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Automation and taxation

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Abstract

Do automation-induced changes in labour and capital income undermine public revenues? Decomposing taxes by source (labour, capital, sales), we analyse the impact of automation on tax revenues and the structure of taxation in nineteen EU countries during 1995–2016. Before 2008 robot diffusion was associated with a decline in total tax revenues and taxes from capital, along with decreasing labour and capital income and output. After 2007, the negative effects diminish. Information and Communication Technologies show a weak negative but persistent effect on total tax revenues and taxes on goods for the full period, and an increase in capital income. Overall, the impact of automation on production and taxation varies over time. Whether automation erodes taxation depends on the technology and stage of diffusion. Concerns about public budgets appear myopic when focusing on the short run and ignoring relevant technological trends.

Keywords: technological change; ICT; robots; fiscal revenues; labor.
JEL classifications: E20, H20, O30

1 Introduction

Taxes on labour contribute to a major share of public revenues. When automation technologies (ATs) diffuse and replace labour at a large scale, the tax base might be undermined. This reasoning is put forward to argue that taxes on automation are needed to ensure the sustainability of public finances (Acemoglu, Manera, and Restrepo 2020; Kovacev 2020; Süssmuth et al. 2020; Guerreiro, Rebelo, and Teles 2022). However, the impact of automation is complex, including many second-order effects. Governments receive taxes from multiple sources in addition to labour, which might also be affected by ATs (cf. Atkinson 2019). Until now, there is limited empirical knowledge on the nexus between automation and public revenues. This study aims to fill this gap, exploring the empirical interactions between automation, production, and their link to taxation.

Guided by a stylized model, we decompose tax revenues by source and link them to three economic effects of automation named replacement, reinstatement, and real income effect. The replacement effect refers to all effects on factor demand and remuneration when human labour is replaced by sophisticated machinery able to execute tasks currently performed by humans (Brynjolfsson and McAfee 2014; Arntz, Gregory, and Zierahn 2016; Frey and Osborne 2017; Korinek and Stiglitz 2019; Nedelkoska and Quintini 2018; Acemoglu and Restrepo 2020; Gregory, Salomons, and Zierahn 2022). The reinstatement effect covers the creation of new tasks and occupations, and the reallocation of labour within and across industries (Dauth et al. 2018; Acemoglu and Restrepo 2019; Bessen 2019; Blanas, Gancia, and Lee 2019; Bessen et al. 2020). The real income effect reflects demand-induced increases in the demand for labour stimulated by rising: (a) real income when reduced production costs affect prices; and (b) factor revenues from capital and labour (Aghion, Jones, and Jones 2017; Graetz and Michaels 2018; Korinek and Stiglitz 2019; Acemoglu and Restrepo 2019).

The model serves as a conceptual framework to guide us through the analysis when addressing the following research questions:

1) What is the relationship between AT diffusion and tax revenues at the country level?
2) What is the relationship between AT diffusion and the composition of taxes by source (labour, capital, goods)?
3) How can these relationships be traced back to the economic effects of automation?

The complexity of tax systems and the multiple phases of technological change make it challenging to directly link the microeconomic impact of automation to macroeconomic consequences and aggregate taxation. With this in mind, we use aggregate tax data from the OECD (2020) to dissect tax accounts into taxes on labour, capital, and goods for nineteen European countries during 1995–2016.

The effects of automation occur at the disaggregate industry level when changes in the production technology induce changes in factor demand, employees' incomes, and the level and composition of output. To understand these effects, we use macro- and industry-level data from EUKLEMS (2019). To map technological change at the industry level to aggregate taxation, we base our analysis on country and country-industry level regressions. We start at the country level by exploring interactions between automation and taxation, along with the links between the structure of production and different tax sources. Next, we analyse the prevalence of the replacement, reinstatement, and real income effects and argue how they help explain the findings from above.

We find that the impact of automation differs by technology and phase of diffusion. During the early phase (1995–2007), robots had a negative impact on aggregate taxes and capital taxes in particular, accompanied by decreasing factor income from capital and labour. For the full period, the negative effects of robots on factor markets and taxation disappear. Information and Communication Technologies (ICT) show effects that are weak but more persistent over time. For the full period, we find a weak negative association with total tax revenues and taxes on goods, and an increase in capital income accompanied by an output shift towards service sectors after 2007.

To guard against various empirical concerns, we conduct a battery of robustness checks such as: accounting for distortions in the aftermath of the 2008 global financial crisis; country-specific confounding factors, for example, related to globalization, demographics, and the structure of tax systems; and the potential endogeneity of the AT diffusion.

Our results suggest that AT diffusion goes through different phases with effects on taxes. Labour offsetting effects and negative effects on income during an early phase seem to be compensated by the creation of new jobs in later periods, accompanied by structural change in the industrial composition.

Thus, concerns about the sustainability of fiscal revenues appear short-sighted when only looking at the early phases of automation. Our framework provides structural arguments that enable a better understanding of the economic impacts of automation and macro-level effects on taxation. To the best of our knowledge, this is the first empirical study providing insights into the impact of automation on public finances.

The rest of the article is structured as follows. In Section 2, we provide an overview of the background on automation and taxation. In Section 3, we introduce a conceptual model. In Section 4, we describe our empirical strategy and the data. Section 5 summarizes the results, while Section 6 provides a series of robustness checks. Section 7 discusses how the empirical results help answer the research questions, and Section 8 concludes.

2 Background on taxation

This section offers a description of tax systems in Europe and an overview of the empirical and theoretical background on the link between taxation and automation.

2.1 Taxation in Europe

Taxes are 'compulsory, unrequited payments to general government' (OECD 2019). On average, among the nineteen European countries covered by our study, the total tax revenue accounted for 37.3% of Gross Domestic Product (GDP) in 2016 ranging from 23.4% in Ireland to 45.7% in Denmark (see Fig. 1).[1] Over time, the average tax-to-GDP ratio weakly fluctuated around 36.4% in 1995 and 37% in 2016, with the lowest ratio during the financial crises (e.g. 34.7% in 2009).

Taxes can be classified by the tax base. For example, taxes are imposed on income from labour, profits and capital gains, property, and trade of goods and services. Compulsory Social Security Contributions (SSC) can equally be considered as taxes charged on labour (OECD 2019, Supplementary Appendix A2). Here, we focus on three broad groups, namely taxes imposed on: (1) labour (T^l) including SSC; (2) capital (T^k) including taxes on profits and property; and (3) goods and services (T^y). These groups differ by their linkage to structural characteristics of the economy, reflected in the labour share, capital share, and aggregate consumption.

The three groups ($T = T^l + T^k + T^y$) cover more than 99.9% of total tax revenue in our sample of nineteen European countries in 2016. On average, taxes on labour accounted for 11.8% of GDP and 31.6% of total taxation, taxes on capital for 13.3% of GDP and 35.1% of total taxation, and taxes on goods for 12% of GDP and 32.5% of total taxation.

Countries differ by the structure of taxation, that is, the relative tax contribution of different sources. The cross-country heterogeneity in the levels, structure, and organization of taxation is driven by a multitude of economic, structural, institutional, and social factors that have emerged historically across nations (Hettich and Winer 2005; Castro and Camarillo 2014; Kiser and Karceski 2017). Empirical measures of such determinants include per capita GDP, industrial structure and economic specialization, civil liberties and governmental efficiency, public and financial policies, trade, exchange rates, foreign direct investment, and public expenditures (Castro and Camarillo 2014; Castañeda Rodríguez 2018). We control for such relevant dimensions in our analysis.

2.2 Taxation and automation

For policymakers, two questions related to the nexus of automation and taxation are important: (1) How do current tax systems influence AT adoption decisions and the emergent path of economic development?; and (2) Does automation affect tax revenues such that it poses a risk to governments' fiscal capacity? The majority of the existing literature

[1] When excluding residual taxes (with OECD-code 6000), as done in our analysis, total taxes account for 37% of GDP. Our analysis includes nineteen European countries: Austria (AT); Belgium (BE); Czech Republic (CZ); Germany (DE); Denmark (DK); Spain (ES); Finland (FI); France (FR); Greece (GR); Ireland (IE); Italy (IT); Lithuania (LT); Latvia (LV); the Netherlands (NL); Portugal (PT); Sweden(SE); Slovenia (SI); Slovakia (SK); and the United Kingdom (UK). The information presented is based on the Global Revenue Statistics Database provided by the OECD (2020).

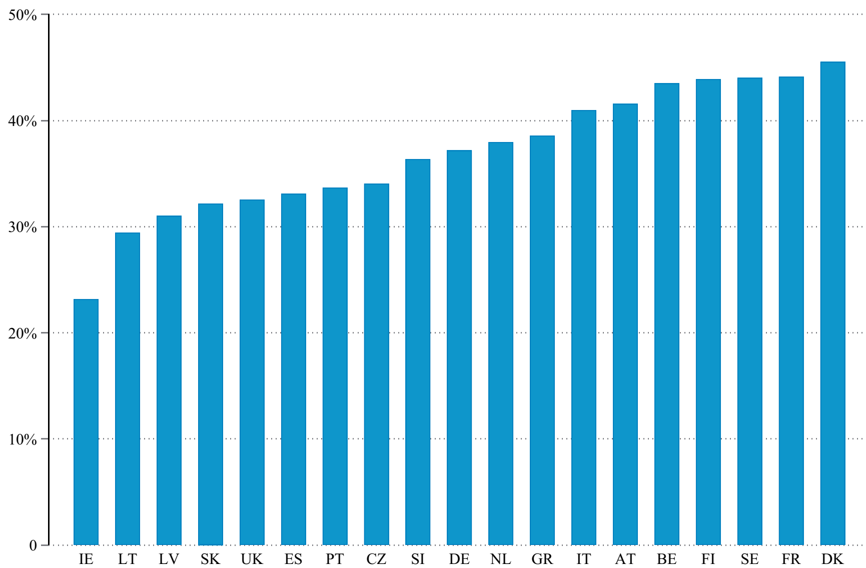

Figure 1. Total tax revenue as a share of gross domestic product in 2016.

