DOCUMENTOS DE TRABAJO

Robots, Exports and Top Income Inequality: Evidence for the U.S.

Andrés César, Guillermo Falcone y Pablo Garriga

Documento de Trabajo Nro. 307
Diciembre, 2022
ISSN 1853-0168
www.cedlas.econo.unlp.edu.ar

Cita sugerida: César, A., G. Falcone y P. Garriga (2022). Robots, Exports and Top Income Inequality: Evidence for the U.S.. Documentos de Trabajo del CEDLAS Nº 307, Diciembre, 2022, CEDLAS-Universidad Nacional de La Plata.

Robots, Exports and Top Income Inequality: Evidence for the U.S.*

Andrés César[†] CEDLAS-UNLP
Guillermo Falcone[‡] CEDLAS-UNLP
Pablo Garriga[§] World Bank

November 2022

Abstract

The last decades have witnessed a revolution in manufacturing production characterized by increasing technology adoption and a strong expansion of international trade. Simultaneously, the income distribution has exhibited both polarization and concentration among the richest. Combining datasets from the U.S. Census Bureau, the U.S. Internal Revenue Service, the International Federation of Robotics, EU KLEMS, and COMTRADE, we study the causal effect of industrial automation on income inequality in the U.S. during 2010–2015. We exploit spatial and time variations in exposure to robots arising from past differences in industry specialization across U.S. metropolitan areas and the evolution of robot adoption across industries. We document a robust positive impact of robotics on income for only the top 1 percent of taxpayers, which is largest for top income fractiles. Therefore, industrial automation fuels income inequality and, particularly, top income inequality. According to our estimates, one more robot per thousand workers results in relative increments of the total taxable income accruing to fractiles P99 to P99.9, P99.9 to P99.99 and P99.99 to P100, of 2.1 percent, 3.5 percent and 5.9 percent, respectively. We also find that robotization leads to increased exports to high-income and upper-middle-income economies, and that this is one of the key mechanisms behind the surge in top income inequality.

JEL Classification: J23, J24, J31, O14, O33.
Keywords: Robots, Automation, Metropolitan areas, United States, Exports, Income inequality, Top incomes.

*We are grateful to seminar participants at Brown University, UNLP, and to many researchers met at the 7th Lindau Meeting on Economic Sciences for helpful comments and discussions. All errors are our responsibility.

[†]Universidad Nacional de La Plata, Center for Distributive, Labor, and Social Studies (CEDLAS), Calle 6 e/ 47 y 48, 1900 La Plata, Argentina. email: andres.cesar@econo.unlp.edu.ar

[‡]Universidad Nacional de La Plata, Center for Distributive, Labor, and Social Studies (CEDLAS), Calle 6 e/ 47 y 48, 1900 La Plata, Argentina. email: guillermo.falcone@econo.unlp.edu.ar

[§]World Bank. email: pgarriga@worldbank.org

I Introduction

Inequality has risen sharply in the U.S. and other industrialized economies over the last forty years. The evolution of the income distribution depicts both polarization and concentration among the richest. While some authors document that distributional conflict is harmful for growth, others link up inequality to political instability and fears of political capture by the superrich.[1] The last decades have also witnessed a revolution in manufacturing production characterized by falling costs and increasing adoption of several technologies such as communication networks, computer-aided design, industrial robots and flexible manufacturing systems, which were in turn accompanied by large expansions in output and international trade flows. Automation technologies threaten the possibilities of routine manual production workers to compete against machines, while highly skilled individuals that work *in tandem* with new technologies, as well as the owners of capital, enjoy a sizeable fraction of the productivity gains (Acemoglu and Restrepo, 2022; Moll, Rachel, and Restrepo, 2022).

In this paper we empirically document that the adoption of a specific type of automation technology, namely *industrial robots*, causes an increase in inequality in the personal income distribution and, particularly, leads to rising inequality among the highest paid individuals, *a.k.a* "top income inequality". We show that: (i) industrial automation increases the income level –and the income share– of *only* the top 1 percent of taxpayers; (ii) income gains are higher for the top income fractiles (i.e. the top 0.1 percent and the top 0.01 percent), which fuels inequality specifically at the very right tail of the income distribution; (iii) automation leads to increasing exports to high-income and upper-middle-income countries; and (iv) the rise in exports is one of the key mechanisms behind the surge in top income inequality.

Technical change is a dynamic process of innovation encompassing the development of new capital equipments, the introduction of new products, organizational changes and continuous learning by doing (Freeman, 1986). The firm's problem (whether to adopt new technologies) characterizes by strong complementarities among several decisions that extend beyond manufacturing production towards design, engineering, organization, marketing and distribution (Milgrom, Qian, and Roberts, 1991). These processes demand strong managerial and investment capabilities, which

[1]For evidence of the increase in income inequality in the U.S. see Piketty and Saez (2003), Atkinson, Piketty, and Saez (2011), Acemoglu and Autor (2011), Saez and Zucman (2016), Autor (2019), among many others. See Galor and Zeira (1993) and Persson and Tabellini (1994) for arguments on inequality and growth. For discussions on inequality and political economy see Benabou (1996), Farhi et al. (2012), Piketty (2014), Scheuer and Wolitzky (2016), Gilens (2014), Bartels (2016).

places big companies one step ahead. Indeed, existing evidence shows that the adoption of automation technologies concentrates on very large firms (Acemoglu, Lelarge, and Restrepo, 2020; Acemoglu et al., 2022), that access to export markets stimulates productivity-enhancing investments within firms (Aw, Roberts, and Xu, 2011; Koch, Manuylov, and Smolka, 2021) and that the production processes of the largest manufacturing firms have become more capital intensive over the last decades (Hubmer and Restrepo, 2022).

Firms adopting robots achieve productivity gains, less costly product redesigns and greater flexibility to adapt their outputs to different quality standards, which translates into higher sales domestically and abroad (Graetz and Michales, 2018; Acemoglu et al., 2020; Koch et al., 2021; Aghion, Antonin, Bunel, and Jaravel, 2022).[2] In this sense, technological upgrading favors the expansion of the most productive firms and results in a permanent fall of the labor share in value added, leading to greater concentration of economic activity among low labor share firms (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020, Martinez, 2021; Kehrig and Vincent, 2021) and, presumably, to higher incomes for their owners, managers and other professionals working in these companies.

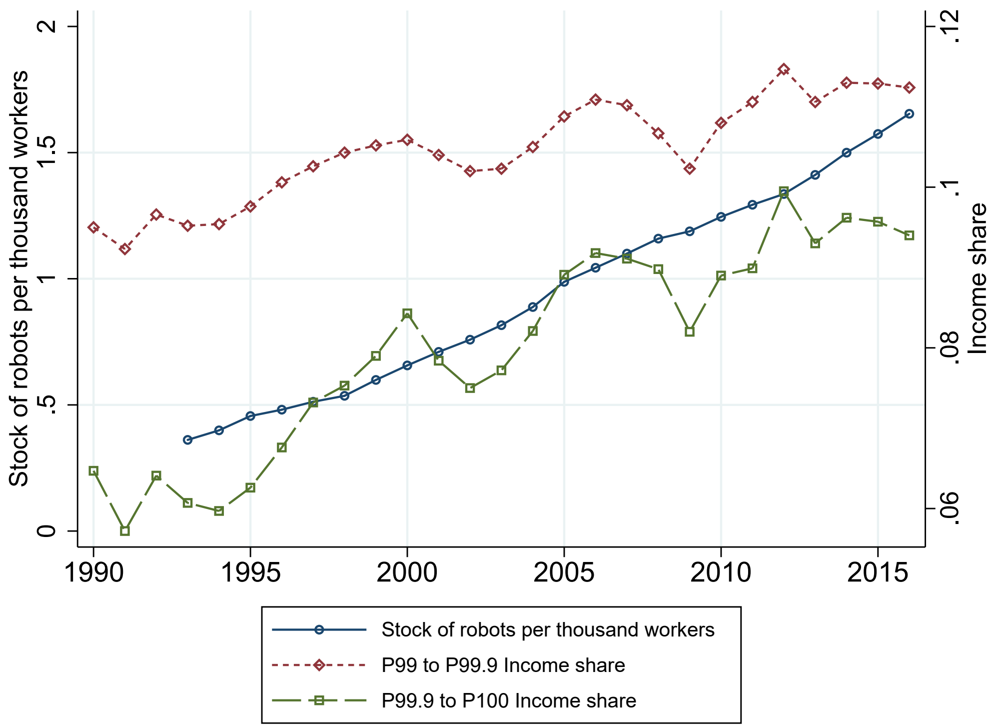
Fig. 1 depicts the evolution of the income share held by the top 1 percent and the number of robots per thousand workers in the U.S. between 1990 and 2016. Both variables increased markedly during this period. Importantly for our research question, the income accrued by the top 0.1 percent grew faster than the income obtained by the following top income fractile (P99 to P99.9).[3] Our empirical analysis investigates if robot adoption is causally related to the observed increases of both top incomes and top income inequality.

To study the causal impact of robotics on top incomes and on exports we combine five sources of data. (i) Robot adoption at the country-industry-year level stems from the International Federation of Robotics (IFR). The IFR reports the annual number of industrial robots (ISO 8373) shipped by robot producers to each industry in different countries. (ii) We employ top income data from the World Inequality Database (WID) that was kindly provided by Sommeiller and Price (2018). This dataset is disaggregated at the level of metropolitan areas for the period 2010–2015. Since it is based on IRS fillings, it has less under-reporting in the upper tail of the income distribution, being

[2] Relatedly, automation is associated both to the reshoring of economic activity back into advanced economies (De Backer, DeStefano, Menon, and Ran Suh, 2018; Faber, 2020; Stemmler, 2019; Krenz, Prettner, and Strulik, 2021) and to increases in import and export intensities (Artuc, Bastos, and Rijkers, 2020; Acemoglu and Restrepo, 2021).

[3] The U.S. income tax data shows that executives, managers, supervisors and financial professionals account for about 60 percent of the top 0.1 percent of income earners and for around 70 percent of the increase in the share of national income accrued to this segment between 1979 and 2005 (Bakija, Cole, and Heim, 2012).

Fig. 1: Robot adoption and Top 1 percent income share in the U.S.



Notes. Pre-tax national income shares obtained from the World Inequality Database. The top 1 percent income share is splitted among two mutually exclusive samples of tax units: 99th to 99.9th percentiles (diamonds-short dash) and 99.9th to 100th percentiles (squares-long dash). The stock of robots in the U.S. is obtained from the International Federation of Robotics (IFR) and the number of workers is sourced from the U.S. Bureau of Labor Statistics.

more accurate to measure top income inequality than household surveys, and specially useful for our purposes. (iii) We use microdata from the 1980 and 1990 U.S. Censuses to calculate the composition of employment by industry and other relevant economic and demographic characteristics at the metropolitan area level. (iv) We exploit industry employment data from EU KLEMS to compute robot penetration both in the U.S. and Europe. (v) We use trade data from UN-COMTRADE to compute a measure of exports per worker at the industry and metropolitan area levels.

We follow Acemoglu and Restrepo (2020) and measure exposure to robots at the local labor market (LLM) level using a shift-share approach, i.e. allocating industrial robot adoption according to the past industry composition of employment across metropolitan areas. We run regressions at the level of LLMs of several measures of income (for mutually exclusive income segments) on local exposure to robots. Robot adoption is potentially endogenous because local economic conditions may have an impact on firm's decisions to invest in robotics and, simultaneously, on income. To address this concern, we follow an instrumental variable design aimed to capture exogenous improvements in technology arising from the widespread use of industrial robots across industrialized economies. In particular, we instrument robot adoption in U.S. industries using the average adoption of robotics across European countries' industries. The instrument should pick up the fraction of U.S. robot purchases that is explained by industry supply shifters such as advances in technology, availability and prices. The instrument isolates the growth in robot use that is due to exogenous technological change. The main identifying assumption is that robot adoption in Europe is not correlated with shocks in the U.S.

Our findings suggest that metropolitan areas more exposed to growing robot adoption experience a relative increase in the total taxable income earned by the top 1 percent of taxpayers, and no impact on the total income accruing to the bottom 99 percent. Within the top 1 percent segment, income gains are larger as we concentrate on higher-paid fractiles. Specifically, an increase in one robot per thousand workers rises the total taxable income accruing to fractiles P99 to P99.9, P99.9 to P99.99 and P99.99 to P100, by 2.1 percent, 3.5 percent and 5.9 percent, respectively. We then focus on two measures of income inequality: (i) income ratios across fractiles, and (ii) income share of each fractile. We document that more exposed locations exhibit a robust relative increment in income inequality and, particularly, in top income inequality. One more robot per thousand workers leads to a relative decline in the income share of the bottom 90 percent of taxpayers of 0.42 percentage points (-0.8 percent) and, conversely, augments the income share of the aforementioned top income fractiles by 0.12 p.p. (1.3 percent), 0.12 p.p. (3.4 percent) and 0.17 p.p. (9.2 percent), respectively.

We also find that locations more exposed to robot adoption exhibit a relative rise in exports per worker, particularly, to high-income and upper-middle-income countries. One more robot per thousand workers leads to an increase in exports per worker of USD 1,011. We document that export growth is one the key mechanisms behind the surge in top incomes and top income inequality.

It is worth noting that while our data is particularly well suited to measure top incomes and top income inequality, they are not as good to study the impact of robots on the different types of workers that belong to the bottom 99 percent of the income distribution. This is beyond the goals of our work but there are several articles that have contributed in this direction (e.g. Acemoglu and Restrepo, 2020; Dauth, Findeisen, Suedekum, and Woessner, 2021; Webb, 2020; Humlum, 2021).

Acemoglu and Restrepo (2020) find that US local labor markets more exposed to robot adoption exhibit relative declines in employment and average wages between 1993 and 2014. Dauth et al.

(2021) find that German workers retained by their plants experience wage gains, while those that switched plants, industries or left manufacturing faced significant earning losses.[4] They also show that robots have benefited workers in occupations with complementary tasks such as managers, legal professionals and technical scientists.

More generally, our paper belongs to a prolific literature studying the relationship between technological change and income inequality. Early contributions emphasize that computer adoption favors the relative demand and wages of high-skilled workers (Bound and Johnson, 1992; Katz and Murphy, 1992).[5] Some years later, this literature shifted to the task-based approach of Autor, Levy, and Murnane (2003). In this setting, tasks that are repetitive are more likely to be codified and automated, while non-routine, problem-solving, communication and complex tasks complement computer capital. Many subsequent papers have shown that machines perform routine tasks previously done by workers in the middle of the skill distribution, which leads to the labor market polarization hypothesis.[6] Recently, Acemoglu and Restrepo (2022) document that between 50 and 70 percent of the change in U.S. wage structure over the last four decades is accounted for by the relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation.

Several recent contributions propose theoretical settings to quantify the impact of automation technologies on income inequality. Guerreiro, Rebelo, and Teles (2021) develop a framework in which a fall in the cost of automation leads to a large increase in income inequality (by increasing the non-routine wage premium) and reduces the welfare of routine workers. Krenz et al. (2021) present a model in which automation increases productivity and leads to the reallocation of previously offshored production back to developed countries, increasing jobs and wages for high-skilled workers but not for low-skilled individuals, which increases the skill premium and income inequality. Hémous and Olsen (2022) incorporate horizontal innovation (i.e. the creation of new products) in an endogenous growth model with automation to study the transitional dynamics of the functional income distribution in the U.S. Moll, Rachel, and Restrepo (2022) argue that automation increases inequality by rising returns to wealth and leading to stagnant wages at the bottom of the income

[4]Other papers that have found a negative effect of robots on the wage of production workers are Webb (2020) and Humlum (2021). In terms of employment, Dauth et al. (2021) find that job losses in manufacturing were offset by employment creation in services and that young workers just entering the labor force were the most affected by robot adoption, adapting their educational choices by substituting away from vocational training towards colleges and universities.

[5]This hypothesis is known as skill-biased technological change. For a review of this extensive literature see Acemoglu and Autor (2011).

[6]E.g. Autor, Katz, and Kearney (2006); Spitz-Oener (2006); Goos and Manning (2007); Michaels, Natraj, and Van Reenen (2014); Autor and Dorn (2013); Goos, Manning, and Salomons (2014); among others.

distribution.[7] Koru (2020) proposes a task-based framework with information frictions (i.e. convex cost of labor) that generates a production function with decreasing returns to scale. Automation enables entrepreneurs to substitute labor with capital and decreases the severity of diseconomies of scale, increasing returns on entrepreneurial skills and top income inequality.

