The Oxford Martin Programme on
Technological and Economic Change

Automation and Taxation

Kerstin Hötte, Angelos Theodorakopoulos, Pantelis Koutroumpis

May 2023

For more information on the Oxford Martin Programme on Technological and Economic Change, please visit: https://www.oxfordmartin.ox.ac.uk/technological-economic-change/

For more information on the Oxford Martin Programme on the Future of Work, please visit: https://www.oxfordmartin.ox.ac.uk/future-of-work/

For more information on the Oxford Martin Programme on the Future of Development, please visit: https://www.oxfordmartin.ox.ac.uk/future-of-development/

Automation and Taxation

Kerstin Hötte,[1,2*] Angelos Theodorakopoulos,[3] Pantelis Koutroumpis[4]

[1] *The Alan Turing Institute, London*
[2] *Institute for New Economic Thinking, University of Oxford*
[3] *Aston Business School, Aston University*
[4] *Oxford Martin School, University of Oxford*

May 2023

Do automation-induced changes in labor and capital income undermine public revenues? Decomposing taxes by source (labor, capital, sales), we analyze the impact of automation on tax revenues and the structure of taxation in 19 EU countries during 1995-2016. Before 2007 robot diffusion was associated with a decline in total tax revenues and taxes from capital, along with decreasing labor and capital income and output. After 2008, the negative effects diminish. ICTs 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 are myopic when focusing on the short-run and ignoring relevant technological trends.

JEL Classification Codes: H2, O3
Keywords: Technological Change, ICT, Robots, Fiscal Revenues, Labor

*Corresponding author: khotte@turing.ac.uk
The authors thankfully acknowledge the contribution of Martina Magli working on an early version of this project. Moreover, the authors are grateful for comments and feedback from their colleagues in the Oxford Martin Programme on Technological and Economic Change and the Future of Work. The authors acknowledge support from the European Union Horizon 2020 Research and Innovation programme under grant agreement No 822330 TECHNEQUALITY. A replication package for the results presented in this paper is available upon request. This paper previously circulated under the titles: "Does automation erode governments' tax base? An empirical assessment of tax revenues in Europe" and "Automation and taxation: An empirical assessment in Europe".

1. Introduction

Taxes on labor contribute to a major share of public revenues. When ATs diffuse and replace labor 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 et al., 2020; Kovacev, 2020; Rebelo et al., 2019; Süssmuth et al., 2020). However, the impact of automation is complex, including many second-order effects. In addition, governments receive taxes from multiple sources in addition to labor, 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 labor is replaced by sophisticated machinery able to execute tasks currently performed by humans (Acemoglu and Restrepo, 2020; Arntz et al., 2016; Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Gregory et al., 2018; Korinek and Stiglitz, 2017; Nedelkoska and Quintini, 2018). The *reinstatement effect* covers the creation of new tasks and occupations, and the reallocation of labor within and across industries (Acemoglu and Restrepo, 2019; Bessen, 2019; Bessen et al., 2020; Blanas et al., 2019; Dauth et al., 2018). The *real income effect* reflects changes in: (a) real income when reduced production costs affect prices; and (b) factor revenues from capital and labor (Acemoglu and Restrepo, 2019; Aghion et al., 2017; Graetz and Michaels, 2018; Korinek and Stiglitz, 2017).

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 (labor, 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 labor, capital, and goods for nineteen European countries during 1995-2016.

The effects of automation, however, 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 analyze the prevalence of the replacement, reinstatement, and real income effect and argue how these effects 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 on capital taxes in particular, accompanied by decreasing factor income from capital and labor. 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 relationship on total tax revenues and taxes on goods, and an increase in capital income accompanied by an output shift towards service sectors after 2008. 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 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. Labor 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 on the impact of automation on public finances.