Source: Author's calculations based on OECD Global Revenue Statistics Database.

Notes: Each bar represents the total tax revenue as a share of gross domestic product in 2016 for the nineteen European countries in our sample, which includes: AT; BE; CZ; DE; DK; ES; FI; FR; GR; IE; IT; LT; LV; NL; PT; SE; SI; SK; and UK, for the period 1995-2016, but is unbalanced since data are not reported for LT, LV and UK in 1995, and DK, PT, SI and SK in 1995–1999. For more details about the country-level sample and construction of variables, see Supplementary Appendix Section A.

addresses the first question by taking as given that tax revenues suffice to finance essential public services. To the best of our knowledge, we are the first to study the second question.

Existing studies mostly take an optimal taxation perspective. Acemoglu, Manera, and Restrepo (2020) argue that the US tax system is biased in favour of capital, which leads to a sub-optimal reduction of the labour share for 'marginally automated jobs'. Applying the optimal taxation framework by Diamond and Mirrlees (1971) to a task-based model calibrated on US tax rates, they show how a tax reform could raise the labour share. Similarly, Süssmuth et al. (2020) analyse the impact of US taxation on the functional distribution of income and find that distributional changes (in favour of the capital share) can be partly attributed to labour and capital tax reforms during 1974–2008. They argue that changes in relative taxes also affect the use of robots.

Other authors propose a robot tax to cope with the negative effects of automation on employment and income equality. In a theoretical study based on the current tax system in the USA, Guerreiro, Rebelo, and Teles (2022) show how a robot tax can be used to reduce inequality, but at the cost of efficiency losses. Gasteiger and Prettner (2022) make a theoretical analysis of a robot tax in an overlapping generations model and show how it could raise the per capita capital stock with positive long-run growth effects.

Theoretical studies on robot taxes argue that these taxes can reduce inequality and secure public revenues. However, it remains controversial whether automation undermines governments' capacity to raise taxes. Atkinson (2019) argues that empirical evidence of a jobless future is poor since many studies ignore important second-order effects. Moreover, even if firms adopt ATs, they still pay taxes on profits, sales, and wages of workers doing non-automated jobs.

Up to date, empirical evidence on the relationship between automation and tax revenues is lacking, and we aim to fill this gap. While studies on optimal taxation focus on the impact of tax systems on the economy, we take the opposite perspective and look at the impact of economic change on taxation. Differently from optimal taxation studies, we do not look at relative tax rates but study aggregate tax revenues. While changes in relative tax rates on labour and capital might have affected the diffusion of ATs in the USA, as argued by Acemoglu, Manera, and Restrepo (2020), data limitations prevent us from investigating changes in relative tax rates in depth. Using data on implicit tax rates on labour and capital, we find that these rates remained roughly constant in most European countries during the past decade.[2] Moreover, our results suggest different diffusion patterns for robots and ICT (see Fig. 2) indicating that there is no straightforward empirical justification that the effects found in this study are driven by distortionary tax reforms.

3 Conceptual framework

This section provides a stylized model to decompose tax revenues by source and link them to the three effects of automation: replacement of labour; reinstatement of labour; and changes in real income.

3.1 Tax revenues

Taxes can be grouped by source (capital, labour, and goods) and total tax revenue in country c is given by:

$$T_c = \underbrace{t_c^l \cdot w_c L_c}_{\substack{\text{Taxes on labour} \\ T_c^l}} + \underbrace{t_c^k \cdot r_c K_c}_{\substack{\text{Taxes on capital} \\ T_c^k}} + \underbrace{t_c^y \cdot p_c Q_c}_{\substack{\text{Taxes on goods} \\ T_c^y}} \tag{1}$$

where $L_c = \sum_{i \in I_c} L_{i,c}$ is aggregate labour given by the sum of labour employed in industries $i \in I_c$ in country c, $K_c = \sum_{i \in I_c} K_{i,c}$ is the capital stock including ATs (industrial robots and ICT), and $p_c Q_c = \sum_{i \in I_c} p_{i,c} Q_{i,c}$ is aggregate demand. Wages, capital prices, and goods prices are given by w_c, r_c, and p_c, respectively. The tax rates t_c^l, t_c^k, and t_c^y are imposed on labour income, capital income, and final demand, respectively.

3.2 Production technology

Automation changes industries' production technology. This can have an impact on industry-level factor demand, that is, labour and capital, and productivity when industry-specific production processes and organization change. In a generic form, the production function of industry i is:

$$Y_{i,c} = f_{i,c}(K_{i,c}, L_{i,c}, A_{i,c}) \tag{2}$$

with $K_{i,c}$ and $L_{i,c}$ as the respective capital and labour whose demand depends on wages $w_{i,c}$ and capital prices $r_{i,c}$, respectively. The capital stock $K_{i,c}$ comprises different types of

[2] See Supplementary Appendix Figure B1. The data on implicit tax rates on labour and capital in Europe, provided by the European Commission, are not directly comparable to the approach used by Acemoglu, Manera, and Restrepo (2020) who calculated effective tax rates on labour and different types of ATs at the micro-level in the USA. It is not straightforward to apply their methodology in a European cross-country setting with very heterogeneous and complex tax systems. The European Commission (2020) computes implicit tax rates on labour and capital as a ratio of actual tax income by source to the potential tax base. Nonetheless, the stable patterns of relative tax (rates) observed in the EU are in stark contrast to the clear-cut divergence in favour of capital observed by Acemoglu, Manera, and Restrepo (2020) in the USA.

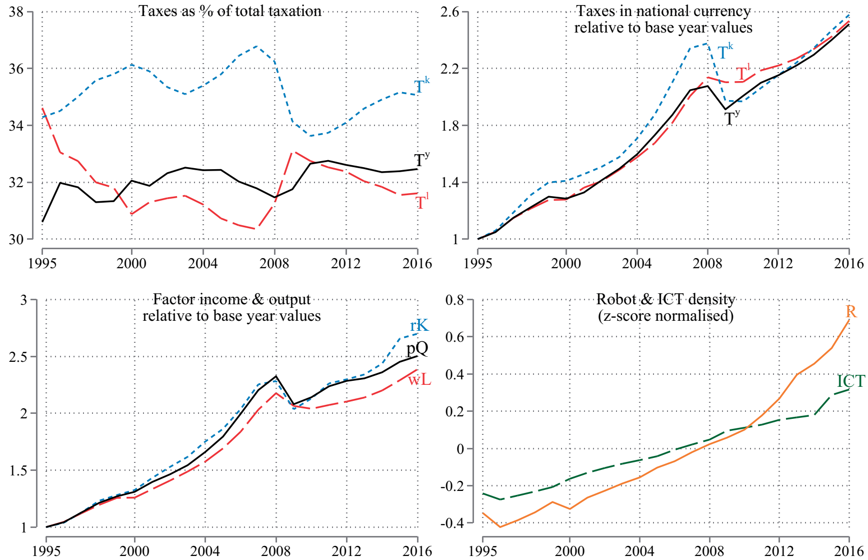

Figure 2. Time series of key variables (averaged across countries).

Source: Author's calculations based on IFR, EUKLEMS, and OECD Global Revenue Statistics Database.

Notes: Each time series represents the average value of the respective variable across all nineteen European countries considered in the country-level sample. T^l, T^k, and T^y refer to taxes on labour, capital, and goods, respectively. *R* and *ICT* capture the robot and ICT density as the ratio of the number of operational robots and ICT capital, respectively, over the number of hours worked in the economy. *wL*, *rK*, and *pQ* are labour compensation, capital compensation, and the value of gross output, respectively. For the top right and bottom left panels, the country-level values of each variable considered are indexed relative to their base year values. For the bottom-right panel, *R* and *ICT* are z-score normalized by subtracting the sample mean and dividing by the standard deviation of the sample. The sample includes nineteen European countries: AT; BE; CZ; DE; DK; ES; FI; FR; GR; IE; IT; LT; LV; NL; PT; SE; SI; SK; and the UK, for the period 1995–2016, but is unbalanced since data are not reported for LT, LV and UK in 1995, and DK, PT, SI and SK in 1995–1999. For more details on the country-level sample and construction of variables, see Supplementary Appendix Section A.

capital, that is, $K_{i,c} = K^n_{i,c} + K^a_{i,c}$ where $K^n_{i,c}$ is non-automation capital and $K^a_{i,c} = ICT_{i,c} + R_{i,c}$ is automation capital with $R_{i,c}$ as industrial robots and $ICT_{i,c}$ as ICTs.[3] Both, robots and ICT, are measures of automation, but capture different concepts. Industrial robots are pure ATs designed to automate manual tasks performed by humans. ICT capital is more general and can be used for various cognitive tasks, complementing or substituting human labour. We assume that all types of capital are rented at the same rate $r_{i,c}$.