Other explanations for the surge in top incomes are the growing size and market capitalization of large companies (Gabaix and Landier, 2008), innovation-led growth (Aghion, Akcigit, Bergeaud, and Blundell, 2019), market returns to "superstar" talent (Rosen, 1981; Kaplan and Rauh, 2013; Gabaix, Lasry, Lions, and Moll, 2016),[8] rent-seeking and poor governance (Bertrand and Mullainathan, 2001; Bivens and Mishel, 2013), industry-specific talent rents (Tervio, 2009), changes in top tax rates (Piketty, Saez, and Stantcheva, 2014) and firm's access to export markets and foreign direct investment (Ma and Ruzic, 2020; Keller and Olney, 2021).

We contribute to the literature by providing robust empirical evidence for the relationship between industrial automation, exports and top income inequality. To the best of our knowledge, this is the first paper combining robot and top income data to investigate the causal effect of robotization on top incomes. Our estimates support the idea that the adoption of a particular form of automation technology, i.e. industrial robots, leads to a greater concentration of income at the very top of the income distribution both within and across U.S metropolitan areas more exposed to rising automation, and that part of these gains are driven by rising exports to high-income and upper-middle-income economies.

The rest of the paper is organized as follows. Section 2 describes the data, the construction of the measure of exposure to robots and presents some descriptive statistics. Section 3 discusses the empirical strategy, the identifying assumptions and shows the results of the balance and pre-trend tests. Section 4 presents the empirical results of the paper and several robustness exercises. Section 5 concludes. Additional tables and figures are reported in the appendix.

[7]Relatedly, Acemoglu, Manera, and Restrepo (2020) argue that the low taxation of equipment and software capital in the U.S. federal tax corporate system (mainly due to the treatment of depreciation allowances) have lead to socially inefficient levels of automation. The findings of Curtis, Garret, Ohrn, Roberts, and Suarez (2021) confront this view. The calibration of Guerreiro et al. (2021) suggests that robots should be taxed for three decades at decreasing rates of 5.1, 2.6 and 0.6 percent, because during this period the labor force still includes older workers that have chosen their occupation in the past.

[8]The canonical model of Rosen (1981) argues that "superstar" workers arise in markets with three main characteristics: (i) consumers enjoy more the good provided by the best producers (i.e. quality matters), (ii) goods are provided using technologies that allow the best producers to provide her products to different consumers at a low cost (i.e. new technologies promote productivity gains and scaling effects), and (iii) there is a close connection between personal reward and market size. The models of knowledge-based hierarchies represent a continuation of these arguments (Garicano and Rossi-Hansberg, 2006; Caliendo and Rossi-Hansberg, 2012).

II Data

II.1 Data description

This section describes the different data sets that we merged in order to empirically test our hypotheses.

Top income data comes from the World Inequality Database (WID).[9] Statistics are calculated using administrative records from the U.S. Internal Revenue Service (IRS). An important feature of these data is that it have less under-reporting in the upper tail of the income distribution, so they are more accurate to measure top income inequality than household surveys. Unfortunately, these data does not allow us to distinguish between different income sources (e.g. labor and capital). The data set reports the total taxable income, the average taxable income and the income share of several income segments at the state and metropolitan area levels. Income segments (or *fractiles*) are separated by the following percentiles: P0, P90, P99, P99.9, P99.99 and P100, so they correspond to exhaustive and mutually exclusive sets of taxpayers. We use metropolitan areas as our preferred definition of local labor markets (LLM). This data set is available for every year of the period 2010–2015. An an example, Fig. A1 (in the appendix) plots the distributions of annual changes in top incomes shares for each of the four top income fractiles that belong to the upper 10 percent of taxpayers: (i) 90th to 99th percentiles, (ii) 99th to 99.9th percentiles, (iii) 99.9th to 99.99th percentiles, and (iv) 99.99th to 100th percentiles (i.e. the top 0.01 percent). This is the type of variation that we exploit in our main regression analysis.

Industrial robots. Robotics data comes from the International Federation of Robotics (IFR). IFR's use of the term "industrial robot" is based on the definition of the International Organization for Standardization: an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes," which can be either fixed in place or mobile for use in industrial automation applications (ISO 8373). This kind of robots are mostly used in manufacturing operations such as welding, painting, assembling, packaging, storage and transportation. During 2010–2015 close to 137 thousand robots were shipped to the U.S., around 45% of these shipments belong to the automotive industry, 17.5% to electrical and electronic products, 5.6% to metal products, 5.4% to rubber and plastic products, 4.2% to food and beverages and 2.2% to pharmaceuticals and cosmetics. The average robot price is USD $50 thousand, and the most expensive units are

[9] This dataset was kindly provided by Estelle Sommeiller and Mark Price in 2018, to whom we are immensely grateful.

around USD $500 thousand (these are for medical use). The IFR reports the number of industrial robots shipped by the major robot producers to each industry in the U.S. and to many other countries around the world. The IFR adopts its own industry coding, which closely follows the International Standard Industrial Classification (ISIC) revision 4.[10] They obtain these information from the robot suppliers and cover around 90% of the world market. The United States imports more than 50 percent of its robots from Europe and Japan. The dataset provides quantities only, and there is no way to measure the quality of machines using these data. Lastly, the dataset does not include a geographic breakdown of shipments within the U.S., so we distribute robots according to the employment distribution across industries in each metropolitan area in 1990, which is computed using the U.S. Census microdata.

U.S. Census data. We use the IPUMS' five percent samples for the year 1990 to calculate the share of employment by industry (which is used to calculate the geographic measure of robot adoption) and other relevant economic and demographic variables at the level of metropolitan areas such as the labor force participation (LFP), female LFP, employment shares in the manufacturing, services, and financial sectors,[11] female share in adult population, fractions of adult population under ages 16-34, 35-49 and 50-65, percentages of adult population with low-skills (primary education or below), middle-skills (secondary education) and high-skills (at least some college), and the immigrant share in adult population. We use the 1980' dataset as well (for robustness and to conduct an exercise of preexisting trends). We had to create a crosswalk to match the metropolitan areas in the U.S. Census data to those in the top income database, which allows us to count on 230 metropolitan areas. Our sample covers 86.4 percent of the total taxable income reported by the IRS and 83.2 percent of the total number of taxpayers during 2010–2015 (see Table A1). The fraction of total taxable income covered in our sample increases as we concentrate in the upper top income fractiles (e.g. from 85.2 percent in the bottom 90 percent to 90.5 percent in the top 0.01 percent) because top income earners are more frequently found in metropolitan areas than in less densely populated areas. Fig. A2 depicts the evolution of total taxable income between 2010 and 2015. The period under study exhibits an average annual income growth of 4.9 percent. The total taxable income covered in our sample represents on average 43.4 percent of U.S. GDP. We return to descriptive statistics in the next subsection.

[10]For the U.S. there is no industry breakdown of shipments before 2000. Also, the U.S. data include Mexico and Canada until 2010. However, these issues do not represent a problem for our estimates because we focus on the period 2010–2015.

[11]The financial sector encompass finance, insurance and real estate activities.

EU KLEMS. To construct the measure of robot penetration we match the IFR data with employment data by country and industry from EU KLEMS (Jägger, 2016). EU KLEMS allows us to work with 17 sectors, so we have recoded the IFR sectors to match the EU KLEMS classification. Once we merge robots with employment data at the industry-country level, we are able to construct two key variables of interest: (i) robot penetration for the U.S., and (ii) robot penetration for European countries (i.e. the instrumental variable).[12] Fig. A3 in the appendix shows that the industry with the fastest adoption of robotics (both in the U.S. and Europe) is automotive and other vehicles. In the U.S., it is followed by electrical and electronic products, miscellaneous manufacturing and rubber and plastics.

We construct a measure of exposure to robots at the local labor market (LLM) level. Our proxy for LLMs are metropolitan areas. Again, as we do not have a geographical breakdown of robot shipments within the U.S., we allocate robot intensity according to the employment share of different industries in each LLM in 1990. These shares do not vary across time so that the measure of exposure to robots does not reflect temporary changes in employment composition.

Exposure to robots of LLM l in year t (ER_{lt}) quantifies the exposition of LLM l to the growing adoption of industrial robots according to its 1990's composition of employment across industries.[13] Formally:

$$\mathrm{ER}_{lt} = \sum_j \frac{\mathrm{Emp}_{lj1990}}{\mathrm{Emp}_{l1990}} \times \frac{\text{Robot Stock}_{jt}}{\mathrm{Emp}_{jt}/1000}$$

where j indexes industries. Emp_{lj1990} is the number of workers in industry j in LLM l in 1990, Emp_{l1990} is the total number of workers in LLM l in 1990, $Robot\ Stock_{jt}$ is the stock of robots at the industry-year level, and EMP_{jt} is the number of workers at the industry-year level. The ratio $\frac{\text{Robot Stock}_{jt}}{\mathrm{Emp}_{jt}/1000}$ is the industry stock of robots per thousand workers in the U.S. We calculate this ratio by merging the IFR and EU KLEMS datasets. Again, this allows us to work with 17 industry groups, corresponding to six non-manufacturing industries: agriculture, forestry and fishing; mining and quarrying; electricity, gas and water supply; construction; education, research and development; and other non-manufacturing; and to eleven manufacturing industries: food and beverages; textiles and apparel; paper, wood and furniture; pharmaceutical and cosmetics; chemical products; rubber

[12] These countries are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Latvia, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom.

[13] Our results are strongly robust to the use of 1980's instead of 1990's Census data to compute industry employment structure and exposure to robots. See Table A12 in the appendix.

and plastics; metal products; electrical products and electronics; industrial machinery; automotive, shipbuilding and aerospace industries; and miscellaneous manufacturing. Fig. A4 in the appendix depicts the distribution of the annual change in exposure to robots across metropolitan areas. The median annual change in ER_{lt} between 2010 and 2015 is 0.28, the mean and standard deviation are 0.35 and 0.23, respectively.

Exports. We employ a publicly available dataset from the United Nations Commodity Trade Statistics Database (UN-Comtrade) to calculate a series of U.S. exports by industry.[14] We match this series with employment from EU KLEMS and compute a measure of exports per worker at the industry level. Then, using the industry composition of employment in 1990, as in ER_{lt}, we compute exports per worker at the metropolitan area level:

$$\text{Exports per worker}_{lt} = \sum_j \frac{\text{Emp}_{lj1990}}{\text{Emp}_{l1990}} \times \frac{\text{Exports}_{jt}}{\text{Emp}_{jt}/1000}$$

where $\frac{\text{Exports}_{jt}}{\text{Emp}_{jt}/1000}$ measures the value of exports per thousand workers in the U.S.

II.2 Descriptive statistics

Table 1 presents descriptive statistics for the main dataset used in this paper, which is an almost perfectly balanced-panel of 230 metropolitan areas across 6 years of the period 2010–2015.[15] Panels correspond to different variables and the columns present descriptive statistics for the distribution of each of these variables during the period under study. Panel A refers to the total annual taxable income (expressed in billions of 2015 U.S. Dollars) accruing to different income fractiles. The mean annual total income of the bottom 90 percent of taxpayers is USD 91.2 billion. This number equals USD 58.1 billion, USD 26.1 billion, USD 12.5 billion, USD 10.1 billion, for percentiles 90 to 99, percentiles 99 to 99.9, percentiles 99.9 to 99.99 and percentiles 99.99 to 100, respectively. Panel B corresponds to the annual taxable income (expressed in thousands of 2015 U.S. Dollars) of the average taxpayer in each income fractile. The average annual income of the bottom 90 percent of taxpayers is USD 37 thousand. By construction the average annual income increases as we move to the right tail of the income distribution: USD 220 thousand for percentiles 90 to 99, USD 902 thousand for percentiles 99 to 99.9, USD 3,889 thousand for percentiles 99.9 to 99.99 and USD

[14] The raw data consists of product-level information on U.S. export values and quantities by destination country at the 6-digit of the Harmonized System. Source: https://comtrade.un.org/db/default.aspx.

[15] Top income data is missing only for four metropolitan areas in the year 2010: Albuquerque (NM), Boise City (ID), Burlington (NC), and Denver-Aurora-Lakewood (CO). Then, the total number of observations is 1376.

25,874 thousand for the top 0.01 percent. The following three panels of Table 1 present different measures of income inequality: total taxable income ratios across fractiles (Panel C), average taxable income ratios across fractiles (Panel D) and taxable income shares of each income fractile (Panel E). For instance, from panel D we read that the average taxpayer in the top 0.01 percent earns on average 5.9 times more than the average taxpayer in the following top income fractile (i.e. the 99.9 to 99.99 percentiles). The bottom 90 percent of taxpayers accumulate on average 50.8 percent of the total taxable income, while the top 1 percent captures for about 20.2 percent of total taxable income (Panel E). The average exports per worker across metropolitan areas is USD 22.2 thousand per year (Panel F). Most of the exports go to high-income and upper-middle-income countries (on average 92.7 percent).

Fig. 2–upper panel (a) depicts the evolution of total taxable income by fractiles between 2010 and 2015. During this period, the total taxable income accruing to the bottom 90 percent of taxpayers increased by 24 percent, while the total incomes of P90 to P99, P99 to P99.9, P99.9 to P99.99 and P99.99 to P100 grew by 26.6 percent, 32.4 percent, 33.8 percent, and 36.5 percent, respectively. Namely, income gains were larger for the top income fractiles, which means that income inequality increased between 2010 and 2015. This is in line with the 1990–2016 trend depicted in Figure 1, which also shows that the income share of the superrich increased more rapidly that the income share of the rich. Incomes of the top 1 percent exhibit a dramatic increase in 2012, which might be due to profit sharing in the wake of the potential international and business tax reforms' proposals released in Congress in October 2011 and February 2012. The 2012' rise in total taxable income is higher for the top income fractiles, which may be linked to the facts that the share of capital gains in total income is higher as we focus on richer individuals (see Fig. A4 in the appendix) and that capital gains are more plastic/mobile than labor incomes (Scheuer and Slemrod, 2020).[16] Our estimates are strongly robust to the exclusion of observations corresponding to the year 2012 (and to exclude any other particular year). Table A2 in the appendix closely follows the format of Table 1 (variables in different panels are the same as in Table 1) but presents the average value of corresponding variables in each year of the period 2010–2015. The same pattern emerges: the period under study exhibits an increase in income concentration at the very top of the personal income distribution. For instance, the income share of the bottom 90 percent of taxpayers decreases from 51.94 percent in 2010 to 50.85 percent in 2015 (-1.09 p.p.); in contrast, the income shares of

[16] For recent evidence on profit shifting by U.S. multinational companies see for instance Guvenen, Mataloni Jr., Rassier, and Ruhl (2022).

P99 to P99.9, P99.9 to P99.99, and P99.99 to P100, rise on average by 0.52 p.p. (4.7 percent), 0.28 p.p. (5.8 percent), and 0.27 p.p. (8.1 percent), respectively. Finally, the boxplots in Fig. 2–lower panel (b) depict the distributions of total taxable income shares across metropolitan areas for each of the four top income fractiles belonging to the upper 10 percent of taxpayers (i.e. the botton 90 percent is excluded) separately for 2010 and 2015. Again: income inequality have increased markedly during this period, especially at the very right end of the income distribution. Exposure to robots also increased very strongly, it almost doubles between 2010 and 1015 (on average, from 1.9 to 3.7 robots per thousand workers).

III Estimation

III.1 Empirical strategy

We perform LLM-level regressions with the following form:

$$Y_{lt} = \beta \mathrm{ER}_{lt} + \mathbf{X}'_{l1990}\gamma + \delta_l + \eta_{st} + \varepsilon_{lt} \tag{3}$$

where Y_{lt} are: (i) the logarithm of total taxable income of five exhaustive and mutually exclusive income fractiles (0th to 90th percentiles, 90th to 99th percentiles, 99th to 99.9th percentiles, 99.9th to 99.99th percentiles, and 99.99th to 100th percentiles), (ii) total taxable income ratios across consecutive fractiles, and (iii) the income share of each fractile. The vector $\mathbf{X}_{l1990}$ includes economic and demographic covariates measured at the baseline year 1990, δ_l and η_{st} are LLM and state$\times$year FE to control for unobserved shocks at the state-level (e.g. profit shifting across states). For instance, the coefficient of interest β captures the effect of a one unit increase in exposure to robots on LLM's total taxable income of different income fractiles.