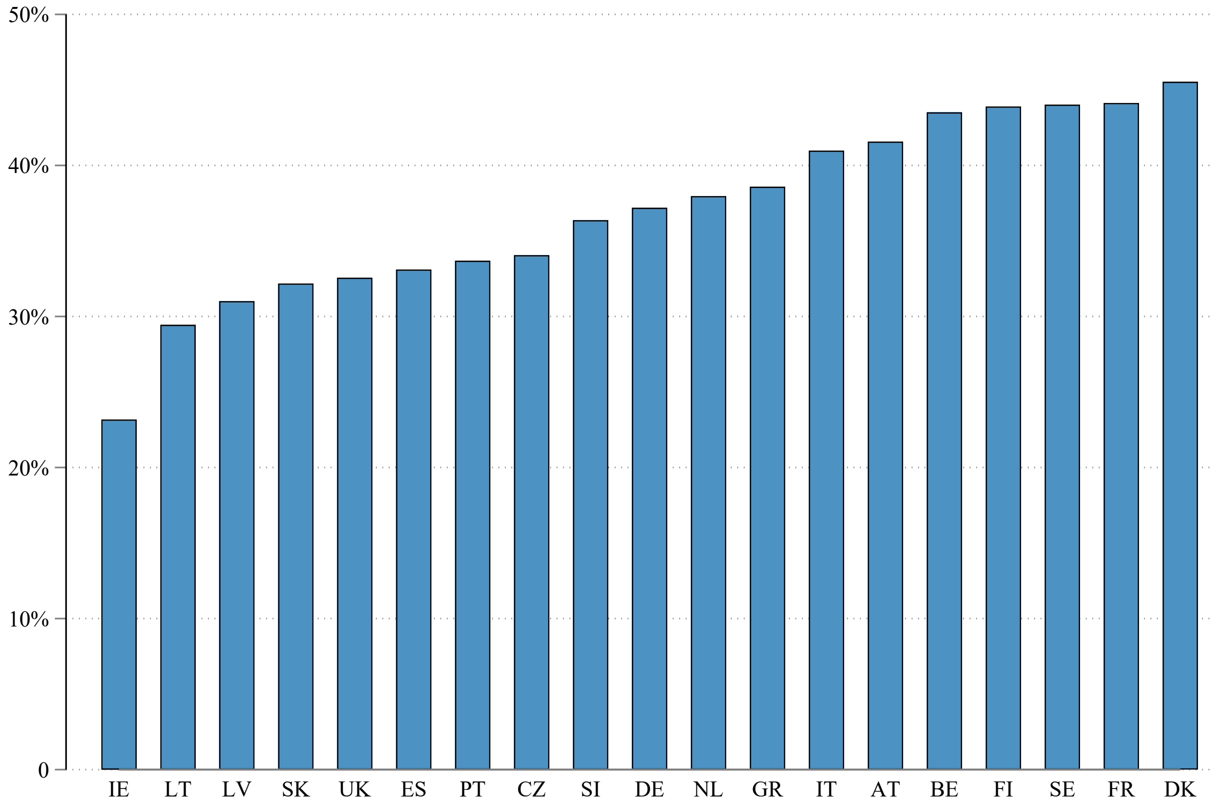
The rest of the paper is structured as follows. In Section 2, we provide an overview of the background on automation and taxation. In Section 3, we introduce a conceptual model. In Section 4, we describe our empirical strategy and the data. Section 5 summarizes the results, while Section 6 provides a 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

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 19 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 over the country level sample and construction of variables, see Online Appendix Section A.

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 figure 1).[1] Over time, the average tax-to-

[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).

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 labor, profits and capital gains, property, and trade of goods and services. Compulsory Social Security Contributions (SSC) can equally be considered as tax revenues charged on labor (OECD, 2019, Annex A.2). Here, we focus on three broad groups, namely taxes imposed on: (1) labor (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 labor 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 labor 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, i.e. 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 which have emerged historically across nations (Castro and Camarillo, 2014; Hettich and Winer, 2005; 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 (Castañeda Rodríguez, 2018; Castro and Camarillo, 2014). 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? (2) Does automation affect tax revenues such that it poses a risk to governments' fiscal capacity? The majority of the existing literature 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 et al. (2020) argue that the US tax system is biased in favor of capital, which leads to a sub-optimal reduction of the labor 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 labor share. Similarly, Süssmuth et al. (2020) analyze the impact of US taxation on the functional distribution of income and find that distributional changes (in favor of the capital share) can be partly attributed to labor 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 US, Rebelo et al. (2019) 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 per the capita capital stock with positive long-run growth effects.