Production technologies differ across industries and countries, leading to different input shares. Production functions are empirically not observable, but we observe industry-level factor inputs, factor costs, and output. This allows us to draw inference about the relationships between inputs, outputs, and the price responsiveness of factor demand. By the definition of a production function, we assume $\frac{\partial f_{i,c}}{\partial L_{i,c}} \geq 0$, $\frac{\partial f_{i,c}}{\partial K_{i,c}} \geq 0$, and $\frac{\partial f_{i,c}}{\partial A_{i,c}} \geq 0$, that is, the quantity of output is non-decreasing in the quantity of inputs and the level of productivity. Moreover, ceteris paribus, we expect factor demand to be negatively related to factor prices, that is, $\frac{\partial L_{i,c}}{\partial w_{i,c}} \leq 0$ and $\frac{\partial K_{i,c}}{\partial r_{i,c}} \leq 0$.

3 $ICT_{i,c}$ and $R_{i,c}$ are not necessarily disjoint.

3.3 Final demand

Final demand is given by the aggregation across industries:

$$p_c Q_c = \sum_{i \in I_c} p^s_{i,c} q_{i,c}(p_{i,c}, Y_c) \tag{3}$$

where $p_{i,c} = (1 + t^y) \cdot p^s_{i,c}$ is i's consumer price including consumption taxes t^y, $p^s_{i,c}$ is i's supply price, and $q_{i,c}(p_{i,c}, Y_c)$ is industry level demand which is a function of the price and income Y_c in country c with $\frac{\partial q_{i,c}}{\partial p_{i,c}} \leq 0$ and $\frac{\partial q_{i,c}}{\partial Y_c} \geq 0$. Assuming market closure, income is composed of labour income $w_c L_c$ and capital income $r_c K_c$, minus tax payments, such that:

$$Y_c = (1 - t^l_c) \cdot w_c L_c + (1 - t^k) \cdot r_c K_c \tag{4}$$

In this stylized representation, for simplicity, we abstain from trade, inter-regional transfers, savings and inter-generational transfers, and household and firm heterogeneity.

3.4 Effects of automation

Automation indirectly affects tax revenues through changes in production technology that translate into changes in factor use, market shares, and final demand. Formally, the aggregate effect on tax revenue is given by the differential

$$dT_c = t^l_c \cdot \left(\frac{\partial w_c}{\partial K^a_c} L_c + w_c \frac{\partial L_c}{\partial K^a_c} \right) + t^k_c \cdot \left(\frac{\partial r_c}{\partial K^a_c} K_c + r_c \frac{\partial K_c}{\partial K^a_c} \right) + t^Y \cdot \left(\frac{\partial P_c}{\partial K^a_c} Q_c + P_c \frac{\partial Q_c}{\partial K^a_c} \right) \tag{5}$$

where $K^a_c = R_c + ICT_c$, with $R_c = \sum_{i \in I_c} R_{i,c}$ and $ICT_c = \sum_{i \in I_c} ICT_{i,c}$.

We study the effect of automation on production and taxation along three effects: replacement; reinstatement; and real income. Even if the distinction between these effects is not clear-cut, we simplify the analysis and assume that the replacement and reinstatement effect is mainly reflected in a changing factor demand, while the real income effect is reflected in final demand and prices. Next, we discuss these effects in detail.

3.4.1 Replacement

The replacement effect is the substitution of human labour by machines when technological progress enables machines to perform tasks previously performed by humans (Acemoglu and Restrepo 2018a). The number of jobs susceptible to automation differs across occupations and industries (Arntz, Gregory, and Zierahn 2016; Frey and Osborne 2017; Hawksworth, Berriman, and Goel 2018; Nedelkoska and Quintini 2018; Webb 2020). Labour replacement may lead to lower employment and wages, which may be offset by an increase in the demand for non-routine tasks and new jobs in expanding sectors (Acemoglu and Restrepo 2018a, b, 2019, 2020). This can also be a driver of income polarization as many middle-income jobs are most susceptible to automation, while many low and high-income occupations are complementary (Autor, Katz, and Kearney 2006).

Empirical results on the replacement effect remain ambiguous (see Hötte, Somers, and Theodorakopoulos 2023, for an overview). Overall, it is consensual in the literature that employees performing automatable tasks are susceptible to replacement by machinery, but it remains controversial whether and to what extent occupation-specific replacement affects aggregate factor incomes.

In automating industries, characterized by $K^a_{i,c} > 0$, employees are potentially replaced by machinery with $\frac{\partial L_{i,c}}{\partial K^a_{i,c}} < 0$ for $i \in \{j | K^a_{j,c} > 0\}$. The effect on wages in industry i can go either way: $\frac{\partial w_{i,c}}{\partial K^a_{i,c}} \lessgtr 0$. On the one hand, the replacement effect exerts downward pressure on wages paid for jobs that can be automated. On the other, automation may complement non-automatable labour, which increases productivity with a positive effect on wages, possibly leading to a polarization of wage income (Autor, Katz, and Kearney 2006). The net impact of the replacement effect on the labour income in industry i depends on the extent to which potential wage increases for non-automatable jobs or new hires of workers that complement AT offset the replacement of automatable jobs. Therefore, we expect a negative sign if the replacement dominates reinstatement in industry i giving $\frac{\partial(w_{i,c}L_{i,c})}{\partial K^a_{i,c}} < 0$.

Ceteris paribus, in the absence of the reinstatement and real income effect, the replacement effect would have a negative impact on total and labour taxes in particular, if the net effect on the wage bill is negative and taxes are sufficiently non-progressive. The progressiveness of taxation is ambiguously related to income polarization. Specifically, in progressive tax systems, those at the top of the income distribution pay higher tax rates and disproportionately more taxes than those at the bottom and the middle. The tax effects of automation-induced polarization at the top and bottom of the income distribution on total revenues are ambiguous. On the one hand, taxes decrease as lower-paid workers pay less taxes. On the other hand, taxes increase as high-paid jobs are taxed relatively more than middle-paid jobs. Which effect dominates depends on the degree of progressiveness. The more progressive the tax system at the top of the distribution, the more likely the effect would be positive. In our analysis, we account for this effect by evaluating the relationship between taxes and wage equality, and the impact of ATs on cross-industry wage inequality.

3.4.2 Reinstatement

Historically, job replacement through automation was often compensated by the emergence of new occupations and the reinstatement of labour (Autor 2015; Aghion, Jones, and Jones 2017; Acemoglu and Restrepo 2019; Bessen 2019). Reinstatement effects occur at different levels of analysis. Within automating industries, automation may induce occupational changes driven by two effects: (1) efficiency gains release resources available for other labour-intensive processes; and (2) automation may require complementary labour inputs to operate the machinery. This effect can be reinforced if automation stimulates capital accumulation, which may also have a positive effect on labour demand.

The reinstatement effect can also occur as a spillover at the aggregate level when productivity growth reduces prices or when income increases lead to market growth and/or changing market shares and sizes of other industries. This can induce the reinstatement of labour in other industries and a cross-industrial reallocation of labour. The employment and income effects may differ across industries, skill, and occupational groups, and the process of reinstatement may be slowed down by labour market frictions and skill mismatches (Arntz, Gregory, and Zierahn 2016; Dauth et al. 2018; Acemoglu and Restrepo 2020; Bessen et al. 2020; Gregory, Salomons, and Zierahn 2022).

The reinstatement effect potentially offsets sector-specific negative employment effects at the aggregate level. Ceteris paribus, the reinstatement effect positively affects labour demand in automating industries and at the country level, that is, $\frac{\partial L_{i,c}}{\partial K^a_{i,c}} > 0, i \in \{j|K^a_{j,c} > 0\}$ and $\frac{\partial L_c}{\partial K^a_c} > 0$. Dependent on wage heterogeneity within and across industries, the reinstatement effect can have ambiguous effects on industry and country-level average wages. However, it has a positive effect on aggregate labour income, that is, $\frac{\partial(w_cL_c)}{\partial K^a_c} > 0$.

3.4.3 Real income

The real income effect is an indirect, composite effect resulting from the replacement and reinstatement of labour, and the impact of automation on capital accumulation, productivity, and prices. Automation may boost productivity, leading to lower output prices and leveraging growth through a higher demand (Acemoglu and Restrepo 2018a;

Graetz and Michaels 2018; Gregory, Salomons, and Zierahn. 2022). Demand is contingent on real income, i.e. nominal income over prices. Both can be affected by automation (Bessen 2019).

The direction of the total effect of automation on aggregate nominal income depends on the net impact of the replacement and reinstatement effect on factor income from labour and capital, $\frac{\partial(w_c L_c + r_c K_c)}{\partial K_c^a} \lesseqgtr 0$. The second part of the real income effect is a productivity-induced change in the aggregate price level. Productivity has a negative effect on unit production costs. Assuming rational AT adoption decisions, ATs increase productivity, that is, $\frac{\partial A_{i,c}}{\partial K_{i,c}^a} \geq 0$, which leads to price reductions when lower unit production costs are passed through to consumers, that is, $\frac{\partial p_{i,c}}{\partial A_{i,c}} \leq 0$ and $\frac{\partial p_{i,c}}{\partial K_{i,c}^a} \leq 0$. In turn, this increases real disposable income, that is, $\frac{\partial Y_c^r}{\partial K_{i,c}^a} \geq 0$ where $Y_c^r = (1-t^l)\frac{w_c}{p_c}L_c + (1-t^k)\frac{r_c}{p_c}K_c$, $\frac{\partial p_c}{\partial p_{i,c}} \geq 0$ and $\frac{\partial p_{i,c}}{\partial K_{i,c}^a} \leq 0$.