A potential concern to estimate this equation by OLS is that the decision to invest in robotics is not exogenous. Exposure to robots is a potentially endogenous regressor as LLM's conditions may have an impact on firm's decisions to invest in robotics and on incomes and income inequality at the same time. To address this endogeneity concern, we follow an instrumental variable approach that has also been used by other papers in this literature (Acemoglu and Restrepo, 2020; Dauth et al., 2021). We predict industry robot penetration in the U.S. using the average industry robot penetration across European countries. Formally, the instrumental variable is:

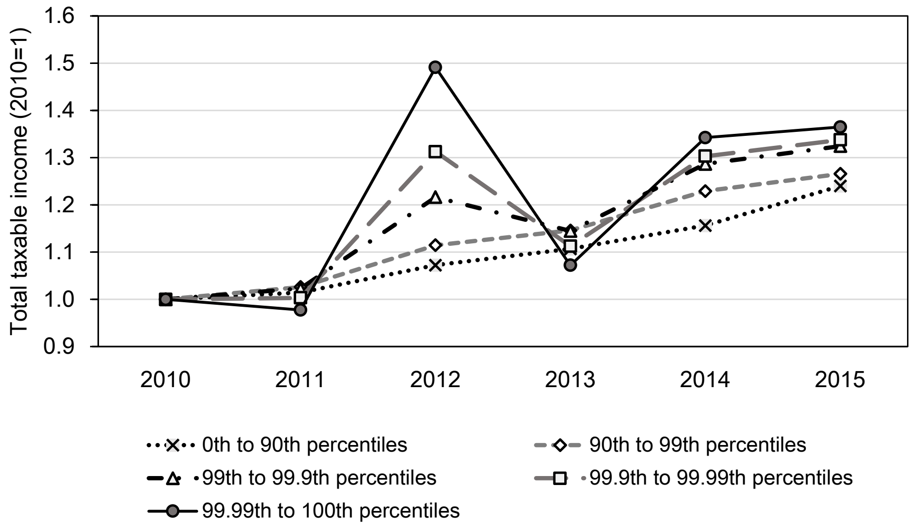
Table 1: Descriptive statistics

	Mean	SD	P10	P25	P50	P75	P90
Panel A: Total Taxable Income (billons of 2015 USD)							
0th to 90th percentiles	91.2	99.7	6.3	17.4	55.1	119.3	305.5
90th to 99th percentiles	58.1	70.8	3.4	9.2	31.3	69.3	214.3
99th to 99.9th percentiles	26.1	35.0	1.1	3.4	11.7	29.2	104.2
99.9th to 99.99th percentiles	12.5	18.2	0.4	1.3	4.8	14.0	53.1
99.99th to 100th percentiles	10.1	16.2	0.2	0.8	2.9	10.7	44.5
Panel B: Average Taxable Income (thousands of 2015 USD)							
0th to 90th percentiles	37	8	27	32	36	41	47
90th to 99th percentiles	220	60	157	178	212	254	292
99th to 99.9th percentiles	902	376	510	646	836	1067	1364
99.9th to 99.99th percentiles	3889	2262	1775	2401	3320	4805	6482
99.99th to 100th percentiles	25874	24824	7744	11876	17888	35235	52486
Panel C: Total Taxable Income Ratios							
90th-99th to 0th-90th pctl.	0.58	0.09	0.47	0.51	0.57	0.63	0.71
99th-99.9th to 90th-99th pctl.	0.40	0.07	0.32	0.35	0.39	0.44	0.49
99th-99.99th to 99.99th-99.9th pctl.	0.43	0.07	0.34	0.38	0.42	0.47	0.51
99.99th-100th to 99.9th-99.99th pctl.	0.66	0.17	0.47	0.53	0.63	0.76	0.87
Panel D: Average Taxable Income Ratios							
90th-99th to 0th-90th pctl.	6.00	0.99	4.88	5.25	5.87	6.55	7.38
99th-99.9th to 90th-99th pctl.	3.99	0.66	3.20	3.48	3.89	4.46	4.86
99th-99.99th to 99.99th-99.9th pctl.	4.12	0.65	3.33	3.64	4.05	4.57	4.94
99.99th-100th to 99.9th-99.99th pctl.	5.91	1.54	4.19	4.77	5.64	6.86	7.84
Panel E: Taxable Income Shares							
0th to 90th percentiles	50.82	6.21	42.07	46.89	51.70	55.48	57.98
90th to 99th percentiles	29.03	1.63	27.12	28.09	29.08	29.96	30.81
99th to 99.9th percentiles	11.53	2.01	9.13	9.96	11.27	12.98	14.47
99.9th to 99.99th percentiles	5.04	1.66	3.17	3.74	4.63	6.13	7.35
99.99th to 100th percentiles	3.59	2.20	1.48	1.99	2.90	4.73	6.42
Panel F: Exports per worker (thousands of 2015 USD)							
Exports per worker	22.2	8.1	12.2	17.3	21.9	26.1	31.1
Exports to HIC per worker	13.8	5.1	7.4	11.0	13.4	16.5	19.8
Exports to UMIC per worker	6.7	2.6	3.8	5.1	6.6	8.1	9.4
Exports to LMIC per worker	1.6	0.6	1.0	1.3	1.6	1.9	2.2
Panel G: Exposure to robots (robots per thousand workers)							
Exposure to robots	2.75	1.83	1.13	1.55	2.24	3.30	5.08
Exposure to robots (IV)	1.58	1.04	0.72	0.95	1.27	1.89	2.80
Number of observations				1376			
Number of metropolitan areas				230			
Number of states				45			

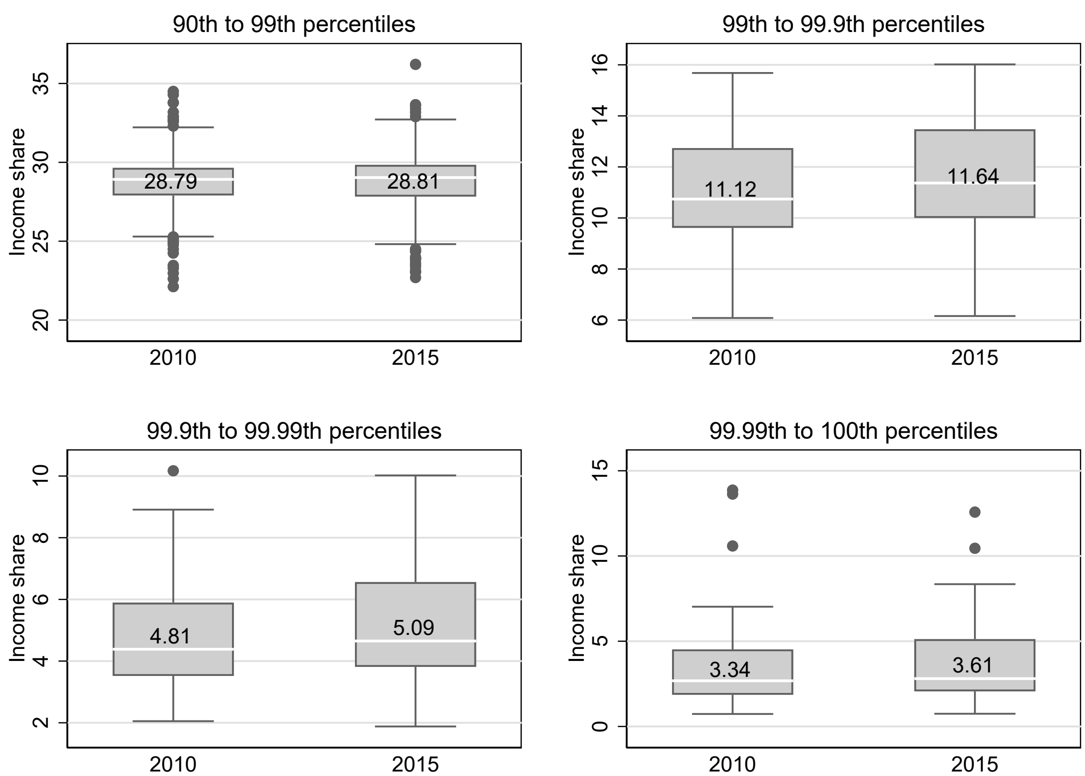
Notes. Income fractiles computed using the 0th, 90th, 99th, 99.9th and 99.99th percentiles of the taxable income distribution in each metropolitan area, and correspond to exhaustive and mutually exclusive sets of taxpayers. Descriptive statistics weighted by metropolitan area's share in total taxable income. Statistics correspond to the full sample period 2010–2015. Exports per worker (Panel F) separated across three mutually exclusive sets of countries: high-income (HIC), upper-middle-income (UMIC), and lower-middle-income plus low-income countries (LMIC).

Fig. 2: U.S. Total taxable income growth

(a) Evolution of total taxable income



(b) Distribution of top 10 percent income shares across MAs



Notes. Panel A plots the evolution of total taxable income by income fractiles during 2010–2015. Total taxable incomes normalized to 1 in 2010. Panel B plots the distributions of the top 10 percent total taxable income shares across metropolitan areas separately for 2010 and 2015. Each subplot corresponds to a different (mutually exclusive) top income fractile. Boxes delimit the percentiles 25 and 75 and brackets mark percentiles 5 and 95. Numbers correspond to the average income share.

$$\mathrm{ER}^{IV}_{lt} = \sum_j \frac{\mathrm{Emp}_{lj1990}}{\mathrm{Emp}_{l1990}} \times \left(\frac{1}{23} \sum_{k \in Europe} \frac{\text{Robot Stock}_{kjt}}{\mathrm{Emp}_{kjt}/1000} \right) \tag{4}$$

where j and k index industries and European countries, respectively; and $\frac{\text{Robot Stock}_{kjt}}{\mathrm{Emp}_{kjt}/1000}$ is the stock of robots per thousand workers in each industry-country pair. Note that we compute a simple average across 23 European countries, which are all the OECD countries with complete information in IFR and EU KLEMS datasets.[17]

The instrument should pick up the part of U.S. robot purchases that are due to exogenous global supply shifts of robots sales. Presumably, variation in robot adoption across European industries and across time captures advances in technology, availability and prices. The main identifying assumptions are: (i) that the evolution of the average industry exposure to robots across European countries is not correlated with shocks in the U.S.; and (ii) that LLMs with a higher initial share of labor allocated to industries with greater advances in robotics technology are not differentially affected by other labor market shocks or trends. The first-stage between ER_{lt} and ER^{IV}_{lt} is very strong, with a linear coefficient of 2.2, a standard error of 0.12 and an R-squared of 0.978 (Fig. 3).

III.2 Balance and pre-trend tests

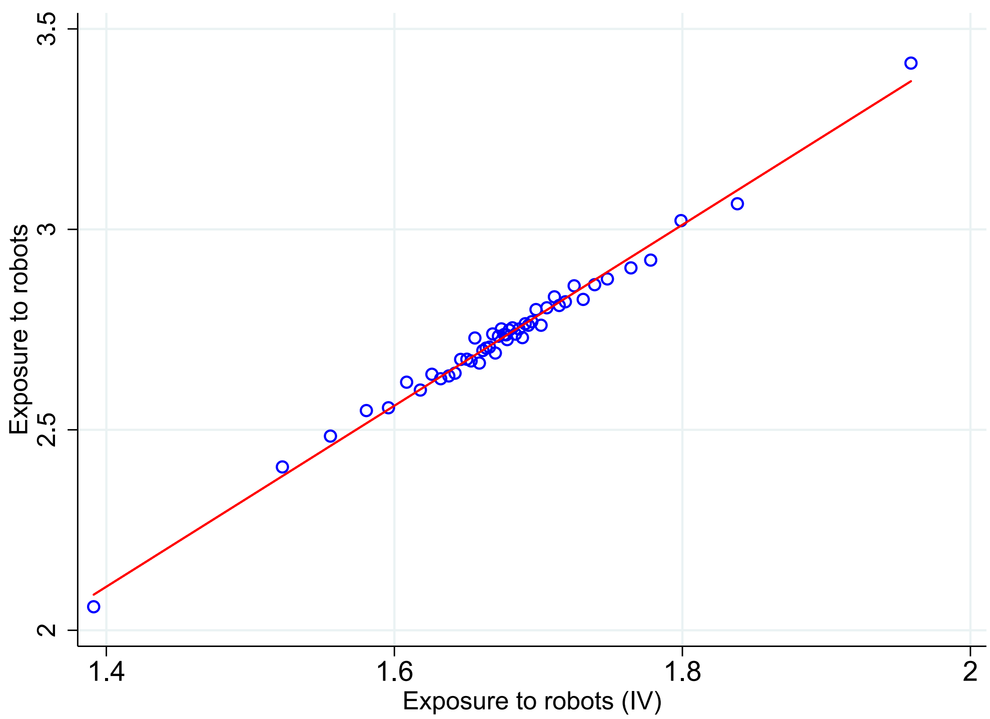
We conduct a balance test to corroborate the plausibility of conditional quasi-random shock assignment, as suggested by Borusyak, Hull, and Jaravel (2020). We regress LLM's baseline characteristics directly on the shocks. This test is useful to select the appropriate set of control variables that should be included in the preferred specification. We run the following OLS regression:

$$X_{l1990} = \gamma_0 + \gamma_1 \Delta ER_{l2010-2015} + \delta_s + \varepsilon_l \tag{5}$$

We regress each variable X_{l1990} (at its 1990 level) on the change in exposure to robotization during 2010–2015 ($\Delta ER_{l2010-2015}$), δ_s are state FE. We consider the following LLM-level observables: the share of U.S. total population living in the LLM, the share of U.S. adult population living in the LLM, women's share in local adult population, immigrant's share in local adult population, fractions of local adult population with low education, middle education and high education, shares of local adult population under ages 16–34, 35–49 and 50–65, labor force participation (LFP) rate, women's LFP rate, local employment shares in agriculture, manufacturing, services and finance.

[17] See footnote 12 for a complete list of these countries.

Fig. 3: First stage regression



Notes. The figure plots the first stage regression for the preferred specification in Tables 2 and 3, column (7). The instrumental variables is constructed as the interaction of metropolitan area's industrial employment composition in 1990 and the average industry exposure to robots in European countries. Observations are grouped into 50 equal-size segments to facilitate the graphic interpretation. Each point represents the (conditional) average of exposure to robots within each segment and the red line represents the linear prediction of U.S. exposure to robots on the instrument.

Results are reported in Table A3 in the appendix, column (1). For completeness we run additional exercises in columns (2) to (4). In column (2), we replace ΔER with the instrument ΔER^{IV}. In column (3), we replace ΔER with a dummy variable that indicates whether ΔER is above the median across LLMs. Column (4) is analogous to column (3) with the difference that the dummy variable is computed based on ΔER^{IV}.

Some imbalances emerge. First, LLMs subsequently more exposed to robots exhibit a higher participation of middle skill individuals and a lower share of high skill people in 1990 than less exposed locations. These LLMs also present a lower fraction of young and a larger participation of senior individuals. LFP rates are also higher in these areas, particularly for women. Finally, these locations have a greater manufacturing employment share, which is expected since most robots are adopted by this sector, and a lower employment share in services, agriculture and the financial industry. We control for these imbalances in the form of preexisting trends, i.e. as the interaction of the 1990 level of each variable with year fixed effects.

An additional concern of our empirical strategy, shared with most exercises of estimation of treatment effects, is whether LLM-level exposure to robots correlates with preexisting LLM-level trends. If that were the case our estimates could be biased by preexisting trends that persisted during the exposure period. Our empirical strategy controls for a large set of trends based on the results from the balance tests just discussed, which substantially ameliorates this concern. As a validity test, we further look at changes in observed variables in a pre-sample period to rule out that their past changes are correlated with later exposure to robots.

We define a pre-sample period from 1980 to 1990. We run the following OLS regression:

$$\Delta X_{l1980-1990} = \gamma_0 + \gamma_1 \Delta ER_{l2010-2015} + \delta_s + \Delta \varepsilon_l \tag{6}$$

For each variable X we regress the change between 1980 and 1990 ($\Delta X_{l1980-1990}$) on the change in exposure to robotization during 2010–2015 ($\Delta ER_{l2010-2015}$); where X are LLM-level observables during the pre-sample period. We consider the same set of variables as in the balance tests.

Results are reported in Table A4 in the appendix, which has the same structure as Table A3. We find that LLMs subsequently more exposed to robots have exhibited an increase in education level and reallocation of employment from manufacturing towards services between 1980 and 1990. Second, locations more exposed to robots in the future have had a growing share of the young and a declining participation of the middle aged in the past. The persistence of these trends during the period under study may potentially bias our estimates. To partially ameliorate this concern we conduct a robustness exercise in which we control for differential past trends (see Table A6). All our are remain strongly robust (for more discussion see the robustness section).