Theoretical studies on robot taxes argue that these taxes can be used to reduce inequality and to secure public revenues. However, it remains controversial whether automation really 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 labor and capital might have affected the diffusion of ATs in the US, as argued by Acemoglu et al. (2020), data limitations prevent us from investigating changes in relative tax rates in depth. Using data on implicit tax rates on labor 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 Figure 2) indicating that there is no straightforward empirical justification that the effects found in this study are driven by distortionary tax reforms.

[2]See Appendix Figure B.1. The data on implicit tax rates on labor and capital in Europe, provided by the European Commission, are not directly comparable to the approach used by Acemoglu et al. (2020) who calculated effective tax rates on labor and different types of ATs at the micro-level in the US. It is not straightforward to apply their methodology in a European cross-country setting with very heterogeneous and complex tax systems. The European Commission computes implicit tax rates on labor and capital as a ratio of actual tax income by source to the potential tax base (European Commission, 2020). Nonetheless, the stable patterns of relative tax (rates) observed in the EU are in stark contrast to the clear-cut divergence in favor of capital observed by Acemoglu et al. (2020) in the US.

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 and reinstatement of labor, and changes in real income.

3.1. Tax revenues

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

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

where $L_c = \sum_{i \in I_c} L_{i,c}$ is aggregate labor given by the sum of labor 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 labor 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, i.e. labor 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 labor 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 capital, i.e. $K_{i,c} = K_{i,c}^n + K_{i,c}^a$ where $K_{i,c}^n$ is non-automation capital and $K_{i,c}^a = ICT_{i,c} + R_{i,c}$ 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 labor. We assume that all types of capital are rented at the same rate $r_{i,c}$.

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

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 $\frac{\partial f_{i,c}}{\partial A_{i,c}} \geq 0$, i.e. the quantity of output is non-decreasing in the quantity of inputs and in the level of productivity. Moreover, ceteris paribus, we expect factor demand to be negatively related to factor prices, i.e. $\frac{\partial L_{i,c}}{\partial w_{i,c}} \leq 0$ and $\frac{\partial K_{i,c}}{\partial r_{i,c}} \leq 0$.

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 labor income $w_c L_c$, 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, 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 the 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 labor 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 et al., 2016; Frey and Osborne, 2017; Hawksworth et al., 2018; Nedelkoska and Quintini, 2018; Webb, 2020). Labor 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 et al., 2006).

Empirical results on the replacement effect remain ambiguous (see Hötte et al., 2022, 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 labor, which increases productivity with a positive effect on wages, possibly leading to a polarization of wage income (Autor et al., 2006). The net impact of the replacement effect on the labor 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 labor taxes in particular, if the net effect on the wage bill is negative and taxes are sufficiently non-progressive. 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. We do not find any evidence that the income distribution proxied by cross-industry wage inequality plays a significant role.

3.4.2. Reinstatement

Historically, job replacement through automation was often compensated by the emergence of new occupations and the reinstatement of labor (Acemoglu and Restrepo, 2019; Aghion et al., 2017; Autor, 2015; 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 labor-intensive processes; and (2) automation may require complementary labor inputs to operate the machinery. This effect can be reinforced if automation stimulates capital accumulation, which may also have a positive effect on labor 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 labor in other industries and a cross-industrial reallocation of labor. The employment and income effects may differ across industries, skill, and occupational groups, and the process of reinstatement may be slowed down by labor market frictions and skill mismatches (Acemoglu and Restrepo, 2020; Arntz et al., 2016; Bessen et al., 2020; Dauth et al., 2018; Gregory et al., 2018).

The reinstatement effect potentially offsets sector-specific negative employment effects at the aggregate level. Ceteris paribus, the reinstatement effect positively affects labor demand in automating industries and at the country level, i.e. $\frac{\partial L_{i,c}}{\partial K^a_{i,c}} > 0, i \in \{j|K^a_{j,c} > 0\}$ 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 labor income, i.e. $\frac{\partial (w_c L_c)}{\partial K^a_c} > 0$.