Whether productivity-induced cost reductions are transmitted to consumers as lower prices is contingent on market competition which might be undermined by an unequal distribution of the benefits of AT diffusion (Andrews, Criscuolo, and Gal 2015, 2016; Autor, Katz, and Kearney 2020; Barkai 2020; Bormans and Theodorakopoulos 2023). Depending on the income elasticity of demand, an increase in real income may induce more consumption, which reinforces the reinstatement effect with positive feedback on labour and capital income.

4 Empirical approach and data

In this section, we provide an overview of the empirical approach and data.

4.1 Overview

Real-world tax systems are complex. Tax revenues are raised through different channels, with many non-linearities arising from threshold levels and exemptions. Uniform and linear macroeconomic tax rates t_c^l, t_c^k, and t_c^y as suggested by our theoretical framework, do not exist. Further, data availability is limited. Data on taxation is only available at the country level, but tax burdens are heterogeneous across households, firms, and industries. Many of the effects of automation occur at the industry or firm level. Therefore, to analyse the effect of automation on taxation, we use an indirect approach. Empirically, we observe tax revenues (T, T^l, T^k, T^y) at the country level, measures for key economic variables (w, L, r, K, p, Q) at the country and country-industry level, and various indicators capturing the economic structure across periods t.

Our procedure consists of the following steps. First, we establish prerequisites that motivate the subsequent steps. This includes testing for associations between taxes and automation, and examining the empirical link between different types of taxes and economic variables. Secondly, we explore the prevalence of each of the three effects: replacement, reinstatement, and real income. Box 1 shows a summary of the effects and the relevant indicators to assess them. Finally, we argue how the three effects help explain the impact of automation on taxation and in turn help us answer the three research questions introduced in Section 1.

4.2 Data

We combine different data sets at different aggregation levels with varying coverage by country, industry, and time. After merging the data, we end up with two samples covering nineteen European countries for the period 1995–2016.[4] The first sample is a country-level panel for the whole economy. The second sample is an industry-level panel covering

[4] List of countries: AT; BE; CZ; DE; DK; ES; FI; FR; GR; IE; IT; LV; NL; PT; SE; SI; SK; UK.

Box 1. Overview of key effects of automation on economic production.

Effect	Description	Indicators
Replacement	Substitution of labour. Decreasing labour demand and wages. Unclear side effects on net capital accumulation, prices, and depreciation.	$\frac{\partial L_{i,c}}{\partial K^a_{i,c}}, \frac{\partial w_{i,c}}{\partial K^a_{i,c}}, \frac{\partial r_{i,c}}{\partial K^a_{i,c}}, \frac{\partial K_{i,c}}{\partial K^a_{i,c}}$ where $K^a_{i,c} = R_{i,c} + ICT_{i,c}$ and $i \in \{j \mid K^a_{j,c} > 0\}$.
Reinstatement	Productivity gains from automation reinstate labour demand in other/newly emerging economic activities. Increasing labour demand and wages.	$\frac{\partial L_c}{\partial K^a_c}, \frac{\partial w_c}{\partial K^a_c}, \frac{\partial r_c}{\partial K^a_c}, \frac{\partial K_c}{\partial K^a_c}, \frac{\partial Services_c}{\partial K^a_c}$.
Real income	Productivity gains reduce unit production costs and prices of final goods, and increase aggregate demand. Distortions in market structure and competition, and an unequal distribution of income gains may undermine this effect.	$\frac{\partial A_c}{\partial K^a_c}, \frac{\partial p_c}{\partial K^a_c}, \frac{\partial Q_c}{\partial K^a_c}, \frac{\partial HHI_c}{\partial K^a_c}$.

only automation-exposed industries. Throughout the article, we define automation-exposed industries as those for which information about the use of robots exists based on robot adoption data collected by the International Federation of Robotics (IFR 2020).[5] The automation-exposed industries include: agriculture; mining and quarrying; ten manufacturing aggregates; electricity, gas, and water supply; construction; and education, research and development (see Supplementary Appendix Table B1).

4.2.1 Tax revenue

Taxes are part of our country-level sample compiled from the OECD Global Revenue Statistics Database (OECD 2020). We retrieve information on taxes by type, that is, labour ($T^l_{c,t}$), capital ($T^k_{c,t}$), and goods ($T^y_{c,t}$), measured in national currency, as a percentage of GDP, and percentage share of total taxation. Time series plots are shown in the top panels of Fig. 2. A kink during the 2008 financial crisis is visible in both relative tax contributions from different sources and total tax revenues. Specifically, we observe a significant decline in capital tax revenues, that puts a relatively larger relative tax burden on labour and goods. Therefore, in the analysis below, we examine whether any effects might differ during the post-2007 period where large structural changes coincided with increases in automation.

4.2.2 Economic variables

Empirical proxies for factor income and consumption at the country level are aggregates of NACE Rev. 2 (ISIC Rev. 4) industry-level data from the EUKLEMS database (Adarov et al. 2019; EUKLEMS 2019; Stehrer et al. 2019). The bottom left panel in Fig. 2 illustrates the evolution of the macroeconomic accounts wL_t, rK_t, and pQ_t, averaged across all countries and normalized to the base year 1995. We see that aggregate revenues from labour increased at a slower rate compared to the other accounts.[6]

[5] We use the term 'automation-exposed' for simplicity while acknowledging that alternative definitions of 'automation-exposed' exist. Robot adoption is a suitable proxy to empirically measure technical automation at the industry level and the IFR data is the best available source for empirical analyses covering a large set of countries, industries, and periods.

[6] For the empirical analyses, we construct various additional indicators used to ensure the robustness of our findings. For details on the construction and use of variables, see Supplementary Appendix A.

4.2.3 Measuring automation

We rely on two measures of automation based on: (1) the stock of operational industrial robots computed following Graetz and Michaels (2018) using data from IFR (2020); and (2) the capital stock of ICT from EUKLEMS (2019).[7] To capture the extent to which robots were incorporated in production technologies, we follow Graetz and Michaels (2018) to construct the robot density measure as the stock of operational robots over the number of hours worked by human labour. Similarly, as a second automation indicator, we use the ICT density measured as net ICT capital stock per hour worked. These measures are computed both at the country-year and industry-year dimension, and for comparability and ease of interpretation they are z-scored normalized by subtracting the sample mean and dividing by the standard deviation of the sample.

We consider these two measures to account for two distinct AT types, differing by the type of task they execute. Specifically, robots are designed to perform manual tasks, while ICTs have a stronger link to cognitive tasks. While robots are pure ATs that execute a well-defined task previously performed by human workers, it is less clear whether this also applies to ICTs. ICTs can be flexibly applied in many tasks and, to some extent, these tasks do not necessarily have a clear analogue in the range of tasks executed by humans.

In our analysis, we use both measures simultaneously and as an interaction term. Robot-ICT interaction, referred to as depth of automation, captures complementarities between the two ATs, that is, the extent to which both manual and cognitive tasks are performed by machinery. Concerns about multicollinearity are ruled out since the correlation between both measures is low, with a correlation coefficient of 0.22. The bottom right panel in Fig. 2 presents a time series plot of the z-score normalized measure of robot and ICT density and suggests that post-2007 the rate of robot diffusion outpaced that for ICTs which exerts a stable rise since 1995.

5 Results

In this section, we present the findings. First, we analyse the direct interactions between ATs and taxation. Next, we outline the results for each of the three channels through which ATs affect the economy: the replacement; reinstatement; and real-income effects.

5.1 Taxation, automation, and the economy

We begin by regressing country-level tax revenues on AT diffusion measures and key indicators that describe the structure of production, that is,

$$\begin{aligned} \mathbb{T}_{c,t} = \beta^R R_{c,t} + \beta^{ICT} ICT_{c,t} + \beta^{RICT} R_{c,t} * ICT_{c,t} \\ + \beta^{DR} D_t * R_{c,t} + \beta^{DICT} D_t * ICT_{c,t} + \beta^{DRICT} D_t * R_{c,t} * ICT_{c,t} + \beta^z Z_{c,t} + \varepsilon_{c,t} \end{aligned} \tag{6}$$

where $\mathbb{T}_{c,t} \in \{T_{c,t}, T^l_{c,t}, T^k_{c,t}, T^y_{c,t}\}$ reflects taxes in: (1) levels, that is, logs of billions of national currency; (2) percentage share of GDP; and (3) percentage share of total taxation. To account for the possible structural break in tax revenues in the aftermath of the 2008 financial crisis, we interact the measures of AT diffusion with a dummy variable D_t that equals one for the pre-2008 period (1995–2007) and zero otherwise. We include country and time FE, and interact the country FE with D_t to capture country-specific effects between the two subperiods. Also, we use a set of controls $Z_{c,t}$, including aggregate income from labour $wL_{c,t}$ and capital $rK_{c,t}$, and other variables that capture country-specific economic characteristics, global shocks, and potential confounding factors that could be

[7] The stock of robots is computed using the perpetual inventory method assuming a depreciation rate of 10% based on robot deliveries and initial period stock values from IFR (2020). For more information see Graetz and Michaels (2018) and Supplementary Appendix A3.