IV Results

IV.1 Robots and top incomes

This section discusses the main findings of the paper. We are interested in the total taxable income, income ratios and income shares of the different income fractiles: 0th to 90th percentiles (i.e. the bottom 90 percent of taxpayers), 90th to 99th percentiles, 99th to 99.9th percentiles, 99.9th to 99.99th percentiles and 99.99th to 100th percentiles (i.e. the top 0.01 percent of taxpayers), at the metropolitan area level.

We present the baseline estimates of equation (3) in Tables 2 and 3. The first column presents fixed effect-ordinary least squares estimates and columns (2) to (7) display fixed effect-two-stage least squares estimates in which exposure to robots is instrumented using robot penetration in European countries as an exogenous shifter. Since column (3) we control for state×year FE to account for unobserved shocks at the state level. The remaining columns (4 to 7) subsequently control for 1990 differences in demographic variables and economic conditions (based on the results of the balance tests discussed in the previous section). Column (4) and onwards control for the fractions of local adult population under ages 16–35, 36–49 and 50–65, and for the shares of local adult population with low skills, middle skills and high skills. Column (5) adds metropolitan area's labor force participation (LFP) and female LFP. Column (6) incorporates the local employment shares in the manufacturing and service sectors. And column (7) controls for the local employment share in the financial industry. All of these variables are included as preexisting trends, calculated as the value of the corresponding variable in 1990 interacted with year dummies for the period 2010–2015. Standard errors are robust against heteroskedasticity and clustered at the state level.[18] All regressions include district and year fixed effects (or, since column (3), state×year FE) and therefore exploit within district variation across time.

Panel A of Table 2 shows that the instrument has a strong predictive power and it is statistically significant at the 1 percent level in all specifications; the hypothesis of weak instrument is strongly

[18] All our results are robust to not using clusters or to clustering standard errors at the metropolitan area level. Not shown but available upon request.

rejected. Note that the magnitude of the first-stage coefficients is above 2, which is line with the fact that during 2010–2015 robot adoption in the U.S. was higher than in the average European country (see Fig. A3).

In Panel B the dependent variable is the logarithm of total taxable income. Results suggest that there is no impact of robots on the total taxable income of the bottom 90% of tax units (Panel B.1). The estimated coefficient is positive but statistically indistinguishable from zero for the total income accruing to the 90th to 99th percentiles (Panel B.2). Our estimates suggest that robots cause an increase in the total income accruing to the top 1 percent of taxpayers (Panels B.3 to B.5). Within the top 1 percent, the magnitude of estimated coefficients is larger as we concentrate in highest paid individuals. One more robot per thousand workers increases the total taxable incomes of taxpayers in percentiles 99 to 99.9, P99.9 to P99.99, and P99.99 to P100 (top 0.01 percent), by 2.1 percent, 3.5 percent, and 5.4 percent, respectively, *ceteris paribus*.

In Table 3 we report the estimates for two measures of income inequality. Panel A corresponds to the total taxable income ratios across consecutive income fractiles. Panel B refers to the total taxable income shares, defined as the participation of each income fractile in the metropolitan area's total taxable income. These estimates show that income inequality goes up as a result of exposure to robots and, in particular, that income inequality increases more strongly among the richest taxpayers. Estimated coefficients in Panel A are positive, statistically significant and increasing in income fractiles. An increase in the robot to worker ratio equal to one leads to an increment in the income ratios of percentiles P90-P99 to P0-P90 (Panel A.1), P99-P99.9 to P90-P99 (A.2), P99.9-P99.99 to P99-P99.9 (A.3), and P99.99-P100 to P99.9-P99.99 (A.4) of 0.004, 0.005, 0.007, and 0.018, respectively.

Estimates in Panel B of Table 3 are negative and statistically significant for the bottom 90 percent of taxpayers because robot-driven income gains concentrate in the top 1 percent of taxpayers (Table 2). Estimated coefficients for the income share of P90 to P99 are statistically indistinguishable from zero, while those for the taxpayers in the top 1 percent are positive and statistically significant (again, in line with the estimates in Table 2). One more robot per thousand worker leads to a relative decline in the income share of the bottom 90 percent of about 0.42 percentage points (-0.8 percent); on the contrary, it leads to relative increases in the income shares of P99 to P99.9, P99.9 to P99.99 and P99.99 to P100 (top 0.01 percent) of around 0.12 p.p. (1.2 percent), 0.12 p.p. (3.4 percent) and 0.17 p.p. (9.2 percent), respectively. In Figure 4 we plot the estimates corresponding to column 7 of Table 3–Panel B as marginal effects, i.e. expressing derivatives as elasticities: dy/dx (x/y).

Overall, our findings suggest that increasing robot adoption generates income gains *only* for the top 1 percent of taxpayers, and that these gains are increasing in income. As a result, industrial automation increases income inequality and, particularly, rises income inequality among the highest paid individuals ("top income inequality").

IV.2 The export channel

In this section we show that robot adoption causes an increase in exports per worker, and that this is a relevant mechanism behind the surge in top incomes.

Table 4 presents the estimates for the effect of robots on exports per worker. The table maintains the same format and estimation strategy as tables 2 and 3. Panel A corresponds to total exports per worker and Panel B presents separate estimates for exports per worker to three separate groups of destination countries based on GDP per capita (using the classification from The World Bank): (i) high-income, (ii) upper-middle-income, and (iii) low-income plus lower-middle-income countries.

Results in Table 4 suggest that one more robot per thousand worker causes an increase in exports per worker of USD 1,011, *ceteris paribus*. Interestingly, estimates in Panel B suggests that there is a reallocation of exports from low-income and lower-middle-income countries towards high-income and upper-middle income countries, in line with the idea that robots are being used to elaborate products that are sold mainly in richer destinations, where firms can presumably make higher profits.

Now we evaluate if the increase in exports per worker is causally related to the rises in top incomes and in top income inequality. To address endogeneity concerns we follow the same IV strategy as in our main regression analysis, instrumenting exports per worker in the U.S. with robot adoption in European countries. Results are in Tables 5 and 6, which follow exactly the formats of Tables 2 and 3. The first stage works in the expected direction and passes the weak IV test (Panel A, Table 5). The estimates in Table 5 suggests that an increase in exports per worker of USD 1000 leads to a rise in the total taxable incomes of taxpayers in percentiles 99 to 99.9, P99.9 to P99.99, and P99.99 to P100 (top 0.01 percent) of 2 percent, 3.5 percent, and 5.9 percent, respectively, *ceteris paribus*. Results in Table 6 show that a rise in exports per worker leads to an increase in income inequality. The magnitude of estimated coefficients, both in Tables 5 and 6 compared to Tables 2 and 3, is almost equal. Our interpretation of this result is that growing sales in international markets is one of the key drivers behind the surge in top income inequality that

Table 2: The effects of robots on income

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First-stage regression							
Exposure to robots (IV)	-	2.247***	2.323***	2.455***	2.437***	2.258***	2.257***
	-	(0.042)	(0.103)	(0.112)	(0.094)	(0.103)	(0.105)
KP F-stat	-	3706.1	705.1	669.4	755.4	670.6	649.6
R-squared	-	0.959	0.972	0.977	0.978	0.980	0.980
Panel B: Log (Total Taxable Income)							
B.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.006	−0.013***	−0.010*	−0.001	−0.003	−0.001	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
B.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.010**	−0.020***	−0.005	0.004	0.003	0.006	0.008
	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
B.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	−0.001	−0.010	0.009	0.016*	0.015*	0.018**	0.021**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
B.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.008	−0.005	0.020	0.028*	0.028**	0.031*	0.035**
	(0.012)	(0.012)	(0.016)	(0.015)	(0.014)	(0.016)	(0.015)
B.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.022	0.004	0.039	0.049*	0.050**	0.052*	0.059**
	(0.020)	(0.021)	(0.028)	(0.026)	(0.025)	(0.028)	(0.027)
Observations	1376	1376	1376	1376	1376	1376	1376
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

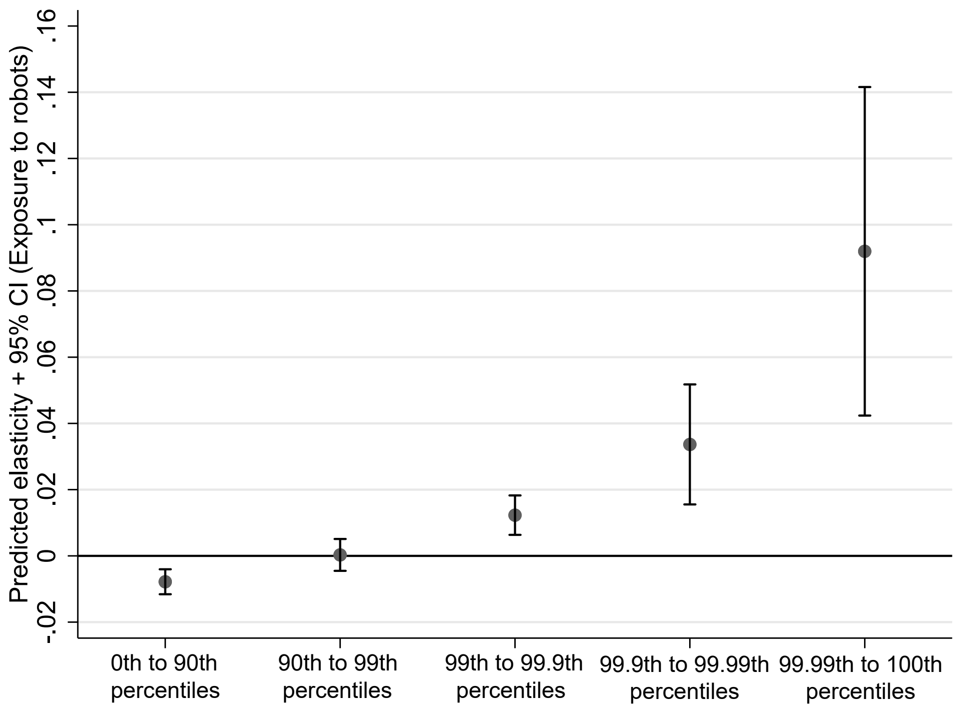
Notes. Dependent variables are the logarithms of total taxable (TT) income accruing to each income fractile. All regressions include metropolitan area and year fixed effects. Column (1): OLS. Columns (2) to (7): 2SLS using industry exposure to robots in European countries weighted by industrial composition at the metropolitan area level as instrument. Preexisting trends at the metropolitan area level in 1990 are: percentages of local adult population under ages 16–34, 35–49 and 50–65, and the fractions of local adult population with low skills (primary education or below), middle skills (secondary education) and high skills (college education) (Column 4 and onwards); local labor force participation (LFP) and female LFP (Column 5 and onwards); local employment shares in the manufacturing and service sectors (Column 6 and 7); and local employment share in the financial industry (Column 7). Standard errors clustered at the state level are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table 3: The effects of robots on income inequality

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total Taxable Income Ratios							
A.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.002	−0.004	0.002	0.003	0.003	0.003	0.004
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.003*	0.003*	0.005***	0.005***	0.005***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.004*	0.003	0.006**	0.006***	0.007***	0.006**	0.007***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
A.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.011*	0.008	0.019**	0.019***	0.020***	0.016***	0.018***
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Panel B: Total Taxable Income Shares							
B.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.069	0.035	−0.392***	−0.400***	−0.417***	−0.390***	−0.424***
	(0.210)	(0.215)	(0.128)	(0.114)	(0.114)	(0.120)	(0.104)
B.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.145*	−0.171*	−0.056	−0.035	−0.032	0.015	0.008
	(0.080)	(0.095)	(0.070)	(0.067)	(0.066)	(0.068)	(0.070)
B.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.039	0.019	0.110***	0.099***	0.104***	0.109***	0.120***
	(0.056)	(0.055)	(0.035)	(0.031)	(0.032)	(0.034)	(0.030)
B.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.063	0.038	0.121***	0.121***	0.125***	0.112***	0.123***
	(0.048)	(0.045)	(0.042)	(0.036)	(0.037)	(0.038)	(0.034)
B.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.111*	0.079	0.216***	0.216***	0.221***	0.154***	0.172***
	(0.068)	(0.062)	(0.074)	(0.064)	(0.064)	(0.046)	(0.047)
Observations	1376	1376	1376	1376	1376	1376	1376
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

Notes. Dependent variables in Panels B.1-B.4 correspond to total taxable (TT) income ratios across consecutive income fractiles. Dependent variables in Panels C.1-C.5 are the participations of each income fractile in metropolitan area's total taxable income.

Fig. 4: Marginal effects of robots on income inequality



Notes. This figure depicts the marginal effects of robots on the total taxable income shares of different income fractiles, expressing derivatives as elasticities: dy/dx (x/y). Regressions are analogous to columns 7 of Table 3–Panel B. The capped lines provide 95 percent confidence intervals.

results from the increasing adoption of industrial robots in the U.S.

Table 4: The effects of robots on exports

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Exports per worker							
Exposure to robots	1073.6***	993.7***	1067.1***	1148.1***	1144.2***	1016.8***	1011.4***
	(50.8)	(58.2)	(68.9)	(58.3)	(65.7)	(86.6)	(89.0)
Panel B: Exports per worker by income of destination countries							
B.2: Exports per worker to high-income countries							
Exposure to robots	507.7***	470.4***	509.7***	550.1***	547.1***	527.3***	523.6***
	(23.5)	(30.8)	(34.8)	(27.7)	(28.8)	(32.1)	(30.7)
B.2: Exports per worker to upper-middle-income countries							
Exposure to robots	612.5***	602.3***	627.3***	646.9***	646.4***	601.8***	601.4***
	(16.0)	(19.7)	(27.0)	(25.4)	(31.1)	(48.8)	(49.8)
B.3: Exports per worker to low- and lower-middle-income countries							
Exposure to robots	−46.6**	−78.9***	−70.0***	−48.9**	−49.3***	−112.3***	−113.6***
	(20.6)	(15.9)	(19.0)	(19.5)	(19.0)	(25.0)	(26.1)
Observations	1376	1376	1376	1376	1376	1376	1376
KP F-stat	-	2768.6	419.0	387.8	538.0	379.7	364.8
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

Notes. Dependent variables are exports per worker (Panel A) and the logarithm of exports per worker (Panel B) at the metropolitan area level. These are calculated as bartik measures, interacting the 1990 industrial composition with the evolution of exports per worker during 2010–2015. The table maintains the exact same format as tables 2 and 3.

IV.3 Robustness exercises

In this section we perform a series of robustness exercises. We estimate several alternatives to our baseline regression to check the robustness of results to: an alternative specification using the first and final years of the data, rule out the influence of outliers, leave aside metropolitan areas with greatest importance of the automotive industry (which exhibits the largest adoption of robotics), exclude any particular year of the period 2010–2015, use 1980's instead of 1990's census data, apply population weights in the regression, and estimate conservative confidence intervals

Table 5: The effects of exports on income

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First-stage regression							
Exposure to robots (IV)	-	2.233***	2.479***	2.818***	2.788***	2.295***	2.282***
	-	(0.154)	(0.228)	(0.214)	(0.207)	(0.264)	(0.272)
KP F-stat	-	205.1	96.6	138.8	144.1	59.7	55.2
R-squared	-	0.821	0.885	0.901	0.906	0.932	0.932
Panel B: Log (Total Taxable Income)							
B.1: Log (TT Income of 0th to 90th percentiles)							
Exports per worker /1000	−0.002	−0.013*	−0.009	−0.001	−0.002	−0.001	0.001
	(0.005)	(0.007)	(0.008)	(0.006)	(0.005)	(0.006)	(0.007)
B.2: Log (TT Income of 90th to 99th percentiles)							
Exports per worker /1000	−0.000	−0.020***	−0.005	0.004	0.003	0.006	0.008
	(0.004)	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)	(0.008)
B.3: Log (TT Income of 99th to 99.9th percentiles)							
Exports per worker /1000	0.008	−0.010	0.008	0.014*	0.013**	0.017*	0.020**
	(0.006)	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)	(0.010)
B.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exports per worker /1000	0.016	−0.005	0.018	0.024**	0.025**	0.030**	0.035***
	(0.011)	(0.012)	(0.014)	(0.010)	(0.010)	(0.014)	(0.013)
B.5: Log (TT Income of 99.99th to 100th percentiles)							
Exports per worker /1000	0.030*	0.004	0.037	0.042**	0.044**	0.051**	0.059***
	(0.018)	(0.020)	(0.023)	(0.017)	(0.018)	(0.023)	(0.022)
Observations	1376	1376	1376	1376	1376	1376	1376
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

Notes. Dependent variables are the logarithms of total taxable (TT) income accruing to each income fractile. Column (1): OLS. Columns (2) to (7): 2SLS using industry exposure to robots in European countries weighted by industrial composition at the metropolitan area level as instrument for exports per worker. The table maintains the exact same format as table 2.