3.4.3. Real income

The real income effect is an indirect, composite effect resulting from the replacement and reinstatement of labor, 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 et al., 2018). 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 labor 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, i.e. $\frac{\partial A_{i,c}}{\partial K_{i,c}^a} \geq 0$, which leads to price reductions when lower unit production costs are passed through to consumers, i.e. $\frac{\partial p_{i,c}}{\partial A_{i,c}} \leq 0$ and $\frac{\partial p_{i,c}}{\partial K_{i,c}^a} \leq 0$. In turn, this increases real disposable income, i.e. $\frac{\partial Y_c^r}{\partial K_{i,c}^a} \geq 0$ where $Y_c^r = (1-t^l)\frac{w_c}{p_c}L_c + (1-t^k)\frac{r_c}{p_c}K_c$ and $\frac{\partial p_c}{\partial p_{i,c}} \geq 0$ 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 et al., 2015, 2016; Autor et al., 2020; Barkai, 2020; Bormans and Theodorakopoulos, 2023). Dependent on the income elasticity of demand, an increase in real income may induce more consumption, which reinforces the reinstatement effect with positive feedback on labor and capital income.

4. Empirical approach and data

In this section, we give an overview of the empirical approach and the 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 analyze 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. Second, 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.

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

Effect	Description	Indicators
Replacement	Substitution of labor. Decreasing labor 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 labor demand in other/newly emerging economic activities. Increasing labor 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.	$\frac{\partial A_c}{\partial K^a_c}$, $\frac{\partial p_c}{\partial K^a_c}$, $\frac{\partial Q_c}{\partial K^a_c}$, $\frac{\partial HHI_c}{\partial K^a_c}$.

4.2. Data

We combine different data sets at different aggregation levels with varying coverage by countries, industries, 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 only automation-intensive industries. Throughout the paper, we define automation-intensive 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-intensive industries include: agriculture; mining and quarrying; ten manufacturing aggregates; electricity, gas and water supply; construction; and education, research and development (see Appendix Table B.1.)

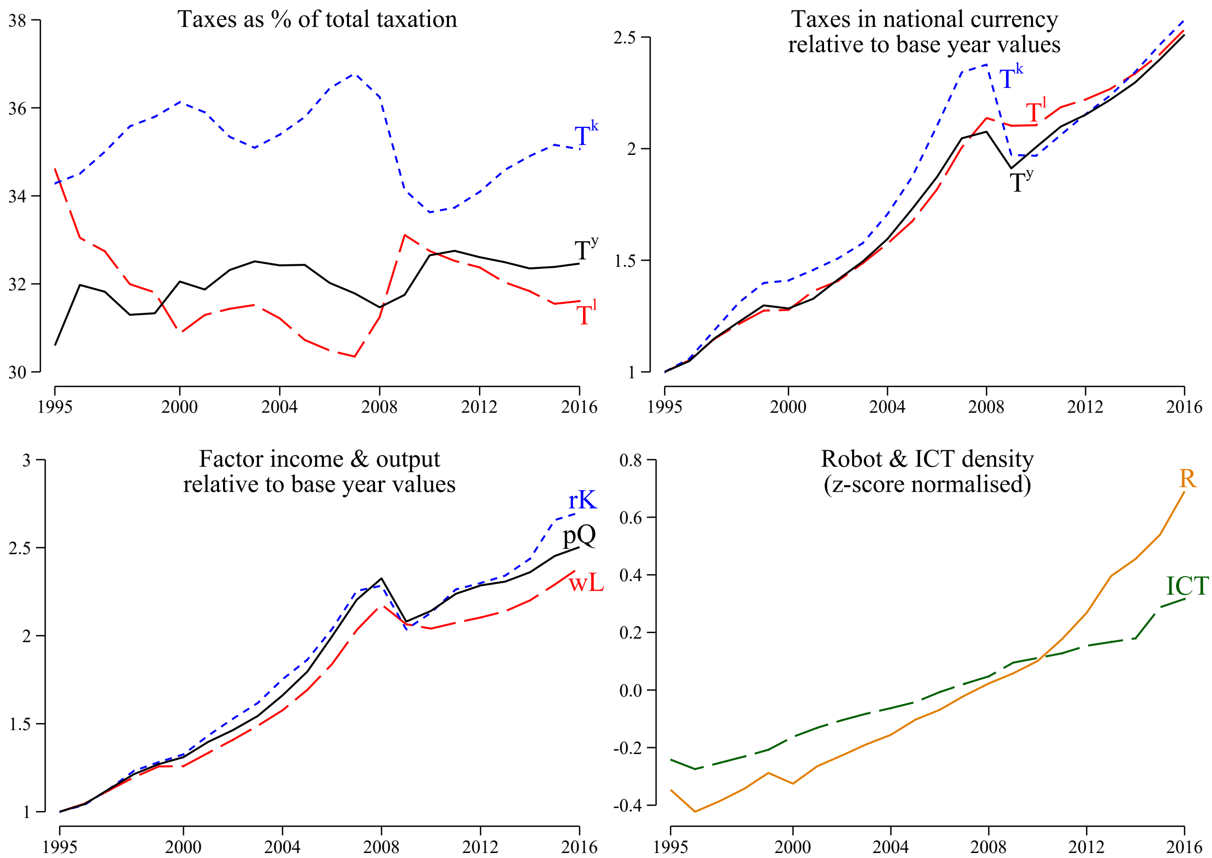
[4] List of countries: AT; BE; CZ; DE; DK; ES; FI; FR; GR; IE; IT; LT; LV; NL; PT; SE; SI; SK; UK.