Table 1. Taxation and automation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Taxes in ln of nat. currency				Taxes as % of GDP				Taxes as % of total tax		
	$\ln T_{c,t}$	$\ln T^l_{c,t}$	$\ln T^k_{c,t}$	$\ln T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	0.002	0.012	0.008	−0.014	0.180	0.176	0.139	−0.135	0.190	0.197	−0.710
	(0.016)	(0.031)	(0.044)	(0.024)	(0.736)	(0.326)	(0.471)	(0.144)	(0.514)	(0.773)	(0.730)
$ICT_{c,t}$	−0.030*	0.034	−0.045	−0.075*	−0.389	0.126	−0.190	−0.326	0.624	−0.139	−0.213
	(0.015)	(0.050)	(0.041)	(0.040)	(0.492)	(0.292)	(0.450)	(0.261)	(0.820)	(0.836)	(0.682)
$R * ICT_{c,t}$	0.014*	−0.003	0.035*	0.024	0.309	−0.164	0.369*	0.104	−0.594**	0.497	−0.038
	(0.008)	(0.016)	(0.019)	(0.016)	(0.248)	(0.108)	(0.186)	(0.092)	(0.248)	(0.316)	(0.224)
$D * R_{c,t}$	−0.069***	−0.098	−0.121**	−0.013	−1.062	−0.428	−1.114**	0.480**	−0.091	−2.555**	2.163**
	(0.020)	(0.061)	(0.052)	(0.050)	(0.651)	(0.340)	(0.499)	(0.238)	(0.763)	(0.894)	(0.782)
$D * ICT_{c,t}$	−0.011	−0.169	−0.072	0.040	−0.165	0.558	−1.149	0.427	1.638	−2.978*	0.782
	(0.028)	(0.189)	(0.073)	(0.061)	(0.894)	(0.652)	(0.859)	(0.388)	(1.596)	(1.678)	(1.461)
$D * R * ICT_{c,t}$	−0.007	0.017	−0.025	−0.002	−0.470	−0.027	−0.594	0.151	0.273	−0.553	0.883
	(0.021)	(0.083)	(0.048)	(0.030)	(0.852)	(0.427)	(0.618)	(0.188)	(0.818)	(0.954)	(0.985)
$wL_{c,t}$	0.455***	0.899**	0.414	0.459***	−0.424**	0.006	0.152	−0.583***	0.445*	0.829***	−1.313***
	(0.123)	(0.340)	(0.252)	(0.056)	(0.194)	(0.093)	(0.143)	(0.086)	(0.218)	(0.278)	(0.200)
$rK_{c,t}$	0.009	0.218	−0.041	0.039	−0.627***	−0.069	0.049	−0.607***	0.383*	0.731***	−1.198***
	(0.079)	(0.209)	(0.118)	(0.101)	(0.178)	(0.089)	(0.117)	(0.075)	(0.200)	(0.206)	(0.196)
Observations	395	395	395	395	395	395	395	395	395	395	395

Source: Author's calculations.
Notes: All regressions use country-level data for nineteen European countries during 1995–2016 and include: GDP growth, gross output share of service industries in the total economy; Herfindahl–Hirschman Index based on the gross output shares of macro-sectors; government consolidated gross debt as % of GDP; government interest payable as % of GDP; net government lending/borrowing as % of GDP; gross fixed capital formation as % of GDP; period average exchange rate; country (c) and year (t) fixed effect, and interact the country FE with the pre-2008 dummy variable D_t. Regressions for Taxes in ln of national currency also include the ln of gross output value (pQ). In the regressions for Taxes in ln of national currency, $wL_{c,t}$, $rK_{c,t}$ and $pQ_{c,t}$ are expressed in natural logarithm (*ln*) while for the last two blocks they are expressed as % of GDP. Standard errors are two-way clustered at the country and year level.

* $P < .05$.
** $P < .01$.
*** $P < .001$.

driving taxes and are correlated with the AT diffusion measures, respectively.[8] To allow the error to be correlated within countries and within years, we use standard errors that are two-way clustered at the country and time dimension.

Results are presented in Table 1.[9] In the first block of columns (Columns 1–4), we see the association of automation with taxes measured in logarithmic national currency units. The second block (Columns 5–8) shows the relationship with taxes measured in percentage GDP. The last block (Columns 9–11) shows the impact on the structure of taxation, that is, on taxes as a share of total taxation. Labour and capital income ($wL_{c,t}$, $rK_{c,t}$) are measured in levels in the first block and as a percentage of total output $pQ_{c,t}$ in the last two blocks to proxy for the labour and capital share.

For the full period, we do not see that robots show any significant uniform effect on taxation. When interacting robots with the pre-2008 dummy variable ($D_t * R_{c,t}$), we find that until 2007, robot diffusion was associated with a decline in total tax revenues and taxes on capital. The last block of columns indicates a shift from capital to goods taxation. For ICT, we observe a weak negative relationship with total tax revenues and taxes on goods for the full period. However, the results are weakly significant and without any clear difference between the pre-2008 and post-2007 periods. The depth of automation, captured by the interaction term ($R * ICT_{c,t}$), shows a weak positive relationship with total tax revenues and taxes on capital for the full period.

Quantitatively, the coefficients of ICTs are weaker than robots, but generally, the effects of both ATs are small. For example, before 2008, an increase in robot density by one standard deviation is associated with a decline in total tax revenues by 0.07% (Column 1) and capital taxes by 0.12% (Column 3). As a quantitative benchmark, the effect of an increase in aggregate labour income by 1% is associated with a 0.46% increase in total taxation (Column 1) and a 0.9% increase in labour taxes (Column 2). The effect on relative taxes is more pronounced, where the 2.6% decline of relative taxes on capital (Column 10) is almost fully offset by a 2.2% increase of relative taxes on goods (Column 11).

The strong statistical and economic significance of the wage bill ($wL_{c,t}$) for taxation is in line with our theoretical framework, whereby automation could affect taxation through the channels of production, income, and distribution. This observation confirms that the concern about shrinking public budgets is only justified if ATs replace labour at a large scale. We examine the empirical validity of this concern in the next section.

5.2 The impact of automation on the economy

5.2.1 Replacement effect

We test for the replacement effect by estimating the following industry-level regressions:

$$\begin{aligned}\mathbb{X}_{i,c,t} = {} & \beta^{R} R_{i,c,t} + \beta^{ICT} ICT_{i,c,t} + \beta^{RICT} R_{i,c,t} * ICT_{i,c,t} \\ & + \beta^{DR} D_t * R_{i,c,t} + \beta^{DICT} D_t * ICT_{i,c,t} + \beta^{DRICT} D_t * R_{i,c,t} * ICT_{i,c,t} + \varepsilon_{i,c,t}\end{aligned} \tag{7}$$

where $\mathbb{X}_{i,c,t} \in \{wL_{i,c,t}, w_{i,c,t}, L_{i,c,t}, rK_{i,c,t}, r_{i,c,t}, K_{i,c,t}\}$ refer to the values, prices, and quantities of labour, and capital, respectively, and i refers to an automation-exposed industry. Again, we include interaction terms with dummies D_t for the pre-2008 period. We control for country-industry, country-year, and industry-year FE to account for unobserved heterogeneity across those dimensions and look at changes over time within country-industries. The

[8] These additional controls include: GDP growth; gross output share of service industries; Herfindahl-Hirschman Index based on the gross output shares of macro-sectors; government consolidated gross debt as % of GDP; government interest payable as % of GDP; net government lending/borrowing as % of GDP; gross fixed capital formation as % of GDP; and period average exchange rate. All regressions for Taxes in ln of national currency also include the ln of gross output value ($pQ_{c,t}$), as a proxy of GDP. For more details on the construction and use of these variables, see Supplementary Appendix A.

[9] For space considerations, estimates of the full set of controls are presented in the Supplementary Appendix C.

Table 2. The replacement effect.

	(1) $\ln wL_{i,c,t}$	(2) $\ln w_{i,c,t}$	(3) $\ln L_{i,c,t}$	(4) $\ln rK_{i,c,t}$	(5) $\ln r_{i,c,t}$	(6) $\ln K_{i,c,t}$
$R_{i,c,t}$	−0.026	0.011	−0.037**	−0.018	−0.003	−0.017
	(0.021)	(0.009)	(0.018)	(0.034)	(0.003)	(0.015)
$ICT_{i,c,t}$	−0.026	0.012	−0.038*	−0.074	−0.005	−0.025
	(0.020)	(0.008)	(0.021)	(0.074)	(0.004)	(0.040)
$R*ICT_{i,c,t}$	−0.007	0.000	−0.008	0.017	−0.002*	0.007
	(0.006)	(0.003)	(0.006)	(0.012)	(0.001)	(0.006)
$D*R_{i,c,t}$	0.017	0.011	0.006	0.025	0.001	0.047
	(0.041)	(0.013)	(0.040)	(0.082)	(0.008)	(0.031)
$D*ICT_{i,c,t}$	0.064***	−0.006	0.070***	0.076	0.007	0.069
	(0.020)	(0.009)	(0.018)	(0.076)	(0.015)	(0.044)
$D*R*ICT_{i,c,t}$	0.012	0.002	0.011	−0.022	0.001	0.011
	(0.013)	(0.004)	(0.013)	(0.033)	(0.006)	(0.019)
Observations	4,812	4,812	4,812	4,757	4,717	4,717

Source: Author's calculations.
Notes: All regressions use industry-level data for seventeen European countries during 1995–2016 for the set of industries susceptible to automation and include: country-industry (*ci*); country-year (*ct*); industry-year (*it*) fixed effects; and country-industry FEs that are further interacted with D_t. All regressions are weighted by the base-sample-year share of each industry's number of hours worked to country-wide hours worked. Standard errors are two-way clustered at the country-industry and year level.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

country-industry FEs are also interacted with D_t to capture country-industry-specific effects between the two subperiods. Standard errors are two-way clustered at the country-industry and year level.