Table 6: The effects of exports on income inequality

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total Taxable Income Ratios							
A.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exports per worker /1000	0.001	−0.004	0.002	0.003	0.003	0.003	0.004
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exports per worker /1000	0.003*	0.003*	0.005***	0.004***	0.004***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
A.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exports per worker /1000	0.004*	0.003	0.006**	0.006***	0.006***	0.006**	0.007***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
A.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exports per worker /1000	0.010*	0.008	0.018**	0.017***	0.018***	0.016***	0.018***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Panel B: Total Taxable Income Shares							
B.1: TT Income Share of 0th to 90th percentiles							
Exports per worker /1000	−0.185	0.035	−0.367***	−0.349***	−0.364***	−0.384***	−0.419***
	(0.178)	(0.217)	(0.124)	(0.102)	(0.101)	(0.123)	(0.112)
B.2: TT Income Share of 90th to 99th percentiles							
Exports per worker /1000	−0.052	−0.172*	−0.053	−0.030	−0.028	0.015	0.008
	(0.046)	(0.100)	(0.065)	(0.058)	(0.058)	(0.067)	(0.070)
B.3: TT Income Share of 99th to 99.9th percentiles							
Exports per worker /1000	0.066	0.019	0.103***	0.086***	0.091***	0.107***	0.118***
	(0.047)	(0.055)	(0.032)	(0.027)	(0.027)	(0.035)	(0.031)
B.4: TT Income Share of 99.9th to 99.99th percentiles							
Exports per worker /1000	0.070	0.039	0.114***	0.105***	0.109***	0.110***	0.122***
	(0.046)	(0.044)	(0.040)	(0.032)	(0.033)	(0.038)	(0.035)
B.5: TT Income Share of 99.99th to 100th percentiles							
Exports per worker /1000	0.100	0.079	0.203***	0.188***	0.193***	0.152***	0.170***
	(0.069)	(0.062)	(0.073)	(0.058)	(0.059)	(0.048)	(0.053)
Observations	1376	1376	1376	1376	1376	1376	1376
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

Notes. Dependent variables in Panels B.1-B.4 correspond to total taxable (TT) income ratios across consecutive income fractiles. Dependent variables in Panels C.1-C.5 are the participations of each income fractile in metropolitan area's total taxable income. Column (1): OLS. Columns (2) to (7): 2SLS using industry exposure to robots in European countries weighted by industrial composition at the metropolitan area level as instrument for exports per worker. The table maintains the exact same format as table 3.

with clustering at the industry level. Although we lose statistical significance in some cases, the main findings of the paper remain robust. Tables are reported in the appendix.

Robustness to controlling for pre-trends. Preexisting tests highlight that LLMs more exposed to robot adoption during 2010–2015 exhibited some differential trends in the 1980–1990 period (e.g. a greater increase in the share of young and high skilled individuals and employment reallocation from manufacturing towards services). To partially address potential biases arising from these differential trends, we control for these variables by including additional preexisting trends in our regression analysis. Results are in Table A6. The first column replicates the preferred specification in columns (7) of Tables 2 and 3. The next specifications subsequently control for additional preexisting trends. Results remain strongly robust. Noticeable, the impact of robots on the total income accruing to the top 1 percent of taxpayers increases by about 20 percent (compared to baseline) when we control for the past manufacturing employment contraction (column 5). This is in line with the idea that automation favors the concentration of economic activity among the largest and most productive manufacturing firms (Acemoglu et al., 2020; Autor et al., 2020).

Robustness to alternative outcomes. The outcome variables in our main regression analysis are computed using the total taxable income accruing to each income fractile. In this exercise we compute the outcomes using the average taxable income in each income group. To calculate this value we simply divide the total taxable income by the number of taxpayers within each income fractile. We maintain the same regression design with district and state-year fixed effects. Results are in Table A7.

Robustness to an alternative specification (2010 versus 2015). The main specification defines observations at the annual level for the period 2010 to 2015, which allows us to estimate the income effects of robots in the short-run, exploiting differences in exposure to robots *within* the same MA across years. In this alternative specification, we keep only the years 2010 and 2015, so we exploit differences in exposure to robots *across* MAs within the same time period. Results are in Table A8.

Robustness to outliers in exposure to robots. Because robot adoption is strongly uneven across industries, there are outliers in the metropolitan area's exposure to robot adoption. To rule out that results are driven by outliers, we perform a robustness exercise in which we exclude extreme values defined as the top and bottom 1 percent of the distribution of exposure to robots.[19]

[19] Most exposed metropolitan areas are Flint (MI), Wichita (KS), and Elkhart-Goshen (IN) with an average exposure to robots of 14.1, 11.1 and 9.3, respectively. At the other extreme, the less exposed areas are Anchorage (AK), Urban Honolulu (HI), and Billings (MT).

Results are in Table A9.

Robustness to excluding metropolitan areas with greatest importance of the automotive industry. Given that the automotive industry depicts the highest adoption of robotics (Fig. A3), there are concerns that our results may be driven by industry-specific shocks. Table A5 presents a summary of Rotemberg weights and shows that the automotive industry explains three-quarters of the identifying variation. To address this issue, we conduct a robustness exercise excluding the metropolitan areas with the highest participation of the automotive industry in local employment.[20] Results are in Table A10.

Robustness to excluding any particular years. The year 2012 could be problematic because it exhibits a large increment in top incomes (levels and shares) and this could be correlated with the robotic intensity of industries. Remember our discussion from Fig. 2Fig. 2–upper panel (a). To take this potential bias into account, we estimate our baseline regression excluding the year 2012. Results are in Table A11. Additionally, our results are strongly robust to exclude any other particular year of the period under study (not shown but available upon request).

Robustness to use 1980's census data. In the main specification we compute our measure of exposure to robots and the control variables at the metropolitan area level using microdata from the 1990's U.S. census. Alternatively, we can calculate these measures using the 1980's U.S. census. Results are in Table A12.

Robustness not use metropolitan area's importance weights. The baseline specification is an unweighted regression, which provides average treatment effects that are weighted by geographic units (i.e., local labor markets). Alternatively, we can use weights given by district's share of country's adult population in 1990. This estimation strategy gives us average treatment effects that are weighted by the number of individuals/population. Results are in Table A13.

Robustness to clustering errors at the industry level. In Bartik (shift-share) regression models such as ours, errors could share common shocks across districts with similar industrial compositions. Adao, Kolesar, and Morales (2019) and Borusyak, Hull and Jaravel (2021) discuss settings of shift-share designs in which confidence intervals obtained following the usual methods tend to be too liberal. We conduct a robustness exercise in which we apply the method of Adao et al. (2019) to correct standard errors for clustering at the original level of the shock variable, that is, the industry level. Under this methodology, the point-estimates of the coefficients are by

[20] These metropolitan areas are Flint (MI), Wichita (KS), and Saginaw (MI), which in 1990 had employed 19.1 percent, 14.3 percent, and 11.7 percent of total workers in the automotive industry, respectively; and exhibit an average exposure to robots of 14.1, 11.1 and 9.3, respectively.

construction the same, while the confidence intervals are estimated more conservatively. We report results in Table A14. We obtain a very large reduction in standard errors, which may be due to the fact that the number of industries is small and there is one industry (automotive) that is significantly larger than the rest (Adao et al., 2019).

V Concluding Remarks

During the last decades the U.S. has experienced two economic phenomena that have had a strong impact on society, public debates and academic literature. On the one hand, economic inequality has risen sharply. On the other hand, international trade has grown tremendously while there has been a massive technological revolution. There is growing body of literature investigating the effects of new technologies and trade on the labor market, productivity, prices, incomes and welfare.

Combining different sources of data (robotics, top incomes, census, industry employment and trade), we empirically document that the adoption of industrial robots have lead to increasing inequality in the personal income distribution and, in particular, to growing inequality among the richest taxpayers ("top income inequality"), and that part of these gains have occurred via increasing exports. Our findings are closely related to the literature that shows that the adoption of automation technologies favors the concentration of economic activity among the largest and most productive manufacturing companies.

We find that metropolitan areas more exposed to increasing robot adoption experience a relative increase in the total taxable income earned by the top 1 percent of taxpayers and no effect on the total income accruing to the bottom 99 percent, than less exposed areas. We document that income gains are greater for the highest paid individuals. An increase in one robot per thousand workers augments the total income of the fractiles P99-P99.9, P99.9-P99.99 and P99.99-P100 by 2.1 percent, 3.5 percent and 5.9 percent, respectively. We then focus on two measures of income inequality: (i) income ratios across consecutive fractiles, and (ii) income shares. We confirm that locations more exposed to robots exhibit a relative increase in income inequality among the richest taxpayers. Specifically, one more robot per thousand workers leads to a relative decline in the income share of the bottom 90 percent of 0.42 percentage points (-0.8 percent) and, conversely, increases the income shares of the aforementioned top income fractiles by 0.12 p.p. (1.2 percent), 0.12 p.p. (3.4 percent) and 0.17 p.p. (9.2 percent), respectively. One of the key mechanisms behind the surge in top incomes is that robotization leads to increased exports to high-income and upper-middle-income economies.

Our paper belongs to a prolific literature studying the relationship between technological change, trade and income inequality. We contribute to this literature by providing novel and robust empirical support for the causal effect of robotics on exports and top income inequality. Our reduced-form analysis estimates the direct effect of robots on income inequality but cannot account for general equilibrium forces neither quantify its level effects. Future research would elucidate if there are any other relevant mechanisms behind our findings and extend the analysis to other economies for validation.

References

Acemoglu, D., and Autor, D. H. (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics*, Vol. 4, 1043-1171.

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). "Competing With Robots: Firm-level Evidence from France," *AEA Papers and Proceedings*, 110, 383-388.

Acemoglu, D., Manera, A., and Restrepo, P. (2020). "Does the US Tax Code Favor Automation?," National Bureau of Economic Research Working Paper 27052.

Acemoglu, D., and Restrepo, P. (2020). "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128(6), 2188-2244.

Acemoglu, D., and Restrepo, P. (2021). "Demograhics and Automation," *Review of Economic Studies*, 89(1), 1-44.

Acemoglu, D., and Restrepo, P. (2022). "Tasks, Automation, and the Rise in US Wage Inequality," *Econometrica*, 90(5), 1973-2016.

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., Foster, E., Goldschlag, N., Haltiwanger, J., Kroff, Z., and Zolas, N. (2022). "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey," National Bureau of Economic Research Working Paper 30659.

Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., and Hémous, D. (2019). "Innovation and Top Income Inequality," *Review of Economic Studies*, 86(1), 1-45.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2022). "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France," working paper.

Artuc, E., Bastos, P., and Rijkers, B. (2020). "Robots, Tasks, and Trade," Centre for Economic Policy Research Discussion Paper 14487.

Atkinson, A. B., Piketty, T., and Saez, E. (2011). "Top Incomes in the Long run of History," *Journal of Economic Literature*, 49(1), 3-71.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279-1333.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). "The Polarization of the US Labor Market," *American Economic Review*, 96(2), 189-194.

Autor, D. H. (2019). "Work of the Past, Work of the Future," *AEA Papers and Proceedings*, 109, 1–32.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). "The Geography of Trade and Technology Shocks in the United States," *American Economic Review*, 103(3), 220-25.

Autor, D. H., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 135(2), 645-709.

Aw, B. Y., Roberts, M. J., and Xu, D. Y. (2011). "RD Investment, Exporting, and Productivity Dynamics," *American Economic Review*, 101(4), 1312-44.

Benabou, R. (1996). "Inequality and growth," *NBER Macroeconomics Annual*, 11, 11-74.

Bertrand, M., and Mullainathan, S. (2001). "Are CEOs Rewarded for Luck? The Ones Without Principals Are," *Quarterly Journal of Economics*, 116(3), 901-932.

Bakija, J., Cole, A., and Heim, B. T. (2012). "Jobs and Income Growth of Top Earners and the Causes of Changing Income Inequality: Evidence from U.S. Tax Return Data".

Bartels, L. (2016). Unequal Democracy: The Political Economy of the New Gilded Age. Princeton University Press.

Bivens, J., and Mishel, L. (2013). "The Pay of Corporate Executives and Financial Professionals as Evidence of Rents in Top 1 Percent Incomes," *Journal of Economic Perspectives*, 27(3), 57-78.

Bound, J., and Johnson, G. (1992). "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations," *American Economic Review*, 82, 371–9.

Caliendo, L., and Rossi-Hansberg, E. (2012). "The Impact of Trade on Organization and Productivity," *Quarterly Journal of Economics*, 127(3), 1393-1467.

Economic Review: Insights, 1(1), 1-12.

Curtis, E. M., Garrett, D. G., Ohrn, E., Roberts, K. A., and Serrato, J. C. S. (2021). "Capital Investment and Labor Demand: Evidence from 21st Century Tax Policy," working paper.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 19(6), 3104-3153.

De Backer, K., DeStefano, T., Menon, C., and Suh, J. R. (2018). "Industrial Robotics and the Global Organisation of Production," OECD Science, Technology and Industry Working Papers 2018/03.

Faber, M. (2020). "Robots and reshoring: Evidence from Mexican local labor markets," *Journal of International Economics*, 127, 103384.

Farhi, E., Sleet, C., Werning, I., and Yeltekin, S. (2012). "Non-linear Capital Taxation Without Commitment," *Review of Economic Studies*, 79(4), 1469-1493.

Freeman, C. (1986). "The Role of Technical Change in National Economic Development," In: A. Amin and J.B. Goddard (eds) Technological Change, Industrial Restructuring and Regional Development, 100-115.

Gabaix, X., and Landier, A. (2008). "Why Has CEO Pay Increased so Much?," *Quarterly Journal of Economics*, 123(1), 49-100.

Gabaix, X., Lasry, J. M., Lions, P. L., and Moll, B. (2016). "The Dynamics of Inequality, *Econometrica*, 84(6), 2071-2111.

Galor, O., and Zeira, J. (1993). "Income Distribution and Macroeconomics," *Review of Economic Studies*, 60(1), 35-52.

Garicano, L., and Rossi-Hansberg, E. (2006). "Organization and Inequality in a Knowledge Economy," *Quarterly Journal of Economics*, 121(4), 1383-1435.

Gilens, M. (2014). Affluence and Influence: Economic Inequality and Political Power in America. Princeton University Press.

Graetz, G., and Michaels, G. (2018). "Robots at work," *Review of Economics and Statistics*, 100(5), 753-768.

Gregory, T., Salomons, A., and Zierahn, U. (2021). "Racing with or Against the Machine? Evidence on the Role of Trade in Europe," *Journal of the European Economic Association*, 20(2), 869-906.

Goos, M., and Manning, A. (2007). "Lousy and Lovely Jobs: The Rising Polarization of

Work in Britain," *Review of Economics and Statistics*, 89(1), 118-133.

Goos, M., Manning, A., and Salomons, A. (2014). "Explaining Job Polarization: Routine-biased Technological Change and Offshoring," *American Economic Review*, 104(8), 2509-26.

Guerreiro, J., Rebelo, S., and Teles, P. (2022). "Should Robots be Taxed?," *Review of Economic Studies*, 89(1), 279-311.

Hémous, D., and Olsen, M. (2022). "The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality," *American Economic Journal: Macroeconomics*, 14(1), 179-223.

Hubmer, J., and Restrepo, P. (2022). "Not a Typical Firm: Capital–Labor Substitution and Firms' Labor Shares," working paper.

Humlum, A. (2021). "Robot Adoption and Labor Market Dynamics," working paper.

Jägger, K. (2016. "EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes."

Kaplan, S. N., and Rauh, J. (2013). "It's the Market: The Broad-based Rise in the Return to Top Talent," *Journal of Economic Perspectives*, 27(3), 35-56.

Katz, L. F., and Murphy, K. M. (1992). "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107(1), 35-78.

Kehrig, M., and Vincent, N. (2021). "The Micro-level Anatomy of the Labor Share Decline," *Quarterly Journal of Economics*, 136(2), 1031-1087.

Keller, W., and Olney, W. W. (2021). "Globalization and Executive Compensation," *Journal of International Economics*, 129, 103408.

