter in the model.

4.2 Calibration

4.2.1 Income process estimation. Our estimation closely follows the definitions and estimation procedure as used in Cocco, Gomes, and Maenhout (2005). We use income data at the household level from 1993 to 2007 when estimating the income profiles of households with low, medium, and high exposure to robots at work. We define the 1993-1998 period as the prerobotization period, while the 1999-2007 period refers to the post-robotization period. We allow the income profile to differ between high, medium, and low robot exposure industries, and between pre- and post-robotization shock.

Since we have a short time series for the post-robotization period, we estimate the permanent-transitory decomposition on the full sample, and therefore focus on the role of changing unemployment risk, as in the empirical analysis. The probability of unemployment (π^u) represents the probability of suffering an unemployment spell throughout the year, and therefore, the corresponding income includes both unemployment subsidy received during the unemployment spell and labor income earning during the rest of that year. The estimation results are presented in Table 9, and Figures 1 and 2.

In 2008, around 70% of the Swedish workforce was a member of an unemployment insurance fund. In addition, some individuals also have private unemployment insurance. Their unemployment benefits are therefore equal to 80% of previous earnings up to a maximum of SEK 680 per day (5-day week). We combine this with the average unemployment duration in Sweden (4.3 months) to compute individual income in a year with an unemployment spell.

We calibrate the correlation between unemployment spells and future permanent labor income with the recent evidence from Braxton et al. (2021). They estimate that unemployment spells are followed by a 15% negative permanent income shock (on average).

4.2.2 Other parameters. Consistent with the analysis in the empirical section we set the starting age in the model to 22. The retirement age is set

Table 9
Labor income process estimation

A. Labor income process: Coefficients in the age polynomials

	PreRobotization (1993-1998)			Post-robotization (1999-2007)		
	$\Omega = L$	$\Omega = M$	$\Omega = H$	$\Omega = L$	$\Omega = M$	$\Omega = H$
	(1)	(2)	(3)	(4)	(5)	(6)
Age	21716.43581***	19841.56108***	13862.27457***	24498.60538***	23692.50904***	26189.74566***
	(532.67)	(915.98)	(646.27)	(462.01)	(1552.38)	(905.57)
$Age^2/10$	−3219.49650***	−2514.56761***	−1259.19925***	−3145.08207***	−2854.63861***	−3641.31613***
	(−341.54)	(−495.86)	(−249.60)	(−262.37)	(−813.51)	(−543.31)
$Age^3/100$	193.65901***	150.46336***	67.73289***	159.89917***	135.59702***	187.17217***
	(273.63)	(390.81)	(176.09)	(181.44)	(517.19)	(371.31)
Constant	−225515.63950***	−208473.29755***	−129141.48317***	−290334.41946***	−256002.39436***	−272652.39247***
	(−394.46)	(−696.21)	(−437.72)	(−381.08)	(−1187.27)	(−673.38)
Observations	43,028	121,374	68,965	46,210	183,669	107,552
R-squared	.9988	.9995	.9997	.9988	.9996	.9988

B. Variance decompositions

	Prerobotization (1993-1998)			Post-robotization (1999-2007)		
	$\Omega = L$	$\Omega = M$	$\Omega = H$	$\Omega = L$	$\Omega = M$	$\Omega = H$
	(1)	(2)	(3)	(4)	(5)	(6)
SD of transitory	0.0864	0.0871	0.0757	0.1130	0.1094	0.0963
SD of permanent	0.0801	0.0701	0.0615	0.0637	0.0664	0.0696

C. Replacement rates and unemployment

	Prerobotization (1993-1998)			Post-robotization (1999-2007)		
	$\Omega = L$	$\Omega = M$	$\Omega = H$	$\Omega = L$	$\Omega = M$	$\Omega = H$
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment replac. rate	77.73%	85.00%	80.30%	78.17%	78.11%	77.34%
Unemployment prob.	8.80%	8.29%	6.68%	7.02%	6.45%	6.65%
Retirement replac. rate	55.86%	50.25%	46.91%	58.73%	56.38%	57.25%