[5] We use the term 'automation-intensive' for simplicity, while acknowledging that alternative definitions of 'automation-intensive' 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.

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, i.e. labor ($T^l_{c,t}$), capital ($T^k_{c,t}$), and goods ($T^y_{c,t}$), measured in national currency, as percentage of GDP, and percentage share of total taxation. Time series plots are shown in the top panels of Figure 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 labor and goods. Therefore, in the analysis below, we examine whether any effects might differ during the post-2008 period where large structural changes coincided with increases in automation.

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 19 European countries considered in the country level sample. $T^l_{c,t}$, $T^k_{c,t}$ and $T^y_{c,t}$ refer to taxes on labor, 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 is labor 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 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 over the country level sample and construction of variables, see Online Appendix Section A.

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 Figure 2 illustrates the evolution of the macroeconomic accounts wL_t, rK_t, pQ_t averaged across all countries and normalized to the base year 1995. We see that aggregate revenues from labor increased slower compared to the other accounts.[6]

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 labor. 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, i.e. 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 Figure 2 presents a time series plot of the z-score normalized measure of robot and ICT density and suggests that post-2008 the rate of robot diffusion outpaced that for ICTs which exerts a stable rise since 1995.

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

[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 Online Appendix A.3.

5. Results

In this section, we present the findings. First we analyze 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 effect.

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, i.e.

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

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, i.e. 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 that equals to one for the pre-2007 period (1995-2007) and zero otherwise. We include country and time FE that are also interacted with D and a set of controls $Z_{c,t}$, including aggregate income from labor $wL_{c,t}$ and capital $rK_{c,t}$, and other variables that capture country-specific economic characteristics, global shocks, and potential confounding factors that could be 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, we see the association of automation with taxes measured in logarithmic national currency units. The second block shows the relationship with taxes measured in percentage GDP. The last block shows the impact on the structure of taxation, i.e. on taxes as a share of total taxation. Labor 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 labor and capital share.

For the full period, we do not see that robots show any significant uniform effect on

[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 over the construction and use of these variables, see Online Appendix A.

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

taxation. When interacting robots with the pre-2007 dummy variable ($D * R_{c,t}$), 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- and post-2008 period. 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.