Koch, M., Manuylov, I., and Smolka, M. (2021). "Robots and Firms," *Economic Journal*, 131(638), 2553-2584.

Koru, . F. (2020). "Automation and Top Income Inequality," working paper.

Krenz, A., Prettner, K., and Strulik, H. (2021). "Robots, reshoring, and the lot of low-skilled workers," *European Economic Review*, 136, 103744.

Ma, L., and Ruzic, D. (2020). "Globalization and Top Income Shares," *Journal of International Economics*, 125, 103312.

Martinez, J. (2021). "Putty-Clay Automation," Centre for Economic Policy Research Discussion Paper 16022.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-five Years," *Review of Economics and Statistics*, 96(1), 60-77.

Milgrom, P., Qian, Y., and Roberts, J. (1991). “Complementarities, Momentum, and the Evolution of Modern Manufacturing,” *American Economic Review*, 81(2), 84-88.

Mion, G., and Opromolla, L. D. (2014). “Managers’ Mobility, Trade Performance, and Wages,” *Journal of International Economics*, 94(1), 85-101.

Moll, B., Rachel, L., and Restrepo, P. (2022). “Uneven Growth: Automation’s Impact on Income and Wealth Inequality,” forthcoming in *Econometrica*.

Persson, T., and Tabellini, G. (1994). “Representative Democracy and Capital Taxation,” *Journal of Public Economics*, 55(1), 53-70.

Piketty, T., and Saez, E. (2003). “Income Inequality in the United States, 1913–1998,” *Quarterly Journal of Economics*, 118(1), 1-41.

Piketty, T. (2014). “Capital in the Twenty-First Century,” Harvard University Press.

Piketty, T., Saez, E., and Stantcheva, S. (2014). “Optimal Taxation of Top Labor Incomes: A Tale of Three Elasticities,” *American Economic Journal: Economic Policy*, 6(1), 230-71.

Rosen, S. (1981). “The Economics of Superstars,” *American Economic Review*, 71(5), 845-858.

Saez, E., and Zucman, G. (2016). “Wealth Inequality in the United States Since 1913: Evidence From Capitalized Income Tax Data,” *Quarterly Journal of Economics*, 131(2), 519-578.

Scheuer, F., and Wolitzky, A. (2016). “Capital Taxation Under Political Constraints,” *American Economic Review*, 106(8), 2304-28.

Scheuer, F., and Slemrod, J. (2020). “Taxation and the Superrich,” *Annual Review of Economics*, 12, 189-211.

Sommeiller, E., and Price, M.. “The New Gilded Age : Income Inequality in the U.S. by State, Metropolitan Area, and County,” Economic Policy Institute.

Spitz-Oener, A. (2006). “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure,” *Journal of Labor Economics*, 24(2), 235-270.

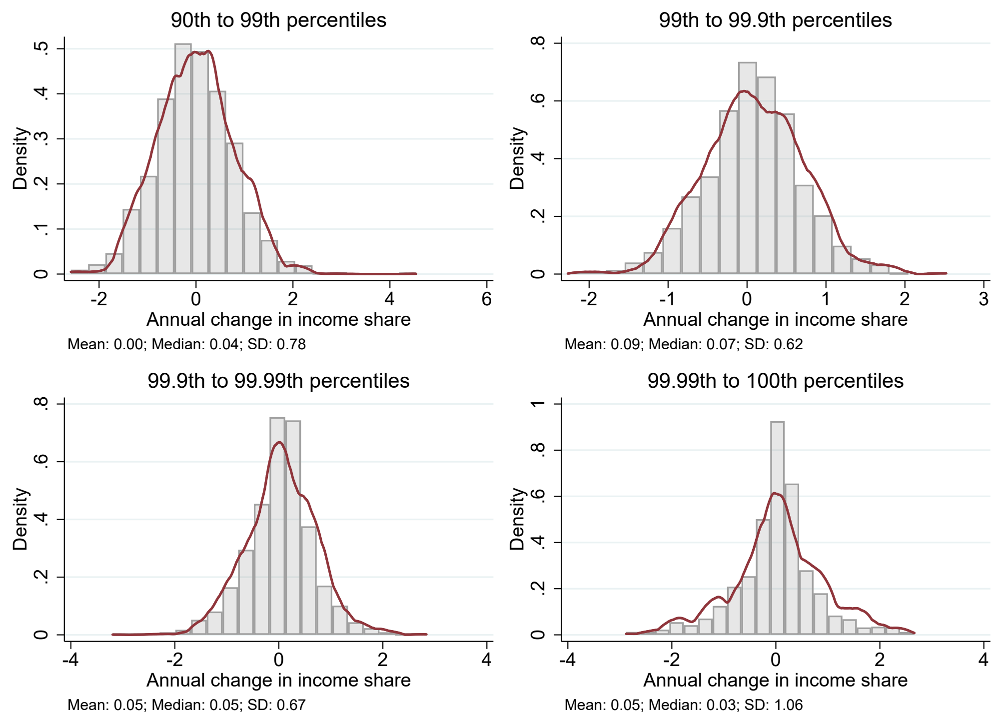
Stemmler, H. (2019). “Does automation lead to de-industrialization in emerging economies? Evidence from Brazil,” Center for European, Governance and Economic Development Research Discussion Paper 382.

Webb, M. (2020). “The Impact of Artificial Intelligence on the Labor Market,” working paper.

Terviö, M. (2009). “Superstars and Mediocrities: Market Failure in the Discovery of Talent,” *Review of Economic Studies*, 76(2), 829-850.

VI Appendix

Fig. A1: Distributions of annual changes in top income shares



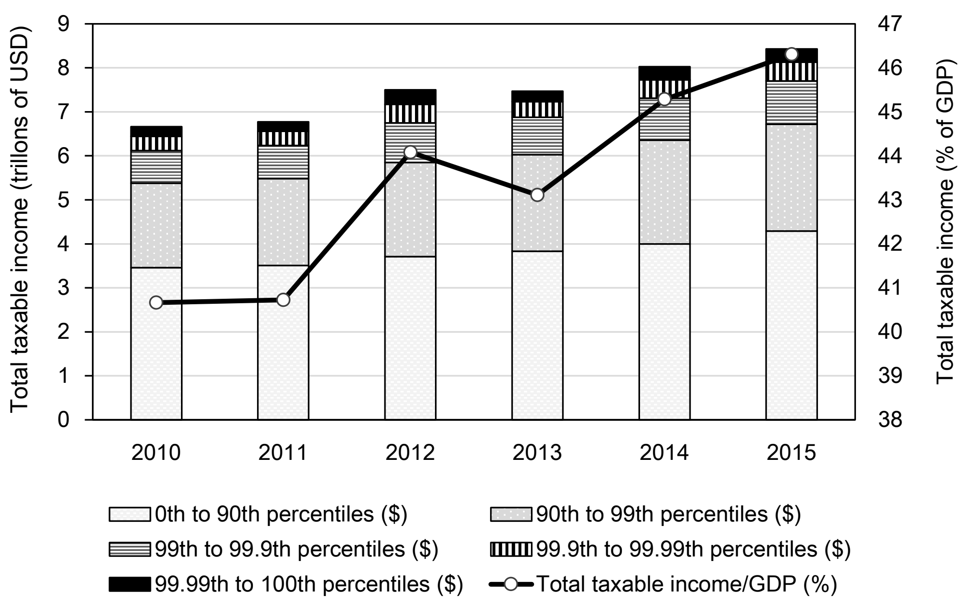
Notes. This figure plots the distributions of annual changes in total taxable income shares for exhaustive and mutually exclusive sets of top incomes (i.e. the four fractiles that compound the top 10 percent of taxpayers) across metropolitan areas during 2010–2015. The bottom-right panel (the richest top 0.01 percent) excludes the 1 percent extreme values. Own calculations using data from the WID (based on IRS).

Table A1: IRS statistics and estimation sample

	(1) IRS *Full sample*	(2) Metropolitan areas *Estimation sample*	(3) Ratio (2)/(1)
Total number of taxpayers (millon)	137	114	0.832
Total taxable income (billon USD)	8634	7464	0.864
Total taxable income by income fractiles (billon USD)			
0th to 90th percentiles	4446	3790	0.852
90th to 99th percentiles	2502	2167	0.866
99th to 99.9th percentiles	970	862	0.888
99.9th to 99.99th percentiles	419	377	0.899
99.99th to 100th percentiles	297	269	0.905

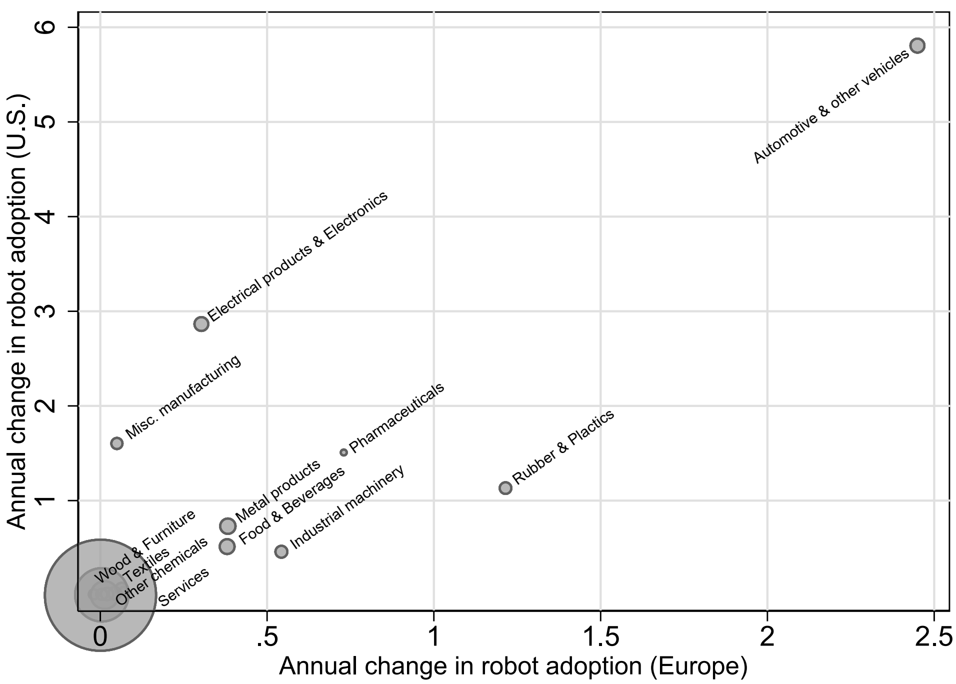
Notes. Numbers are averaged for the period 2010–2015. Column (1) covers the complete list of districts available in the Internal Revenue Service (IRS) data. Column (2) covers the metropolitan areas that were successfully matched across the IRS and the 1990's US Census data, which is the sample used to conduct our estimates. Column (3) presents a simple ratio between columns (1) and (2) that indicates the coverage of our estimation sample.

Fig. A2: Evolution of total taxable income



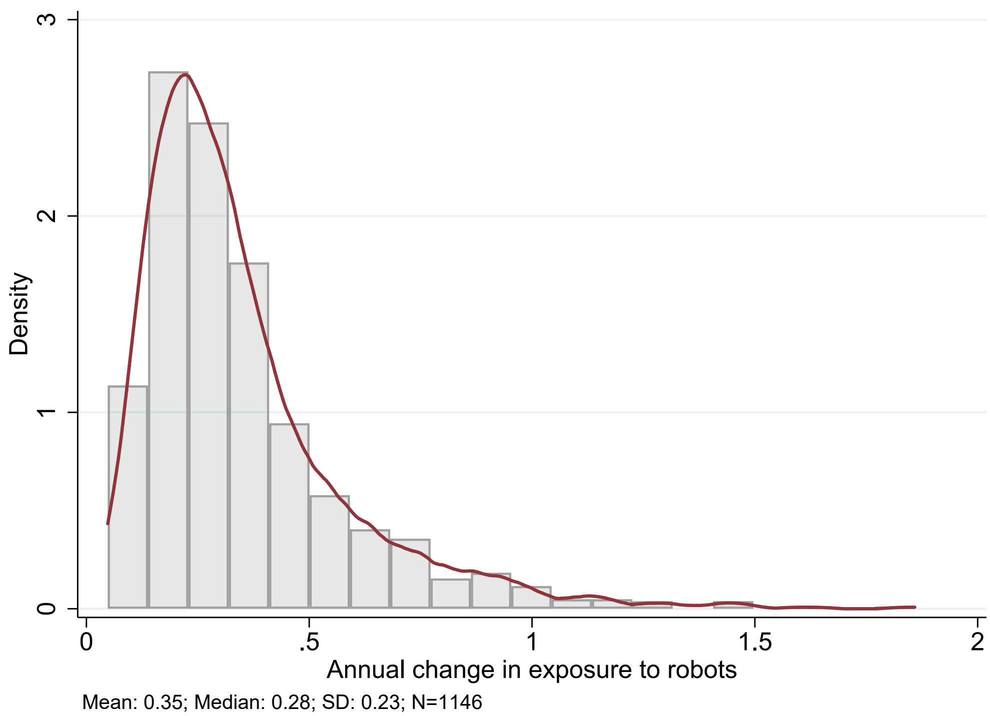
Notes. The figure plots the evolution of total taxable income covered in our estimation sample of metropolitan areas for the period 2010–2015. Bars are expressed in constant 2015 USD (left axis). They are disaggregated across five mutually exclusive income fractiles: (i) bottom 90 percent, (ii) percentiles 90 to 99, (iii) percentiles 99 to 99.9, (iii) percentiles 99.9 to 99.99, and (iii) top 0.01 percent. The black line plots the evolution of total taxable income expressed as a percentage of gross domestic product (right axis). Own calculations using data from the IFR and the World Bank.

Fig. A3: Industry robot adoption in U.S. and Europe during 2010–2015



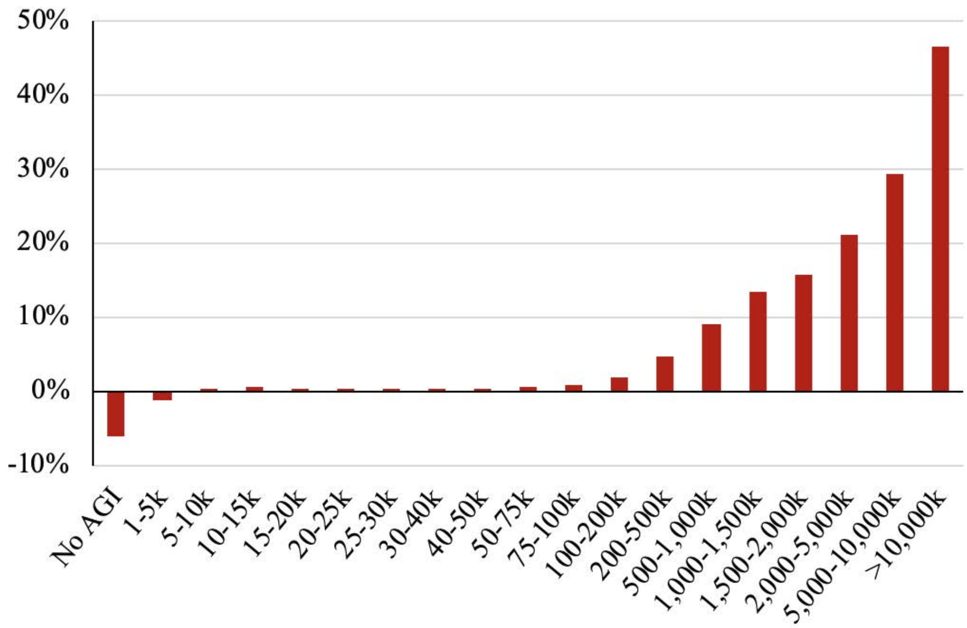
Notes. The figure plots industries according to their average annual growth in robot per thousand workers between 2010 and 2015 in the United States (vertical axis) and European countries (horizontal axis). The size of the markers indicate the average US employment in the industry during 2010–2015. N=17 (11 manufacturing industries). Sources: IFR and EU KLEMS.

Fig. A4: Annual change in exposure to robots during 2010–2015



Notes. The figure plots the distribution of the annual change in exposure to robots across metropolitan areas. Own calculations using data from the IFR, EU KLEMS and the 1990's census.

Fig. A5: Capital gains as a share of taxable income



Notes. This figure was taken from Scheuer and Slemrod (2020). It exibits the net capital gains as a share of adjusted gross income across income groups (in U.S. Dollars) in the United States for the year 2016. Source: IRS.