This table presents an overview of the estimates for labor income process estimation. In panel A, we report the coefficient estimates from the age polynomial regressions for households with low ($\Omega = L$), medium ($\Omega = M$), and high ($\Omega = H$) exposure to robot risk separately for the pre- and post-robotization periods. Panel B reports the estimates of the standard deviation of permanent and transitory labor income shocks estimated from the full observation period for households with low ($\Omega = L$), medium ($\Omega = M$), and high ($\Omega = H$) exposure to robot risk. Panel C presents the replacement rate for income during an unemployment state, the probability of suffering an unemployment spell throughout the year and the retirement replacement ratio. The probability of unemployment represents the probability of suffering an unemployment spell throughout the year, and therefore, the corresponding income includes both unemployment subsidy received during the unemployment spell and labor income earning during the rest of that year. See Section C.2 of the Internet Appendix for details about the estimation procedure.

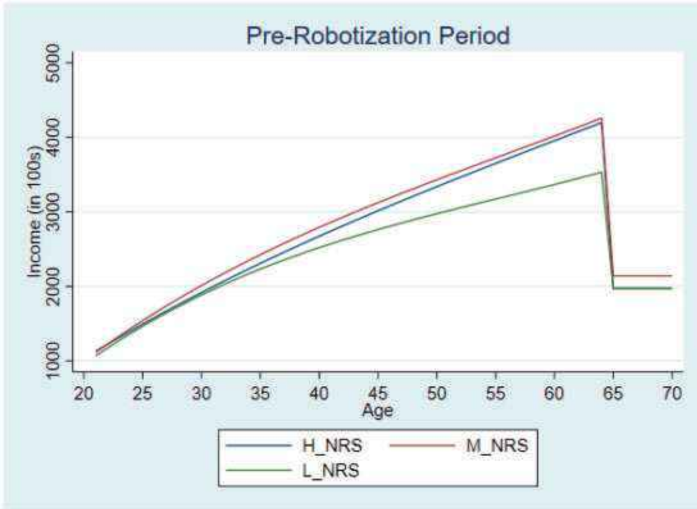

Figure 1
Labor income process estimates: Prerobotization period
This figure presents the labor income processes estimated from the LINDA database for the pre-robotization period (i.e., 1993-1998) for three groups of households with low ($\Omega = L$), medium ($\Omega = M$), and high ($\Omega = H$) exposure to robot risk, respectively. Labor income refers to the broad income definition that includes labor income and government transfers excluding any capital income. See Section C.2 of the Internet Appendix for details about the estimation procedure.

to 65 and the maximum age to 100, but these are only relevant for solving the dynamic programming problem, since the simulation results naturally focus on preretirement households. More precisely, the statistics computed from the simulations are based on the same age distribution as the one observed in the sample for the empirical analysis.

We calibrate the coefficient of risk aversion (γ) to 5 for the three groups. We then use the discount factor (β) and EIS (ψ), to match the initial wealth-to-income ratio of each.[42] More specifically, we define $\psi^H = 0.2$, $\psi^M = 0.275$ and $\psi^L = 0.4$ and $\beta^H = 0.98$, $\beta^M = 0.975$ and $\beta^L = 0.994$.

We calibrate the correlation between survival probabilities and income using data from Statistics Sweden, which reports average life expectancy as a function of age for four different income quartiles. To avoid discrete jumps in survival probabilities at the cutoff values for those quartiles, we map this into a continuous function of income. More specifically, we compute mean income in each quartile in our data and use that to fit separate regression of survival probabilities on log income, for each age.[43] This gives us both a vector

42 Alternatively we could fix one of those (discount rate or EIS) and only consider heterogeneity in the other, but this would require more heterogeneity along that one dimension.

43 Differences in survival probabilities are naturally very small at young ages but increase at later ages, hence the importance of running separate regressions for each age.