Table 1: Taxation and automation

	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)	(0.737)	(0.327)	(0.471)	(0.146)	(0.516)	(0.774)	(0.731)
$ICT_{c,t}$	-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)	(0.493)	(0.293)	(0.450)	(0.261)	(0.821)	(0.837)	(0.683)
$R * ICT_{c,t}$	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)	(0.249)	(0.317)	(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)	(0.500)	(0.238)	(0.766)	(0.895)	(0.783)
$D * ICT_{c,t}$	-0.011	-0.169	-0.072	0.040	-0.165	0.558	-1.149	0.427	1.638	-2.978*	0.782
	(0.028)	(0.190)	(0.073)	(0.061)	(0.896)	(0.652)	(0.860)	(0.388)	(1.598)	(1.681)	(1.463)
$D * R * ICT_{c,t}$	-0.007	0.017	-0.025	-0.002	-0.470	-0.027	-0.594	0.151	0.273	-0.553	0.883
	(0.022)	(0.083)	(0.049)	(0.030)	(0.853)	(0.428)	(0.619)	(0.189)	(0.821)	(0.957)	(0.987)
$wL_{c,t}$	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)	(0.179)	(0.089)	(0.117)	(0.075)	(0.200)	(0.207)	(0.196)
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Quantitatively, the coefficients of ICTs are weaker than robots, but generally, the effects of both ATs are small. For example, before 2007, an increase in robot density by one standard deviation was associated with a decline in total tax revenues by 0.07% and capital taxes by 0.12%. As a quantitative benchmark, the effect of an increase in aggregate labor income by 1% is associated by a 0.46% increase in total taxation and 0.9% increase in labor taxes. The effect on relative taxes is more pronounced, and we can see that the decline of relative taxes on capital by 2.6% is almost fully offset by an increase of relative taxes on goods by 2.2%.

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 labor at a large scale. We examine the empirical vailidity 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, running the following industry level regressions:

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

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 labor and capital, respectively, and i refers to an automation-intensive industry Again, we include interaction terms with dummies D for the pre-2007 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. Again, the FEs are also interacted with D. Standard errors are two-way clustered at the country-industry and year level.

Table 2: The replacement effect

	$\ln wL_{i,c,t}$	$\ln w_{i,c,t}$	$\ln L_{i,c,t}$	$\ln rK_{i,c,t}$	$\ln r_{i,c,t}$	$\ln K_{i,c,t}$
$R_{i,c,t}$	-0.026	0.010	-0.036*	-0.018	-0.003	-0.017
	(0.020)	(0.009)	(0.017)	(0.033)	(0.003)	(0.015)
$ICT_{i,c,t}$	-0.024	0.012	-0.036*	-0.079	-0.005	-0.028
	(0.020)	(0.008)	(0.020)	(0.071)	(0.004)	(0.039)
$R * ICT_{i,c,t}$	-0.007	0.000	-0.007	0.017	-0.002*	0.007
	(0.006)	(0.003)	(0.005)	(0.012)	(0.001)	(0.005)
$D * R_{i,c,t}$	0.017	0.012	0.005	0.024	0.001	0.047
	(0.040)	(0.012)	(0.039)	(0.081)	(0.007)	(0.030)
$D * ICT_{i,c,t}$	0.063***	-0.005	0.068***	0.081	0.007	0.074*
	(0.020)	(0.009)	(0.017)	(0.073)	(0.015)	(0.042)
$D * R * ICT_{i,c,t}$	0.012	0.002	0.010	-0.022	0.001	0.009
	(0.013)	(0.004)	(0.013)	(0.032)	(0.005)	(0.017)
N	4897	4897	4897	4842	4802	4802

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. All regressions use industry level data for nineteen European countries during 1995-2016 for the set of industries susceptible to automation, and include: country-industry (ci); country-year (ct); and industry-year (it) fixed effects that are further interacted with D. 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.

Table 2 presents results. Over the whole period, we find weak support for the replacement effect in automation-intensive industries when robots diffuse, i.e. 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. However, we do not find any effect on the wage bill and a positive correlation with wages, suggesting an unevenly distributed replacement effect. Replacement happens, but higher wages in non-replaced jobs tend to offset any impact on the wage bill ($wL_{i,c,t}$).

The impact of ICT diffusion qualitatively differs across sub-periods: Before 2007, it shows a net positive effect on employment, 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 before 2007 is statistically and economically stronger, even though quantitatively small. Before 2007, we also find a weak positive association between ICTs and capital accumulation. 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:

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

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 labor 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-2007 interaction terms, a set of country level controls $Z_{c,t}$, and country and year FE that are further interacted with D.[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 2007. However, this effect diminishes in the second subperiod and the correlation between ICT and labor 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 labor associated with ATs is only temporary.

The depth of automation captured by $R * ICT_{c,t}$ shows a positive effect on employment before 2007, 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 over the construction and use of variables, see Online Appendix A.