Table A2: Descriptive statistics: by year

	2010	2011	2012	2013	2014	2015
Panel A: Total Taxable Income (billons of 2015 USD)						
0th to 90th percentiles	82.5	85.8	88.7	91.4	95.7	103.1
90th to 99th percentiles	51.1	54.0	56.6	58.1	63.4	65.2
99th to 99.9th percentiles	22.5	23.5	26.7	25.4	28.9	29.5
99.9th to 99.99th percentiles	10.7	10.9	13.5	11.8	14.0	14.1
99.99th to 100th percentiles	8.4	8.3	11.9	9.1	11.4	11.3
Panel B: Average Taxable Income (thousands of 2015 USD)						
0th to 90th percentiles	36	36	36	36	37	40
90th to 99th percentiles	208	209	219	218	228	238
99th to 99.9th percentiles	830	827	951	865	950	989
99.9th to 99.99th percentiles	3535	3454	4372	3594	4122	4258
99.99th to 100th percentiles	23051	21691	32237	22526	27670	28066
Panel C: Total Taxable Income Ratios						
90th-99th to 0th-90th pctl.	0.56	0.57	0.59	0.59	0.60	0.58
99th-99.9th to 90th-99th pctl.	0.39	0.38	0.42	0.39	0.40	0.40
99th-99.99th to 99.99th-99.9th pctl.	0.42	0.41	0.46	0.41	0.43	0.43
99.99th-100th to 99.9th-99.99th pctl.	0.65	0.63	0.73	0.62	0.66	0.66
Panel D: Average Taxable Income Ratios						
90th-99th to 0th-90th pctl.	5.79	5.88	6.09	6.03	6.25	5.98
99th-99.9th to 90th-99th pctl.	3.89	3.85	4.23	3.87	4.04	4.04
99th-99.99th to 99.99th-99.9th pctl.	4.08	4.01	4.40	3.97	4.13	4.12
99.99th-100th to 99.9th-99.99th pctl.	5.82	5.65	6.60	5.57	5.95	5.91
Panel E: Taxable Income Shares						
0th to 90th percentiles	51.94	51.76	49.40	51.23	49.76	50.85
90th to 99th percentiles	28.79	29.13	28.54	29.44	29.44	28.81
99th to 99.9th percentiles	11.12	11.17	12.01	11.35	11.86	11.64
99.9th to 99.99th percentiles	4.81	4.74	5.61	4.78	5.21	5.09
99.99th to 100th percentiles	3.34	3.20	4.43	3.20	3.73	3.61
Panel F: Exports per worker (thousands of 2015 USD)						
Exports per worker	20.2	21.9	22.6	22.8	23.2	22.4
Exports to HIC per worker	12.7	13.7	14.2	14.0	14.3	14.0
Exports to UMIC per worker	5.8	6.5	6.7	7.1	7.3	6.8
Exports to LMIC per worker	1.6	1.6	1.7	1.7	1.6	1.6
Panel G: Exposure to robots (robots per thousand workers)						
Exposure to robots	1.91	2.22	2.52	2.88	3.28	3.70
Exposure to robots (IV)	1.26	1.38	1.51	1.65	1.77	1.90
Number of observations				1376		
Number of metropolitan areas				230		
Number of states				45		

Notes. Notes. Statistics correspond to the mean value of the corresponding variable (panel) in each year (column). Income fractiles computed using the 0th, 90th, 99th, 99.9th and 99.99th percentiles of the taxable income distribution in each metropolitan area, correspond to exhaustive and mutually exclusive sets of taxpayers. Statistics weighted by metropolitan area's share in annual total taxable income.

Table A3: Balance tests

	Change in exposure to robots	Change in exposure to robots (IV)	High exposure to robots	High exposure to robots (IV)
Share of total population	0.0004	0.0004	0.0009	−0.0000
	(0.0008)	(0.0020)	(0.0021)	(0.0022)
Share of adult population	0.0004	0.0005	0.0009	−0.0000
	(0.0008)	(0.0020)	(0.0022)	(0.0022)
Women's share in adult population	−0.0010	−0.0028	−0.0004	−0.0013
	(0.0017)	(0.0043)	(0.0035)	(0.0028)
Immigrant's share in adult population	0.0006	−0.0093	−0.0009	−0.0093
	(0.0051)	(0.0123)	(0.0122)	(0.0103)
Share with low-skills	−0.0023	0.0029	−0.0061	−0.0013
	(0.0026)	(0.0062)	(0.0067)	(0.0082)
Share with middle-skills	0.0073	0.0584***	−0.0069	0.0306***
	(0.0085)	(0.0141)	(0.0126)	(0.0118)
Share with high-skills	−0.0050	−0.0613***	0.0129	−0.0293**
	(0.0108)	(0.0180)	(0.0170)	(0.0148)
Share of young (16–34)	−0.0054	−0.0228**	−0.0055	−0.0164*
	(0.0040)	(0.0110)	(0.0081)	(0.0094)
Share of middle-age (35–49)	0.0034	0.0082	0.0058	0.0048
	(0.0021)	(0.0064)	(0.0041)	(0.0048)
Share of senior (50–65)	0.0020	0.0147**	−0.0004	0.0116*
	(0.0026)	(0.0065)	(0.0055)	(0.0062)
LFP rate	0.0073	0.0053	0.0187**	0.0036
	(0.0059)	(0.0141)	(0.0089)	(0.0099)
Women's LFP rate	0.0046	−0.0065	0.0186*	−0.0022
	(0.0068)	(0.0147)	(0.0098)	(0.0111)
Employment share in agriculture	−0.0089**	−0.0148*	−0.0127*	−0.0085
	(0.0043)	(0.0084)	(0.0076)	(0.0078)
Employment share in manufacturing	0.0350***	0.0957***	0.0462***	0.0605***
	(0.0076)	(0.0236)	(0.0082)	(0.0071)
Employment share in services	−0.0260***	−0.0809***	−0.0335***	−0.0520***
	(0.0079)	(0.0230)	(0.0107)	(0.0101)
Employment share in finance	−0.0030	−0.0137**	0.0019	−0.0078*
	(0.0021)	(0.0056)	(0.0038)	(0.0042)
Observations	230	230	230	230

Notes. Each coefficient corresponds to a separate regression. All dependent variables (in rows) are expressed in levels and correspond to the year 1990. Explanatory variables (in columns) are expressed in changes between 2010 and 2015. Column (1): Change in ER; Column (2): Change in ER^{IV}; Column (3): Change in ER above the median; Column (4): Change in ER^{IV} above the median. Regressions control for state fixed effects. Standard errors clustered at the state level are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table A4: Pre–trend tests

	Change in exposure to robots	Change in exposure to robots (IV)	High exposure to robots	High exposure to robots (IV)
Share of total population	0.0001	0.0002	0.0003	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Share of adult population	0.0001	0.0002	0.0002	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Women's share in adult population	0.0001	0.0003	−0.0015	−0.0005
	(0.0008)	(0.0020)	(0.0011)	(0.0013)
Immigrant's share in adult population	0.0020	−0.0002	0.0061	0.0006
	(0.0020)	(0.0051)	(0.0039)	(0.0034)
Share with low-skills	0.0008	−0.0015	0.0027	−0.0019
	(0.0011)	(0.0025)	(0.0026)	(0.0021)
Share with middle-skills	−0.0038**	−0.0007	−0.0121***	0.0007
	(0.0019)	(0.0043)	(0.0040)	(0.0037)
Share with high-skills	0.0030*	0.0022	0.0094**	0.0012
	(0.0017)	(0.0048)	(0.0038)	(0.0036)
Share of young (16–34)	0.0028*	0.0067	0.0079***	0.0059**
	(0.0015)	(0.0041)	(0.0026)	(0.0029)
Share of middle-age (35–49)	−0.0033**	−0.0082**	−0.0054*	−0.0062*
	(0.0014)	(0.0039)	(0.0031)	(0.0032)
Share of senior (50–65)	0.0005	0.0016	−0.0024	0.0003
	(0.0012)	(0.0028)	(0.0027)	(0.0024)
LFP rate	−0.0004	−0.0059	0.0049	−0.0005
	(0.0017)	(0.0041)	(0.0030)	(0.0020)
Women's LFP rate	−0.0011	−0.0030	0.0020	0.0000
	(0.0014)	(0.0034)	(0.0032)	(0.0028)
Employment share in agriculture	0.0013	0.0016	0.0026	0.0020
	(0.0009)	(0.0021)	(0.0020)	(0.0015)
Employment share in manufacturing	−0.0062***	−0.0194***	−0.0073*	−0.0129***
	(0.0024)	(0.0074)	(0.0039)	(0.0046)
Employment share in services	0.0050*	0.0179**	0.0046	0.0109***
	(0.0026)	(0.0075)	(0.0034)	(0.0038)
Employment share in finance	−0.0002	−0.0006	0.0015	0.0005
	(0.0005)	(0.0014)	(0.0012)	(0.0009)
Observations	230	230	230	230

Notes. All variables are expressed in period changes. Each coefficient corresponds to a separate regression. Dependent variables in row panels. Changes in row variables refer to years 1980-1990. Explanatory variables in columns. Changes in column variables refer to years 2010-2015. Column (1): Change in ER; Column (2): Change in ER^{IV}; Column (3): Change in ER above the median; Column (4): Change in ER^{IV} above the median. Regressions control for state fixed effects. Standard errors clustered at the state level are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table A5: Summary of Rotermberg weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.001	-0.000	0.001
Positive	1.001	0.100	0.999

Panel B: Industries with positive Rotemberg weight

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share
Automotive & other vehicles	0.752	6.008	-0.013	2.921
Electrical products & electronics	0.153	3.530	0.275	3.689
Metal products	0.031	1.026	-0.239	2.074
Pharmaceuticals	0.023	2.001	0.220	1.389
Other manufacturing, repair & instalation	0.020	1.582	0.109	1.415
Rubber & plastic products	0.015	1.197	-0.460	1.174
Machinery and equipment	0.007	0.264	-0.475	1.758
Wood/Paper products, printing & reproduction	0.000	0.028	-1.532	3.607
Electricity, gas & water supply	0.000	0.034	-0.036	1.093
Professional, scientific & technical act.	0.000	0.008	0.320	2.035

Notes. This table reports statistics about the Rotemberg weights. Weights for a given industry are aggregated across years. Panel A reports the share and sum of negative and positive Rotemberg weights separately. Panel B reports the ten industries with highest positive Rotemberg weights. The g_k is the national industry growth in exposure to robots during 2010–2015, $\hat{\beta}_k$ is the coefficient from the just-identified regression, and Ind Share is the industry share (multiplied by 100 for legibility).

Table A6: Robustness to controlling for 1980–1990 pre-trends

	(1)	(2)	(3)	(4)	(5)
A.1: Log (TT Income of 0th to 90th percentiles)					
Exposure to robots	0.001	-0.000	0.003	0.003	0.004
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
A.2: Log (TT Income of 90th to 99th percentiles)					
Exposure to robots	0.008	0.007	0.009	0.009	0.011
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
A.3: Log (TT Income of 99th to 99.9th percentiles)					
Exposure to robots	0.021^{**}	0.020^{**}	0.020^{**}	0.021^{**}	0.025^{***}
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)					
Exposure to robots	0.035^{***}	0.035^{***}	0.034^{**}	0.035^{**}	0.042^{***}
	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
A.5: Log (TT Income of 99.99th to 100th percentiles)					
Exposure to robots	0.059^{***}	0.060^{***}	0.056^{**}	0.059^{**}	0.070^{***}
	(0.021)	(0.021)	(0.023)	(0.023)	(0.022)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles					
Exposure to robots	0.004	0.004	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles					
Exposure to robots	0.005^{***}	0.005^{***}	0.004^{**}	0.004^{**}	0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles					
Exposure to robots	0.007^{***}	0.007^{***}	0.006^{**}	0.007^{**}	0.008^{***}
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles					
Exposure to robots	0.018^{***}	0.018^{***}	0.016^{**}	0.018^{***}	0.019^{***}
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
C.1: TT Income Share of 0th to 90th percentiles					
Exposure to robots	-0.424^{***}	-0.421^{***}	-0.370^{***}	-0.384^{***}	-0.438^{***}
	(0.104)	(0.110)	(0.118)	(0.118)	(0.120)
C.2: TT Income Share of 90th to 99th percentiles					
Exposure to robots	0.008	0.003	0.005	-0.003	-0.009
	(0.070)	(0.071)	(0.075)	(0.079)	(0.081)
C.3: TT Income Share of 99th to 99.9th percentiles					
Exposure to robots	0.120^{***}	0.121^{***}	0.104^{***}	0.106^{***}	0.130^{***}
	(0.030)	(0.031)	(0.033)	(0.034)	(0.034)
C.4: TT Income Share of 99.9th to 99.99th percentiles					
Exposure to robots	0.123^{***}	0.124^{***}	0.109^{***}	0.116^{***}	0.136^{***}
	(0.034)	(0.034)	(0.037)	(0.037)	(0.036)
C.5: TT Income Share of 99.99th to 100th percentiles					
Exposure to robots	0.172^{***}	0.174^{***}	0.153^{***}	0.166^{***}	0.182^{***}
	(0.047)	(0.047)	(0.055)	(0.053)	(0.049)
Observations	1376	1376	1376	1376	1376
PT 1990-1980 change in immigrant's share	-	Yes	Yes	Yes	Yes
PT 1990-1980 change in skill comp.	-	-	Yes	Yes	Yes
PT 1990-1980 change in age comp.	-	-	-	Yes	Yes
PT 1990-1980 change in sector empl.	-	-	-	-	Yes

Notes. Column (1) is analogous to column (7) of Tables 2 and 3. Preexisting trends at the metropolitan area level expressed in changes between 1980 and 1990 are: change in the share of immigrants in adult population (Column 2 and onwards); changes in the percentages of local adult population with middle education and high education (Columns 3 and 4); and changes in local employment shares in manufacturing and services (Column 4).

Table A7: Robustness to alternative outcomes

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Log (Average Taxable Income)							
A.1: Log (ATI of 0th to 90th percentiles)							
Exposure to robots	0.005	0.003	−0.006	−0.001	−0.002	−0.003	−0.002
	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
A.2: Log (ATI of 90th to 99th percentiles)							
Exposure to robots	0.001	−0.005	−0.003	0.004	0.003	0.002	0.003
	(0.004)	(0.003)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
A.3: Log (ATI of 99th to 99.9th percentiles)							
Exposure to robots	0.011*	0.005	0.013	0.016**	0.016**	0.016*	0.018**
	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
A.4: Log (ATI of 99.9th to 99.99th percentiles)							
Exposure to robots	0.019*	0.010	0.023	0.028**	0.029**	0.028**	0.033***
	(0.011)	(0.011)	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)
A.5: Log (ATI of 99.99th to 100th percentiles)							
Exposure to robots	0.033*	0.019	0.043*	0.049**	0.051**	0.050**	0.057***
	(0.019)	(0.019)	(0.024)	(0.019)	(0.020)	(0.023)	(0.021)
Panel B: Average Taxable Income Ratios							
B.1: ATI Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.026	−0.048	0.015	0.027	0.027	0.026	0.028
	(0.039)	(0.042)	(0.023)	(0.021)	(0.021)	(0.022)	(0.021)
B.2: ATI Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.036**	0.036**	0.061***	0.051***	0.053***	0.049***	0.054***
	(0.018)	(0.017)	(0.019)	(0.016)	(0.016)	(0.016)	(0.016)
B.3: ATI Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.039*	0.026	0.057**	0.061***	0.064***	0.058**	0.065***
	(0.022)	(0.022)	(0.026)	(0.021)	(0.022)	(0.026)	(0.023)
B.4: ATI Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.101*	0.072	0.169**	0.175***	0.181***	0.143***	0.161***
	(0.054)	(0.052)	(0.068)	(0.055)	(0.056)	(0.051)	(0.050)
Observations	1376	1376	1376	1376	1376	1376	1376
Year x State FE	-	-	Yes	Yes	Yes	Yes	Yes
PT Demographics	-	-	-	Yes	Yes	Yes	Yes
PT LFP rates	-	-	-	-	Yes	Yes	Yes
PT Sector shares in empl.	-	-	-	-	-	Yes	Yes
PT Finance share in empl.	-	-	-	-	-	-	Yes

Notes. Analogous to Tables 2 and 3. The outcome variables are the logarithm of average taxable income in each income fractile (Panel A) and average taxable income ratios across income fractiles (Panel B).