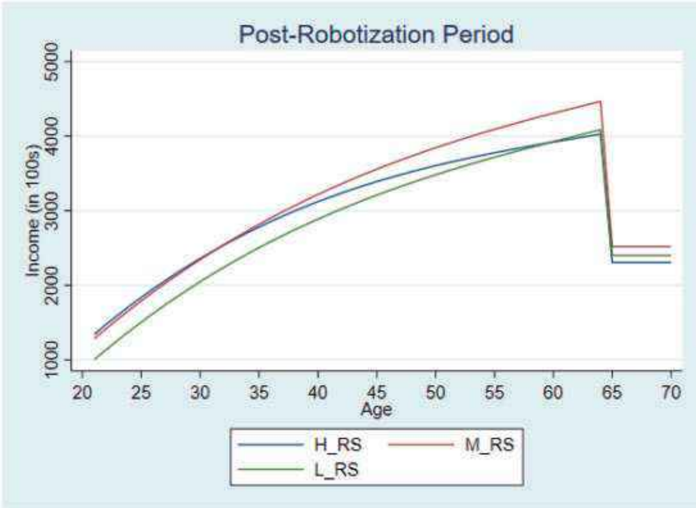

Figure 2
Labor income process estimates: Post-robotization period
This figure presents the labor income processes estimated from the LINDA database for the post-robotization period (i.e., 1999-2007) for three groups of households with low ($\Omega = L$), medium ($\Omega = M$), and high ($\Omega = H$) exposure to robot risk, respectively. Labor income refers to the broad income definition that includes labor income and government transfers excluding any capital income. See Section C.2 of the Internet Appendix for details about the estimation procedure.

of intercepts and a vector of slope coefficients, which we then feed into the model, resulting in different survival probabilities as a function of (permanent) income for each age.

We set the real riskless rate to 1% and the equity premium to 4%. The total volatility of stock returns (including the idiosyncratic component) is set to 30%, capturing the limited diversification of household portfolios (Calvet, Campbell, and Sodini 2007). The probability of a return tail event and the return realization are set to 2% and 51.5%, respectively (from Fagereng, Gottlieb, and Guiso 2017).[44] Finally, we set the per-period participation cost F to 0.4% and 0.05% of yearly income.[45] A crucial point is that these costs are identical for all three groups (high, medium and low robot exposure), so that differences in asset allocation decisions are fully driven by the parameters of the stochastic environment (both before and after the shock) and by the wealth dynamics in the simulations.

44 The equity premium value of 4% takes into account the tail event state.

45 Following the evidence in Lusardi and Mitchell (2014) we consider two groups with high and low financial literacy hence different participation costs.

Table 10
Fit of the model: Model-implied moments versus their empirical counterparts

	Model				Data			
	$\Omega = L$	$\Omega = M$	$\Omega = H$	All	$\Omega = L$	$\Omega = M$	$\Omega = H$	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth-income ratio	3.04	1.31	0.90	1.43	3.03	1.29	0.86	1.41
Stock market participation	0.88	0.75	0.62	0.73	0.75	0.74	0.69	0.73
Conditional risky share	0.65	0.77	0.72	0.74	0.69	0.74	0.73	0.73

This table compares the model-implied moments and their empirical counterparts for wealth-income ratio, stock market participation and conditional risky share for households with low ($\Omega = L$), medium ($\Omega = M$), and high ($\Omega = H$) exposure to robot risk separately, and for the full population. The full population moments from the model are computed using the empirical weights for each of the three groups.

4.3 Results

4.3.1 Baseline economy. Table 10 reports the model-implied moments and their empirical counterparts for wealth-to-income ratio, stock market participation and conditional risky share. We report results for each of the three groups ($\Omega = L$, M and H) separately, and for the full population. The full population moments from the model are computed using the empirical weights for each of the three groups.

The model matches extremely well the wealth-to-income ratios in the data, both for the total population, and for each of the three groups individually. This was expected since these were the moments that were targeted in the calibration. However, the empirical conditional risky shares are also very well matched, even though all three groups have the same coefficient of relative risk aversion and face the same stock market participation costs.[46] The average stock market participation rate is also exactly the same in the model and in the data (73%), and in both cases, it is a decreasing function of robot risk exposure. However, the gradient is steeper in the model, relative to its empirical counterpart.

4.3.2 Robotization shock and portfolio channel decomposition. Having documented that the model closely replicates the behavior of Swedish households along the dimensions that are important for our analysis, we now use it to evaluate the impact of the portfolio channel that we document. We proceed in the following steps:

1. We first replicate the 1999 equilibrium by simulating the model in the absence of the robotization shocks, so with the policy functions $C_t = C(:;\Omega, NRS)$ and $\alpha_t = \alpha(:;\Omega, NRS)$. $W_{\Omega}^{noshock}$ denotes the average wealth of each group ($\Omega = L$, M, and H) in these simulations.