Table 3: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^w_{c,t}$
$R_{c,t}$	-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)	(0.579)	(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)	(0.697)	(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)	(0.923)	(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)
N	395	395	395	395	395	395

Notes: $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

The effects of robots and ICTs before 2007 are qualitatively the opposite. While robots show a negative effect, ICTs are associated with an increase in wages. This may be indicative of an unequal distribution of job replacements, affecting those at the bottom of the wage distribution relatively stronger. However, we do not see any significant association with the Gini-coefficient $Gini^w_{c,t}$ that measures wage inequality *across* industries. 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. ICT exhibits a strong negative correlation with the service share prior to 2007 and an opposite effect for the full period.

We find small but significant negative effects of both ICTs and robots on capital before 2007. 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:

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

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 labor, capital and total factor productivity. In line with equation (8), we control for the same set of country level controls $Z_{c,t}$, except for TFP, and include country and year FE that are further interacted with D, and cluster standard errors at the country and year level. Results are presented in Table 4.

Table 4: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL + rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	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)	(0.020)	(0.011)
$ICT_{c,t}$	0.024	0.104***	0.055	0.041	0.021	0.011	-0.002	0.002	0.007
	(0.052)	(0.036)	(0.042)	(0.047)	(0.023)	(0.028)	(0.028)	(0.019)	(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)	(0.014)	(0.010)	(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)	(0.034)	(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)	(0.041)	(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)	(0.031)	(0.022)
N	395	395	395	395	309	309	309	309	309

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Before 2007, we observe statistically strongly significant negative effects of robot diffusion on factor income from both labor and capital, on output and on prices. Quantitatively, the effects are small, but non-negligible, ranging between -0.28% to -0.13% if robot density increases by one standard deviation. During this period, robots also exhibited a small negative effect on capital productivity ($KProd_{c,t}$) but a positive one on TFP. 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 labor productivity, which is however, not significant. TFP is calculated as 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).

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

Before 2007, 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.

6. Robustness checks

In this section, we discuss the key parts of further analysis we have undertaken to ensure the robustness of our findings.[11]

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, i.e. $t-1$, $t-2$ and $t-3$, instrument for the contemporaneous AT diffusion measures. The estimates are consistent with the baseline results.

Furthermore, we apply an alternative IV approach inspired by Blanas et al. (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 except c as an instrument for robot

[11]For a more detailed presentation and discussion of the results, see the Online Appendix Sections D-E.

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-based and both IV approaches support our analysis qualitatively, but given the level of aggregation, the IV approaches suffer from weak instruments.[12]

6.2. Further tests

In a series of further checks, we include additional controls, such as trade, corporate taxation, and distribution. 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. This data are available between 2003-2016, and thus only the results for the post-2008 period are comparable with the baseline analysis. Next, we repeat all baseline country level regressions and include, as an additional control, the effective tax rate ($ETR_{c,t}$) sourced from Eurostat and only available between 2006-2016.

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 ($Imports_{c,t}^{\%GDP}$) and exports ($Exports_{c,t}^{\%GDP}$) as percentage of GDP.

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

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. The results are robust across subsamples of countries (see Online Appendix F).[13]

[12] 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 Online Appendix Section D.

[13] Another concern may be related to population aging, as it may affect the structure of demand, employment shares across industries, savings, and labor supply, which may interact with automation. Acemoglu and Restrepo (2017) discuss that aging may incentivize AT adoption and offset any negative effects arising from labor scarcity. However, they do not provide empirical evidence. Since aging is

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.[14]

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 time 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 follow. 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 (labor, 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 with the observation of declining factor revenues during this period. This decline in taxes can be mainly attributed to decreasing capital taxes and a 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

a long term trend, we hope concerns related to aging are sufficiently captured by country and year FEs. An in depth analysis in this direction could be a fruitful avenue for future research.

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

the challenges of measuring capital and productivity consistently over time (Adarov et al., 2019; Ahmad et al., 2016; Stehrer et al., 2019).

While we find weak support for a declining aggregate labor demand that can be associated with robots before 2007, the effect diminishes over time supporting the existence of a reinstatement effect. In automation-intensive industries, we do not find any strong labor 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 labor market polarization.

In contrast to robots, the impact of ICTs is more persistent over time 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 basis 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-2007s, 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-intensive industries before 2007, contradicting the idea that ICTs automate tasks. Instead, it suggests that ICTs may have stimulated investment in these sectors during 1996-2007. 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-2007. 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 labor and production (see e.g. Hötte et al., 2022).