Table A8: Robustness to 2010–2015 period specification

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.006	−0.013**	−0.010	−0.001	−0.002	−0.001	0.000
	(0.006)	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)	(0.006)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.008	−0.017***	−0.004	0.006	0.005	0.007	0.009
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	0.002	−0.007	0.011	0.017*	0.017**	0.016	0.019*
	(0.009)	(0.008)	(0.010)	(0.009)	(0.008)	(0.010)	(0.010)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.012	0.000	0.024	0.030*	0.030**	0.025	0.030*
	(0.015)	(0.014)	(0.017)	(0.015)	(0.015)	(0.018)	(0.017)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.029	0.013	0.048	0.053**	0.053**	0.043	0.049*
	(0.025)	(0.024)	(0.030)	(0.027)	(0.026)	(0.031)	(0.030)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.001	−0.003	0.003	0.004*	0.004*	0.004*	0.004**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.004	0.004*	0.006**	0.005**	0.005**	0.003	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.005*	0.004	0.007*	0.007**	0.007**	0.005	0.006*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.013*	0.011	0.023**	0.022**	0.022**	0.016**	0.017**
	(0.007)	(0.007)	(0.011)	(0.009)	(0.009)	(0.008)	(0.008)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.139	−0.064	−0.462***	−0.451***	−0.463***	−0.396***	−0.430***
	(0.237)	(0.245)	(0.157)	(0.139)	(0.137)	(0.137)	(0.131)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.119	−0.140	−0.056	−0.029	−0.026	0.040	0.034
	(0.081)	(0.091)	(0.076)	(0.076)	(0.073)	(0.071)	(0.074)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.055	0.039	0.117***	0.102***	0.106***	0.091**	0.101**
	(0.064)	(0.064)	(0.042)	(0.039)	(0.039)	(0.044)	(0.040)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.077	0.059	0.140**	0.131***	0.133***	0.101**	0.112**
	(0.059)	(0.057)	(0.055)	(0.050)	(0.048)	(0.048)	(0.047)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.126	0.107	0.261**	0.247***	0.250***	0.164***	0.183***
	(0.083)	(0.080)	(0.103)	(0.092)	(0.089)	(0.062)	(0.070)
Observations	460	460	460	460	460	460	460

Notes. Analogous to Tables 2 and 3. The sample is restricted to the first and final years of data: 2010 and 2015.

Table A9: Robustness to the exclusion of outliers

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.008	−0.018**	−0.013*	−0.004	−0.005	−0.003	−0.001
	(0.008)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.009	−0.023***	−0.007	0.004	0.003	0.006	0.009
	(0.007)	(0.006)	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	−0.004	−0.018***	0.001	0.009	0.009	0.011	0.016*
	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)	(0.010)	(0.009)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.001	−0.018	0.004	0.015	0.015	0.017	0.023
	(0.014)	(0.011)	(0.015)	(0.012)	(0.013)	(0.016)	(0.015)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.010	−0.017	0.012	0.026	0.027	0.026	0.037
	(0.023)	(0.019)	(0.025)	(0.021)	(0.022)	(0.026)	(0.025)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.001	−0.004	0.003	0.004	0.004	0.004	0.004
	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.002	0.002	0.003**	0.003*	0.003*	0.002	0.003
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.003	0.001	0.003	0.004	0.004	0.003	0.004
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.009	0.004	0.013	0.014*	0.015*	0.010	0.013*
	(0.007)	(0.006)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.095	0.046	−0.345**	−0.368**	−0.384***	−0.349**	−0.396***
	(0.267)	(0.279)	(0.163)	(0.146)	(0.147)	(0.149)	(0.135)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.084	−0.107	0.013	0.026	0.028	0.086	0.077
	(0.100)	(0.123)	(0.070)	(0.071)	(0.071)	(0.074)	(0.079)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.027	−0.004	0.076**	0.070*	0.075*	0.075*	0.090**
	(0.072)	(0.071)	(0.038)	(0.038)	(0.039)	(0.040)	(0.037)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.050	0.012	0.081*	0.088**	0.091**	0.072*	0.089**
	(0.060)	(0.053)	(0.047)	(0.044)	(0.046)	(0.043)	(0.041)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.102	0.053	0.175**	0.184**	0.189**	0.116**	0.142**
	(0.081)	(0.070)	(0.088)	(0.079)	(0.081)	(0.053)	(0.061)
Observations	1340	1340	1340	1340	1340	1340	1340

Notes. Analogous to Tables 2 and 3. Regressions exclude metropolitan areas in the bottom and top 1 percent of the distribution of exposure to robots.

Table A10: Robustness to exclude areas with greatest importance of automotive

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.004	−0.013	−0.007	0.002	−0.001	0.002	0.005
	(0.008)	(0.009)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.007	−0.020***	−0.003	0.007	0.005	0.008	0.012
	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	0.002	−0.010	0.010	0.017*	0.015*	0.018*	0.023**
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)	(0.010)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.011	−0.006	0.019	0.026*	0.025*	0.028	0.035**
	(0.015)	(0.016)	(0.018)	(0.014)	(0.015)	(0.017)	(0.016)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.027	0.003	0.035	0.045*	0.045*	0.045	0.056**
	(0.026)	(0.026)	(0.029)	(0.023)	(0.025)	(0.029)	(0.027)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.002	−0.005	0.002	0.003	0.003	0.003	0.003
	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.004	0.003	0.005**	0.004**	0.004**	0.004*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.005	0.003	0.006*	0.006**	0.006**	0.005*	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.013*	0.009	0.019**	0.019***	0.020**	0.015**	0.018**
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.117	0.015	−0.372**	−0.384***	−0.395***	−0.359**	−0.413***
	(0.255)	(0.270)	(0.151)	(0.137)	(0.142)	(0.144)	(0.128)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.141	−0.176	−0.061	−0.039	−0.035	0.018	0.007
	(0.102)	(0.122)	(0.081)	(0.076)	(0.077)	(0.083)	(0.087)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.043	0.017	0.094**	0.084**	0.086**	0.086**	0.102***
	(0.070)	(0.071)	(0.040)	(0.038)	(0.041)	(0.042)	(0.038)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.075	0.043	0.114**	0.114**	0.115**	0.097**	0.116***
	(0.060)	(0.058)	(0.050)	(0.044)	(0.048)	(0.046)	(0.043)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.140*	0.100	0.226***	0.225***	0.229***	0.157***	0.187***
	(0.081)	(0.078)	(0.087)	(0.074)	(0.078)	(0.057)	(0.060)
Observations	1358	1358	1358	1358	1358	1358	1358

Notes. Analogous to Tables 2 and 3. Regressions exclude metropolitan areas in the top 1 percent of the distribution of 1990's employment share in the automotive industry, which are Flint (MI), Saginaw (MI), and Wichita (KS).

Table A11: Robustness to the exclusion of year 2012

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	-0.006	-0.012^{*}	-0.010	-0.002	-0.003	-0.001	0.001
	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	-0.010^{*}	-0.020^{***}	-0.005	0.005	0.004	0.006	0.008
	(0.005)	(0.005)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	-0.001	-0.011	0.009	0.016^{**}	0.016^{**}	0.018^{**}	0.021^{**}
	(0.007)	(0.007)	(0.010)	(0.008)	(0.007)	(0.009)	(0.009)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.006	-0.006	0.020	0.029^{**}	0.029^{**}	0.032^{**}	0.037^{***}
	(0.012)	(0.012)	(0.015)	(0.012)	(0.012)	(0.015)	(0.013)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.020	0.002	0.041^{*}	0.051^{**}	0.052^{***}	0.054^{**}	0.062^{***}
	(0.021)	(0.020)	(0.025)	(0.020)	(0.020)	(0.024)	(0.022)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	-0.002	-0.004	0.002	0.003	0.003	0.003	0.004
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.003^{*}	0.003^{*}	0.005^{***}	0.005^{***}	0.005^{***}	0.004^{**}	0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.004	0.002	0.006^{**}	0.007^{***}	0.007^{***}	0.006^{**}	0.007^{***}
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.010	0.007	0.019^{**}	0.020^{***}	0.021^{***}	0.017^{***}	0.019^{***}
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	-0.048	0.054	-0.396^{***}	-0.414^{***}	-0.429^{***}	-0.401^{***}	-0.440^{***}
	(0.216)	(0.218)	(0.133)	(0.119)	(0.118)	(0.123)	(0.106)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	-0.143^{*}	-0.164^{*}	-0.054	-0.035	-0.032	0.014	0.006
	(0.082)	(0.096)	(0.071)	(0.068)	(0.067)	(0.067)	(0.071)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.035	0.015	0.110^{***}	0.102^{***}	0.107^{***}	0.113^{***}	0.125^{***}
	(0.057)	(0.056)	(0.035)	(0.032)	(0.033)	(0.035)	(0.030)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.057	0.031	0.122^{***}	0.125^{***}	0.129^{***}	0.116^{***}	0.129^{***}
	(0.050)	(0.046)	(0.044)	(0.039)	(0.039)	(0.039)	(0.035)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.098	0.063	0.218^{***}	0.221^{***}	0.225^{***}	0.159^{***}	0.180^{***}
	(0.071)	(0.063)	(0.080)	(0.070)	(0.069)	(0.049)	(0.050)
Observations	1146	1146	1146	1146	1146	1146	1146

Notes. Analogous to Tables 2 and 3. Regressions exclude the year 2012.

Table A12: Robustness to use 1980 as baseline year

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.006	−0.013*	−0.010	−0.001	−0.003	−0.001	0.001
	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.010*	−0.020***	−0.005	0.004	0.003	0.006	0.008
	(0.005)	(0.005)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	−0.001	−0.010	0.009	0.016*	0.015**	0.018*	0.021**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)	(0.009)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.008	−0.005	0.020	0.028**	0.028**	0.031**	0.035***
	(0.012)	(0.012)	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.022	0.004	0.039	0.049**	0.050**	0.052**	0.059***
	(0.020)	(0.020)	(0.024)	(0.019)	(0.020)	(0.024)	(0.021)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.002	−0.004	0.002	0.003	0.003	0.003	0.004
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.003*	0.003*	0.005***	0.005***	0.005***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.004*	0.003	0.006**	0.006***	0.007***	0.006**	0.007***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.011*	0.008	0.019**	0.019***	0.020***	0.016***	0.018***
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.069	0.035	−0.392***	−0.400***	−0.417***	−0.390***	−0.424***
	(0.210)	(0.215)	(0.128)	(0.114)	(0.114)	(0.120)	(0.104)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.145*	−0.171*	−0.056	−0.035	−0.032	0.015	0.008
	(0.080)	(0.095)	(0.070)	(0.067)	(0.066)	(0.068)	(0.070)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.039	0.019	0.110***	0.099***	0.104***	0.109***	0.120***
	(0.056)	(0.055)	(0.035)	(0.031)	(0.032)	(0.034)	(0.030)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.063	0.038	0.121***	0.121***	0.125***	0.112***	0.123***
	(0.048)	(0.045)	(0.042)	(0.036)	(0.037)	(0.038)	(0.034)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.111*	0.079	0.216***	0.216***	0.221***	0.154***	0.172***
	(0.068)	(0.062)	(0.074)	(0.064)	(0.064)	(0.046)	(0.047)
Observations	1376	1376	1376	1376	1376	1376	1376

Notes. Analogous to Tables 2 and 3. Exposure to robots and preexisting trends calculated using 1980's census data.

Table A13: Robustness to use population weights

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.001	−0.004	−0.011***	−0.009***	−0.009***	−0.009	−0.010
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.005	−0.012**	−0.008	−0.003	−0.004	0.001	−0.001
	(0.006)	(0.005)	(0.007)	(0.006)	(0.007)	(0.009)	(0.009)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	0.003	−0.005	−0.000	0.005	0.004	0.008	0.007
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.010)	(0.011)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.009	−0.002	0.008	0.016	0.015	0.021	0.020
	(0.010)	(0.008)	(0.011)	(0.011)	(0.012)	(0.016)	(0.016)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.019	0.001	0.020	0.032*	0.031	0.041	0.040
	(0.014)	(0.011)	(0.018)	(0.017)	(0.019)	(0.026)	(0.027)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.003	−0.006	0.001	0.003	0.003	0.004*	0.004*
	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.003**	0.002***	0.003***	0.003***	0.003***	0.002*	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.002*	0.001	0.003*	0.005**	0.004**	0.005*	0.005*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.005	0.001	0.008*	0.011**	0.010**	0.010	0.010
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	0.007	0.142	−0.218*	−0.291**	−0.273**	−0.355**	−0.353**
	(0.199)	(0.198)	(0.123)	(0.116)	(0.134)	(0.140)	(0.139)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.121*	−0.142*	−0.017	−0.002	0.001	0.084	0.074
	(0.068)	(0.079)	(0.047)	(0.057)	(0.055)	(0.066)	(0.065)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.040	0.011	0.079***	0.095***	0.092***	0.106***	0.108***
	(0.052)	(0.051)	(0.027)	(0.023)	(0.027)	(0.032)	(0.033)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.038	0.003	0.069**	0.089***	0.084***	0.086*	0.088*
	(0.040)	(0.035)	(0.030)	(0.024)	(0.031)	(0.047)	(0.048)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.036	−0.013	0.086**	0.108***	0.096**	0.079	0.082
	(0.054)	(0.045)	(0.040)	(0.033)	(0.045)	(0.074)	(0.075)
Observations	1374	1374	1374	1374	1374	1374	1374

Notes. Analogous to Tables 2 and 3. This table gives average treatment effects that are weighted by population of working age instead of the unit of analysis. Each metropolitan area is weighted by its share in population of working age in 1980.

Table A14: Inference based on AKM confidence intervals

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.1: Log (TT Income of 0th to 90th percentiles)							
Exposure to robots	−0.006	−0.013**	−0.010*	−0.001	−0.003	−0.001	0.001
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
A.2: Log (TT Income of 90th to 99th percentiles)							
Exposure to robots	−0.010	−0.020***	−0.005	0.004	0.003	0.006	0.008
	(0.009)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
A.3: Log (TT Income of 99th to 99.9th percentiles)							
Exposure to robots	−0.001	−0.010	0.009	0.016**	0.015**	0.018**	0.021**
	(0.010)	(0.007)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
A.4: Log (TT Income of 99.9th to 99.99th percentiles)							
Exposure to robots	0.008	−0.005	0.020**	0.028***	0.028***	0.031***	0.035***
	(0.010)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
A.5: Log (TT Income of 99.99th to 100th percentiles)							
Exposure to robots	0.022**	0.004	0.039***	0.049***	0.050***	0.052***	0.059***
	(0.011)	(0.008)	(0.009)	(0.009)	(0.008)	(0.011)	(0.010)
B.1: TT Income Ratio of 90th-99th to 0th-90th percentiles							
Exposure to robots	−0.002***	−0.004***	0.002***	0.003***	0.003***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
B.2: TT Income Ratio of 99th-99.9th to 90th-99th percentiles							
Exposure to robots	0.003***	0.003***	0.005***	0.005***	0.005***	0.004***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B.3: TT Income Ratio of 99th-99.99th to 99.99th-99.9th percentiles							
Exposure to robots	0.004***	0.003***	0.006***	0.006***	0.007***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B.4: TT Income Ratio of 99.99th-100th to 99.9th-99.99th percentiles							
Exposure to robots	0.011***	0.008***	0.019***	0.019***	0.020***	0.016***	0.018***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
C.1: TT Income Share of 0th to 90th percentiles							
Exposure to robots	−0.069***	0.035**	−0.392***	−0.400***	−0.417***	−0.390***	−0.424***
	(0.026)	(0.018)	(0.028)	(0.031)	(0.028)	(0.030)	(0.034)
C.2: TT Income Share of 90th to 99th percentiles							
Exposure to robots	−0.145***	−0.171***	−0.056***	−0.035***	−0.032***	0.015*	0.008
	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)
C.3: TT Income Share of 99th to 99.9th percentiles							
Exposure to robots	0.039***	0.019**	0.110***	0.099***	0.104***	0.109***	0.120***
	(0.011)	(0.008)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)
C.4: TT Income Share of 99.9th to 99.99th percentiles							
Exposure to robots	0.063***	0.038***	0.121***	0.121***	0.125***	0.112***	0.123***
	(0.007)	(0.005)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)
C.5: TT Income Share of 99.99th to 100th percentiles							
Exposure to robots	0.111***	0.079***	0.216***	0.216***	0.221***	0.154***	0.172***
	(0.008)	(0.006)	(0.010)	(0.011)	(0.009)	(0.012)	(0.009)
Observations	1376	1376	1376	1376	1376	1376	1376

Notes. Analogous to Tables 2 and 3. Standard errors are clustered at the industry level based on Adao, Kolesar and Morales (2019).