Table 2 presents results. Over the whole period, we find weak support for the replacement effect in automation-exposed industries when robots diffuse, that is, we observe decreasing employment, but the effect is statistically and economically weak. An increase in robot deployment by one standard deviation is associated with 0.04% less employment (Column 3). However, we do not find any effect on the wage bill (Column 1) and a positive but statistically insignificant correlation with wages (Column 2), suggesting an unevenly distributed replacement effect. Replacement happens, but higher wages in non-replaced jobs appear to offset any impact on the wage bill ($wL_{i,c,t}$).

The impact of ICT diffusion qualitatively differs across subperiods. Before 2008, it shows a net positive effect on employment (Column 3), but a negative one for the full period, which is about as large as the impact of robots. The positive impact on employment and the wage bill (Column 1) before 2008 is statistically and economically stronger, even though quantitatively small. Before 2007, we also find a positive association between ICTs and capital accumulation (Column 6) similar in magnitude to that for employment (Column 3), albeit statistically insignificant. Otherwise, we do not find any noteworthy effect of ATs on capital.

5.2.2 Reinstatement effect

We empirically test the reinstatement effect with the following country-level regressions:

$$\begin{aligned}\mathbb{Y}_{c,t} = {} & \beta^R R_{c,t} + \beta^{ICT} ICT_{c,t} + \beta^{RICT} R_{c,t} * ICT_{c,t} \\ & + \beta^{DR} D_t * R_{c,t} + \beta^{DICT} D_t * ICT_{c,t} + \beta^{DRICT} D_t * R_{c,t} * ICT_{c,t} + \beta^z Z_{c,t} + \varepsilon_{c,t}\end{aligned} \tag{8}$$

Table 3. The reinstatement effect.

	(1) $\ln w_{c,t}$	(2) $\ln L_{c,t}$	(3) $\ln r_{c,t}$	(4) $\ln K_{c,t}$	(5) $Services_{c,t}$	(6) $Gini^{w}_{c,t}$
$R_{c,t}$	−0.040	0.032*	−0.053	0.000	−1.167**	0.007
	(0.032)	(0.017)	(0.033)	(0.022)	(0.443)	(0.006)
$ICT_{c,t}$	−0.011	0.028	0.077**	0.058	2.535***	0.009
	(0.036)	(0.027)	(0.034)	(0.036)	(0.578)	(0.010)
$R * ICT_{c,t}$	−0.011	−0.002	−0.049***	−0.014	−0.522*	0.001
	(0.012)	(0.009)	(0.016)	(0.018)	(0.251)	(0.004)
$D * R_{c,t}$	−0.188**	−0.070*	−0.082	−0.093**	−0.139	0.008
	(0.069)	(0.040)	(0.052)	(0.043)	(0.695)	(0.016)
$D * ICT_{c,t}$	0.336***	−0.204***	0.049	−0.143**	−4.783***	0.014
	(0.094)	(0.033)	(0.060)	(0.068)	(0.920)	(0.018)
$D * R * ICT_{c,t}$	−0.223***	0.064***	−0.035	0.050	1.901**	−0.012
	(0.062)	(0.011)	(0.031)	(0.037)	(0.664)	(0.010)
Observations	395	395	395	395	395	395

Source: Author's calculations.
Notes: Regression results to test the reinstatement effect for nineteen European countries during the period 1995–2016. All regressions include: GDP growth, government consolidated gross debt as % of GDP; government interest payable as % of GDP; net government lending/borrowing as % of GDP; gross fixed capital formation as % of GDP; value-added TFP–calculated as the residual from an OLS regression of value-added volumes (VA) on a translog production function with capital volumes (K) and total hours worked (L); period average exchange rate; country (c) and year (t) fixed effect, and interact the country FE with the pre-2008 dummy variable D_t. Standard errors are two-way clustered at the country and year level.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

where $\mathbb{Y}_{c,t} \in \{w_{c,t}, L_{c,t}, r_{c,t}, K_{c,t}, Services_{c,t}, Gini^{w}_{c,t}\}$. The main effects of interest are those of automation on aggregate labour market outcomes $w_{c,t}$ and $L_{c,t}$. Moreover, we examine qualitative features of the effect by testing whether automation is a driver of capital accumulation ($K_{c,t}$ and $r_{c,t}$) and the cross-industrial reallocation of output from goods to services captured by the output share of services $Services_{c,t}$. With $Gini^{w}_{c,t}$ we evaluate the potential effects on cross-industrial wage inequality. Again, we include pre-2008 interaction terms with D_t, a set of country-level controls $Z_{c,t}$, country and year FE, and interact the country FE with D_t to capture country-specific effects between the two subperiods.[10] We cluster standard errors at the country and year level. Regression results are presented in Table 3.

At the country level, we find a relatively strong negative effect of ICT diffusion on employment $L_{c,t}$ before 2008 (Column 2). However, this effect diminishes in the second subperiod and the correlation between ICT and labour becomes even positive for the full period, not statistically significant though. For robots, we find smaller but qualitatively similar effects. This suggests that the initial replacement of labour associated with ATs is only temporary.

The depth of automation captured by $R_{c,t} * ICT_{c,t}$ shows a positive effect on employment before 2008, which is quantitatively smaller. Hence, declines in employment have been smaller in countries where ICTs and robots were adopted simultaneously.

[10] The country level controls $Z_{c,t}$ are similar to those in Equation (6) and include: GDP growth; government consolidated gross debt as % of GDP; government interest payable as % of GDP; net government lending/borrowing as % of GDP; gross fixed capital formation as % of GDP; value-added TFP–calculated as the residual from an OLS regression of value-added volumes (VA) on a translog production function with capital volumes (K) and total hours worked (L); and period average exchange rate. For more details on the construction and use of variables, see Supplementary Appendix A.

The effects of robots and ICTs before 2008 are qualitatively the opposite. While robots show a negative effect, ICTs are associated with an increase in wages (Column 1). This may be indicative of an unequal distribution of job replacements affecting those at the bottom of the wage distribution relatively more. However, we do not see any significant association with the Gini coefficient $Gini^{w}_{c,t}$ that measures wage inequality across industries (Column 6). Hence, the effect of unevenly distributed job replacement and reinstatement would be a within-sector effect. Generally, the diffusion of robots is negatively associated with the output share of services (Column 5). ICT exhibits a strong negative correlation with the service share before 2008 and an opposite effect for the full period.

We find small but significant negative effects of both ICTs and robots on capital before 2008. Our measure of capital, as obtained from EUKLEMS, is based on index data and includes physical capital (e.g. dwellings, machinery) and intangibles (e.g. intellectual property), whereby robots and ICT are a subset of $K_{c,t}$. A decline in the domestic capital stock may indicate various kinds of changes, such as a decrease in the absolute amount, compositional changes, or outsourcing of capital services.

5.2.3 Real income effect

We evaluate the real income effect of automation by studying the impact on: (1) aggregate factor incomes; and (2) productivity and output prices $p_{c,t}$, while accounting for market expansion reflected in output $Q_{c,t}$ and sales $pQ_{c,t}$ based on the following regressions:

$$\begin{aligned}\mathbb{Y}_{c,t} = {} & \beta^{R} R_{c,t} + \beta^{ICT} ICT_{c,t} + \beta^{RICT} R_{c,t} * ICT_{c,t} \\ & + \beta^{DR} D_t * R_{c,t} + \beta^{DICT} D_t * ICT_{c,t} + \beta^{DRICT} D_t * R_{c,t} * ICT_{c,t} + \beta^{z} Z_{c,t} + \varepsilon_{c,t}\end{aligned} \tag{9}$$

where $\mathbb{Y}_{c,t} \in \{wL_{c,t}, rK_{c,t}, (wL_{c,t} + rK_{c,t}), pQ_{c,t}, Q_{c,t}, p_{c,t}, LProd_{c,t}, KProd_{c,t}, TFP_{c,t}\}$ with $LProd_{c,t}$, $KProd_{c,t}$, and $TFP_{c,t}$ measuring labour, capital, and total factor productivity, respectively. In line with equation (8), we control for the same set of country-level controls $Z_{c,t}$, except for TFP, include country and year FE, and interact the country FE with D_t to capture country-specific effects between the two subperiods. Standard errors are clustered at the country and year level. Results are presented in Table 4.

Before 2008, we observe statistically strongly significant negative effects of robot diffusion on factor income from both labour and capital (Columns 1–2), on output (Column 5), and on prices (Column 6). Quantitatively, the effects are small, but non-negligible, ranging between −0.28% (Column 1) to −0.13% (Column 6) if robot density increases by one standard deviation. During this period, robots also exhibited a small negative effect on capital productivity $KProd_{c,t}$ (Column 8) but a positive one on TFP (Column 9).[11] The negative effect on $KProd_{c,t}$ measured as output ($Q_{c,t}$) per unit of capital ($K_{c,t}$) indicates that the decline in output is relatively stronger than the decline in capital use. We observe a qualitatively similar effect on labour productivity (Column 7), which, however, is not significant.