2. Starting from the 1999 equilibrium above, we then simulate the model for 8 years in the presence of the robotization shocks, so with the policy functions

46 Interestingly, the model is even able to replicate the hump-shape pattern in risky share, as a function of robot risk exposure, that we observe in the data.

$C_t = C(:;\Omega, RS)$ and $\alpha_t = \alpha(:;\Omega, RS)$. W_{Ω}^{shock} denotes the average wealth of each group ($\Omega = L$, M, and H) in last year of the simulations. This is the model predicted outcome for 2007.

The difference between W_{Ω}^{shock} and $W_{\Omega}^{noshock}$ ($\Delta W_{\Omega}^{shock}$) measures the average change in wealth, for each group, following the robotization shock.

To isolate the contribution of the portfolio channel, we require a third set of simulations.

3. Starting in the 1999 equilibrium, simulate the model for 8 years in the presence of the robotization shocks but with the risky shares that would have been observed in the absence of the robotization shock.[47] $W_{\Omega}^{shock\_oldalpha}$ denotes the average wealth of each group ($\Omega = L$, M, and H) in last year of the simulations. This is the model predicted outcome for 2007, in the presence of the robotization shock, but without households adjusting their portfolio allocations.

The difference between $W_{\Omega}^{shock\_oldalpha}$ and $W_{\Omega}^{noshock}$ ($\Delta W_{\Omega}^{shock\_oldalpha}$) measures the average change in wealth, for each group, that would have happened following the robotization shock, if households had not adjusted their policy functions. Finally, we compute the ratio:

$$(\Delta W_{L}^{shock\_oldalpha} - \Delta W_{H}^{shock\_oldalpha})/(\Delta W_{L}^{shock} - \Delta W_{H}^{shock}). \tag{12}$$

We obtain a value of 15%, which indicates that 15% of the differences in (change in) wealth due to the robotization shock, result from the portfolio reallocation behavior of households. Hence, this result reinforces and supports the empirical results that the portfolio channel represents a relevant wealth accumulation factor, amplifying the inequality-enhancing effects of automation.

5. Conclusions

This paper uses an extensive administrative panel and auxiliary data on industrial robots to analyze the effect of increased automation on household wealth accumulation and on the underlying economic mechanisms. We find evidence of statistically and economically significant effects of rapid adoption of industrial robots on household wealth accumulation. Our findings are robust to correcting for the endogeneity of exposure to robots, and when controlling for a rich set of household characteristics, macroeconomic and institutional regional factors, and industry factors and trends. We conduct numerous sensitivity checks to verify the robustness of our findings.

We consider a number of explanations through which industrial robots may affect household wealth accumulation. Beyond the income and savings channels, our results point to a more nuanced mechanism, which we label

[47] The actual portfolio allocations are still changing, even for the same decision rules, both because wealth is changing and because the agent is aging.

as the *portfolio channel*. In particular, we show that households that are more exposed to increased automation attain lower levels of financial wealth, mainly because they reduce, or fully eliminate, their stock market exposure in response to increases in their human capital risk. We scrutinize other alternative mechanisms, including changes in labor income or changes in household savings behavior. Our numerous findings strongly suggest that the patterns of statistical and economic significance we document in wealth analysis are not a mere product of income or savings effects but, in addition, are driven by the portfolio channel.

We then study the potential distributional effects of increased automation and find that the negative impacts of automation on stock market participation and wealth accumulation are only operative for less-educated households, while we find no such effects for their better-educated counterparts. These results suggest that rapid automation can further widen the wealth gap between high- and low-skilled individuals.

Building on our empirical findings, we solve a life cycle model of consumption and portfolio choice with automation risk and endogenous stock market participation. We first calibrate the model to match the wealth accumulation of households with high, medium, and low robot exposure in the data, and show that the calibrated model replicates very well asset allocations of these three groups. We then perform a counterfactual analysis, where we isolate the role of portfolio channel in explaining the differences in wealth accumulation across households, and find that the portfolio rebalancing in response to the robotization shock generates 15% of the differences in (change in) wealth, confirming that it is indeed an important mechanism driving the differences in wealth accumulation, in line with our empirical results.

All in all, our paper highlights an important mechanism driving the negative effects of increased automation on household wealth accumulation, and contributes to the current discussion on the economic consequences of increased automation.

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