After 2007, the impact of robots diminishes, and we observe only a weak expansion of output $Q_{c,t}$ (Column 5) that can be associated with robot diffusion. The impact of ICT is much less remarkable. Before 2008, we find that ICTs are associated with decreasing capital incomes (Column 2). This effect is reversed after 2007. Further, we find that ICT exhibited a positive effect on labour productivity (Column 7) and a negative one on TFP (Column 9) before 2008, but both effects diminish after 2007.

Before 2008, the depth of automation exhibits roughly the same effects on factor markets and productivity as robots, but these are weakly significant. Hence, the effects of robots are quantitatively stronger when robots and ICT are adopted simultaneously, suggesting the presence of synergies between these two types of ATs.

[11] TFP is the residual from an OLS regression of gross output volumes (Q) on a translog production function with capital volumes (K), total hours worked (L), and intermediate input volumes (M).

Table 4. The real income effect.

	(1) $\ln wL_{c,t}$	(2) $\ln rK_{c,t}$	(3) $\ln (wL+rK)_{c,t}$	(4) $\ln pQ_{c,t}$	(5) $\ln Q_{c,t}$	(6) $\ln p_{c,t}$	(7) $\ln LProd_{c,t}$	(8) $\ln KProd_{c,t}$	(9) $\ln TFP_{c,t}$
$R_{c,t}$	−0.001	−0.021	−0.014	0.003	0.076**	−0.026	0.022	0.027	−0.010
	(0.042)	(0.033)	(0.031)	(0.031)	(0.030)	(0.022)	(0.030)	(0.019)	(0.011)
$ICT_{c,t}$	0.024	0.104***	0.055	0.041	0.021	0.011	−0.002	0.002	0.007
	(0.051)	(0.036)	(0.042)	(0.047)	(0.023)	(0.028)	(0.028)	(0.021)	(0.013)
$R * ICT_{c,t}$	−0.009	−0.040*	−0.022	−0.021	0.005	−0.005	−0.000	−0.007	0.002
	(0.016)	(0.022)	(0.019)	(0.019)	(0.010)	(0.010)	(0.013)	(0.009)	(0.005)
$D * R_{c,t}$	−0.275***	−0.201***	−0.246***	−0.214***	−0.155***	−0.131***	−0.067	−0.068*	0.022*
	(0.075)	(0.060)	(0.064)	(0.066)	(0.048)	(0.026)	(0.040)	(0.037)	(0.012)
$D * ICT_{c,t}$	0.087	−0.226*	−0.040	0.013	0.008	−0.007	0.171***	−0.007	−0.111***
	(0.085)	(0.114)	(0.097)	(0.098)	(0.036)	(0.058)	(0.039)	(0.043)	(0.025)
$D * R * ICT_{c,t}$	−0.113**	−0.005	−0.065	−0.100*	−0.056**	−0.031	−0.113***	−0.017	0.090***
	(0.047)	(0.059)	(0.053)	(0.056)	(0.023)	(0.045)	(0.033)	(0.035)	(0.022)
Observations	395	395	395	395	309	309	309	309	309

Source: Author's calculations.
Notes: Regression results to test the real income effect for nineteen European countries during the period 1995–2016. Labour productivity (*LProd*) is measured as the share of gross-output volumes (Q) over the total number of hours worked. Capital productivity (*KProd*) is measured as the share of gross output volumes (Q) over capital stock volumes (K). TFP is calculated as the residual from an OLS regression of gross-output volumes (Q) on a translog production function including capital volumes (K), total number of hours worked (L), and intermediate input volumes (M). All regressions include: GDP growth, government consolidated gross debt as % of GDP; government interest payable as % of GDP; net government lending/borrowing as % of GDP; gross fixed capital formation as % of GDP; period average exchange rate; country (c) and year (t) fixed effect, and interact the country FE with the pre-2008 dummy variable D_t. Standard errors are two-way clustered at the country and year level.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

6 Robustness checks

In this section, we discuss the key parts of further analysis we have undertaken to ensure the robustness of our findings.[12]

6.1 Endogeneity

Ideally, we would like to measure the pure impact of technological progress in ATs as an exogenous driver of AT diffusion to see how it affects the economy and public revenues. However, we only observe patterns of AT adoption, which may endogenously depend on economic dynamics.

To alleviate such endogeneity concerns, we employ three robustness checks that rely on lagged data and Instrumental Variables (IV). First, we use lagged ($t-1$) instead of contemporaneous (t) robot and ICT density as explanatory variables to allow for effects that may take one period to materialize. Next, we use an IV approach where deeper lags, that is, $t-1$, $t-2$, and $t-3$ instrument for the contemporaneous AT diffusion measures. The estimates are consistent with the baseline results.

In the same spirit, we apply an alternative IV approach inspired by Blanas, Gancia, and Lee (2019) following the idea that AT imports from other countries should be driven by technological advances in ATs, but are exogenous to the economic dynamics in country c. For this, we use robot and ICT product imports by all countries in the world except c as an instrument for robot and ICT diffusion in c. We obtain qualitatively similar point estimates, but the validity tests indicate a weak explanatory power in the first stage. Summing up, the lag and both IV approaches support our analysis qualitatively, but given the level of aggregation, the IV approaches suffer from weak instruments.[13]

Furthermore, we use as explanatory variables lead ($t+1$) instead of contemporaneous (t) values of the AT diffusion measures, to explore the presence of reverse causality. While some estimated coefficients lose statistical significance, this does not hold for all of them. However, these findings cannot be necessarily interpreted in favour of the presence of reverse causality since both measures of AT diffusion are highly persistent over time with an autocorrelation coefficient close to unity, i.e. approximately 0.95.

Overall, given the findings in this section and the empirical constraints to credibly pin down causality, we do not interpret our results as causal, but rather as associations that provide as much supporting evidence as possible to help us improve our understanding of the link between ATs and taxes.

6.2 Further tests

In a series of further checks, we include additional controls, such as trade, corporate taxation, income distribution, and demographics, use alternative measures for the robot stock variable, and explore the presence of data outliers. For some variables, we have incomplete time and country coverage. Thus, we abstain from including them in our main analysis.

First, we test the sensitivity of our results against changes in the tax systems. While comprehensive data covering the whole range of different taxes is not available, we proxy tax reforms using data on corporate taxation for a smaller period but for all countries in our sample. We use two different data sources.

Second, we repeat all baseline country-level regressions and include as an additional control the corporate tax rate ($CRT_{c,t}$) sourced from KPMG. These data are available between 2003 and 2016, and thus only the results for the post-2007 period are comparable with the baseline analysis. Next, we repeat all baseline country-level regressions and include, as an

[12] For a more detailed presentation and discussion of the results, see the Supplementary Appendix Sections D–G.

[13] We have also experimented with alternative external IV approaches by constructing Bartik-style IVs, but we ran into similar issues in terms of instrument validity. See Supplementary Appendix Section D.

additional control, the effective tax rate ($ETR_{c,t}$) sourced from Eurostat and only available between 2006 and 2016.

Another concern regarding the robustness of our results may arise from the impact of trade. To capture the country-specific impact of trade, we repeat all baseline country-level regressions and include, as additional controls, the country-level imports ($Imports^{\%GDP}_{c,t}$) and exports ($Exports^{\%GDP}_{c,t}$) as a percentage of GDP.

To explore the nexus between distribution and taxation, we examine the progressiveness of taxation. We rely on the same empirical specifications used in the tax regressions (Table 1), but now the regressions include, as an additional control, the Gini coefficient measuring cross-industry wage inequality ($Gini^{w}_{c,t}$). We do not find any significant relationship between the Gini coefficient and taxation, nor does the inclusion of the Gini coefficient alter the results.

Next, we examine whether our results are sensitive to possible links between ageing and demographics (Acemoglu and Restrepo 2022; Abeliansky and Prettner 2023). Population ageing and demographic change in developed countries may induce labour shortages and higher wages. This can be a driver of automation if firms anticipating these demographic trends invest in machinery to replace retiring workers, which would also affect tax revenues from labour. To capture these links and a possible omitted variable bias arising from the link between ageing and automation, we repeat all the baseline country-level regressions, controlling for the annual population growth rate following Abeliansky and Prettner (2023). We estimate two different specifications where we introduce population growth as an additional control (1) in contemporaneous values and (2) in one-year-lagged values to allow for possible time lags in the response of automation decisions to demographic change. The results are qualitatively and quantitatively consistent with those in the baseline specification.

Furthermore, we check the robustness of our results to alternative measures or ways to construct the robot stock variable. Robot deliveries can be 'inaccurate' at the sector level since the IFR cannot report very few deliveries for compliance issues. In addition, there are many discrepancies between the values of the deliveries and the change in the stock (the latter going up while the deliveries don't, for example). Therefore, we first re-estimate all baseline results where the robot variable is based on the robot stock directly reported by the IFR. Next, we repeat this exercise by calculating the robot stock à la Graetz and Michaels (2018) but now assuming a 5% or 15% depreciation rate instead of 10% used in the baseline results.[14] Results remain robust to these alternative measures of the stock of robots.

Finally, we also ensure that the results are not driven by countries or regions that exhibit exceptionally high rates of robot adoption, such as Germany or, more generally, Western Europe. Noteworthy, excluding Germany from the baseline tax regressions leads to a loss of significance for the capital taxes during the pre-2008 period (see Supplementary Table G57, Columns 3, 7, and 10). Since Germany is a key manufacturing country we find this result to align with our expectations but we do not observe any meaningful change in our model when we look at the full period or other estimates. Overall, the results are robust across subsamples of countries (see Supplementary Appendix G).

Overall, the results from these exercises are qualitatively consistent with our main findings, albeit in some cases of lower statistical significance, which might be due to differences in the data coverage.[15]

[14] The correlation between these alternative measures and the robot variable used in the baseline results is close to perfect, that is, 0.99.

[15] For a detailed presentation of the results and data used see Supplementary Appendix Section E.

7 Discussion

Our results suggest that when talking about the impact of automation on taxation, it is important to be specific about the type of ATs and period under consideration. Robots and ICTs are conceptually and economically different as they can replace manual or cognitive tasks, and their utilization is heterogeneous across industries. Further, we have shown that we cannot extrapolate observations from the late 1990s and early 2000s, when both robots and ICTs were less mature and not widely deployed, to the years that followed. Our theoretical framework introduced various compensation mechanisms of how direct industry-specific effects may cancel out at the macroeconomic level, which is the relevant level of analysis for a study of taxation impacts.

7.1 Answering the research questions

Now, we return to the research questions outlined in Section 1:

1) What is the relationship between AT diffusion and tax revenues at the country level?
2) What is the relationship between AT diffusion and the composition of taxes by source (labour, capital, goods)?
3) How can these relationships be traced back to the economic effects of automation?

Robot diffusion exhibited a negative effect on taxation, but only before 2008, which matches the observation of declining factor revenues during this period. This decline in taxes can be mainly attributed to decreasing capital taxes and relatively higher taxation of goods. The decline of capital taxes is consistent with a lower capital stock. However, this result needs to be taken with a grain of salt. Domestic capital as captured by the EUKLEMS data is derived from national accounting data and based on an index of various types of capital goods, including dwellings, machinery, and intangibles. A decline in the capital stock may indicate a homogeneous decline, but also compositional changes or outsourcing of capital services. An in-depth analysis is beyond the scope of this article, focusing on taxation, but the observations can be well related to other studies discussing the challenges of measuring capital and productivity consistently over time (Ahmad et al. 2016; Adarov et al. 2019; Stehrer et al. 2019).

While we find weak support for a declining aggregate labour demand that can be associated with robots before 2008, the effect diminishes over time, supporting the existence of a reinstatement effect. In automation-exposed industries, we do not find any strong labour replacement effect. There is a weak decline in employment over the whole period, but the effects are statistically and economically weakly significant. We also cannot find evidence that robots have been a driver of labour market polarization.

In contrast to robots, the impact of ICTs is more persistent, showing a negative association with tax revenues over the full period. However, the effects are small, statistically weakly significant, and diminish when looking at taxes in relation to GDP. Hence, concerns that ICT as a technology that may automate cognitive tasks and negatively affect the tax bases cannot be supported empirically. However, similar to robots, we find that ICT diffusion is associated with a shift from capital taxation towards other sources of tax revenues in the pre-2008s, at weaker statistical significance though. Again, a possible explanation is provided by the simultaneous decline of capital at the macro level, which is subject to the same measurement considerations discussed above for robots.

Differently from robots, we find that ICTs were associated with increasing employment and capital utilization in automation-exposed industries before 2008, contradicting the idea that ICTs automate tasks. Instead, it suggests that ICTs may have stimulated investment in these sectors during 1995–2007. However, the effect seems temporary. At the macro level, we find opposite effects. ICTs were associated with a declining output share of the service sector and negative employment effects pre-2008. In the long run, the impact of

ICT on aggregate employment and services reversed, suggesting ICT diffusion to be associated with a structural reallocation across sectors. This aligns with other studies where ICT adoption leads to a changing demand for skills, and the cross- and within-industry reallocation processes of labour and production (see e.g. Hötte, Somers, and Theodorakopoulos 2023).

The productivity effects of robots and ICT differ, but both diminish after 2007. Robots are associated with rising TFP but declining capital productivity. Both effects are stronger if ICTs and robots are adopted simultaneously. However, ICTs alone show the opposite effect. The TFP-increasing effect of robots is consistent with earlier observations made by Graetz and Michaels (2018). In their study, robot diffusion is further associated with declining prices, which is consistent with the pre-2008 results of this paper. Given the limitations of measuring productivity and the non-persistence of the effect, it is hard to derive conclusions based on this finding in the context of the real income effect.

Overall, our results do not support the concern that ATs threaten governments' tax bases. We confirm that factor incomes are important sources of taxation, particularly from labour. Governments that care about fiscal sustainability need to monitor their evolution. However, so far, we do not find statistical evidence that these incomes will be strongly negatively affected in the long run. Technology diffusion is an inherently dynamic process with adoption lags, learning, creative destruction, and hysteresis until the economic benefits of technological advancement unfold. The differential findings across periods highlight that it may be insufficient to focus on a short period when studying the impact of ATs on the economy and fiscal revenues.

This has implications for the discussion about countervailing measures, such as the introduction of a robot tax to prevent excessive automation (Acemoglu and Restrepo 2020; Kovacev 2020; Süssmuth et al. 2020; Guerreiro, Rebelo, and Teles 2022). Such a tax may undermine the incentives to invest in ATs but has been justified by eroding fiscal revenues. Acknowledging that there may be other reasons for robot taxation (e.g. distributional concerns), our study suggests that the justification based on fiscal revenues does not have an empirical base. However, there may be other relevant reasons to introduce such kind of taxation, for example, concerns about the distribution of the rents to automation, which is beyond the scope of this study.

7.2 Challenges of taxation analyses

Before concluding, we want to highlight a few challenges. First, tax systems are complex and have been subject to reform policies before and after the financial crisis in 2008, which was a key driver of structural reforms. This may undermine the capacity to identify the impact of technological change on taxation and production, as the heterogeneous nature of these reforms is hard to capture consistently, especially in a set of heterogeneous countries with diverse cultures of taxation that evolved differently over decades. We cope with this by using interaction terms to capture differences in the results between the two periods and conducting a battery of checks to account for various confounding factors.

A second challenge related to the tax data is the notion of endogeneity, where two types of endogeneity might be relevant. First, we do not know to what extent automation and its economic impacts are affected by particular tax rules. We cope with this problem through a series of robustness checks using data on corporate tax rates as additional controls and find that this does not affect our results. Moreover, when checking country-level time series data on implicit taxes on labour and capital, we do not observe any remarkable changes in relative tax rates, which differs from observations for the USA (Acemoglu, Manera, and Restrepo 2020). In our sample, there is no ex-ante clear indication that changes in AT diffusion in Europe can be attributed to distortionary taxation.

A second concern about endogeneity arises from the cyclicality of investment decisions. In particular, we do not know whether we observe the impact of AT diffusion on the economy or vice versa. We cope with this through a series of robustness checks using lagged instead of contemporaneous AT diffusion in the regression and through two types of IV approaches relying on lagged AT and trade data. We find that our findings remain robust against these alternative specifications.

Finally, our analysis only briefly touched upon distributional effects. Conceptually, we have implicitly assumed a linear relationship between country-level wage and capital income, consumption, and taxation. However, households with different income levels consume and save differently, and employees earning different wages face different tax rates dependent on tax progressiveness. Inequality is a major issue in the literature on automation. We tested the relationship between inequality and taxation, but could not detect any significant relationship. This may be due to data limitations and non-linearities, which are not trivial to detect and could be part of an interesting future research agenda.

8 Conclusion

The nexus between taxation and automation is complex and requires careful monitoring of the economic side effects of technological change. Preceding studies argued that policymakers should be concerned about the sustainability of public finances when ATs undermine the tax base.

Our study confirms that factor income from labour and capital are indeed major sources of tax revenues, which could justify the concern that AT-driven job replacement may undermine the tax base. However, we do not find empirical support for such concerns for a set of European economies during 1995–2016. We find some support for robot-driven labour replacement and declines in factor income with a negative association with tax income. Yet, this effect is small and disappears post-2007 and the impact on taxes is quantitatively very small compared to other determinants of taxation. Post-2007, we find that almost all effects diminish, supporting the idea that other macroeconomic compensation effects (i.e. reinstatement and real-income effects) materialize, which may offset the negative impact on taxes. ICTs are different and do not show any noteworthy effect on factor income or taxation.

Contrasting to discussions in the literature focusing on the impact of ATs on labour, our results suggest an important role of capital. We observe for both robots and ICT a relative shift of taxation away from capital, which may be explained by declining capital stock in the pre-2008 period. This may be a compositional effect that arises from the way of measuring capital in aggregate data. A deeper analysis is beyond the scope of this work, but it can be related to the literature on the measurement of productivity and capital valuation in the digital age (Ahmad et al. 2016).

Concerns remain regarding the strict exogeneity of our automation measures, and our results should not be interpreted as causal evidence. Nevertheless, our results suggest that there is no empirical evidence that tax revenues are negatively affected by AT in the long run. Whether automation undermines taxation depends on the technology and the stage of diffusion, and concerns about public budgets may be short-sighted if they focus on the short term and ignore other technological trends.

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Supplementary data

Supplementary material is available on the OUP website. These are the online appendix and the replication package contained in the zip folder htk_replication_package.zip. The replication package includes the Stata code used to produce all tables and figures and all associated publicly available data. However, the proprietary dataset 'World Robotics 2016' with information on robot deliveries and stock is purchased from the commercial provider International Federation of Robotics - IFR (https://ifr.org/) and, therefore, we are not allowed to make the data public. Any interested researcher can purchase the data directly from IFR. The replication package provides detailed information about the data sources, variables, and steps to estimate all results, export tables and plot figures for both the manuscript and online appendix.

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