The productivity effects of robots and ICT differ, but both diminish after 2008. 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-2007 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 labor. 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 advance unfold. The differential findings across periods highlight that it may be insufficient to focus on a short time period when studying the impact of ATs on the economy and fiscal revenues.

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 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 labor and capital, we do not observe any remarkable changes in relative tax rates, which differs from observations for the US (Acemoglu et al., 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 a 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 labor and capital are indeed major sources of tax revenues, that 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 labor replacement and declines in factor income with a negative association with tax income. Yet, this effect is small and disappears post-2008 and the impact on taxes is quantitatively very small compared to other determinants of taxation. Post-2008, we find that almost all effects diminish, supporting the idea that other macroeconomic compensation 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 labor, 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-2007 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).

Overall, our findings suggest that there is no empirical evidence supporting that tax revenues are negatively affected by ATs in the long run. Whether automation erodes taxation depends on the technology and the stage of diffusion, and concerns about public budgets might be short-sighted when focusing on the short term and ignoring other technological trends.

References

Acemoglu, D., A. Manera, and P. Restrepo (2020). Does the US Tax Code Favor Automation? NBER Working Paper No. 27052, National Bureau of Economic Research.

Acemoglu, D. and P. Restrepo (2017). Secular stagnation? The effect of aging on economic growth in the age of automation. *American Economic Review 107*(5), 174–179.

Acemoglu, D. and P. Restrepo (2018a). Artificial intelligence, automation and work. NBER Working Paper No. 24196, National Bureau of Economic Research.

Acemoglu, D. and P. Restrepo (2018b). Modeling automation. In *AEA Papers and Proceedings*, Volume 108, pp. 48–53.

Acemoglu, D. and P. Restrepo (2019). Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives 33*(2), 3–30.

Acemoglu, D. and P. Restrepo (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society 13*(1), 25–35.

Adarov, A., R. Stehrer, et al. (2019). Tangible and Intangible Assets in the Growth Performance of the EU, Japan and the US. Research Report 442, Vienna Institute for International Economic Studies.

Aghion, P., B. F. Jones, and C. I. Jones (2017). Artificial intelligence and economic growth. NBER Working Paper No. 23928, National Bureau of Economic Research.

Ahmad, N., P. Schreyer, et al. (2016). Are GDP and productivity up to the challenges of the digital economy? *International Productivity Monitor 30*, 4–27.

Andrews, D., C. Criscuolo, and P. N. Gal (2015). Frontier Firms, Technology Diffusion and Public Policy. Technical report, OECD Productivity Working Papers November 2015 No. 2.

Andrews, D., C. Criscuolo, and P. N. Gal (2016). The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy. Technical report, OECD Productivity Working Papers November 2016 No. 2.

Arntz, M., T. Gregory, and U. Zierahn (2016). The risk of automation for jobs in OECD countries. Technical report, OECD Social, Employment and Migration Working Papers No. 189.

Atkinson, R. D. (2019). The Case Against Taxing Robots. Technical report, Information Technology and Innovation Foundation.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics 135*(2), 645–709.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *The Journal of Economic Perspectives 29*(3), 3–30.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006). The polarization of the us labor market. *American economic review 96*(2), 189–194.

Barkai, S. (2020). Declining labor and capital shares. *The Journal of Finance 75*(5), 2421–2463.

Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Economic Policy 34*(100), 589–626.

Bessen, J., M. Goos, A. Salomons, and W. van den Berge (2020). Firm-Level Automation: Evidence from the Netherlands. In *AEA Papers and Proceedings*, Volume 110, pp. 389–93.

Blanas, S., G. Gancia, and S. Y. T. Lee (2019). Who is afraid of machines? *Economic Policy*.

Bormans, Y. and A. Theodorakopoulos (2023). Productivity Dispersion, Wage Dispersion and Superstar Firms. *Economica ,forthcoming*.

Brynjolfsson, E. and A. McAfee (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Castañeda Rodríguez, V. M. (2018). Tax determinants revisited. An unbalanced data panel analysis. *Journal of Applied Economics 21*(1), 1–24.

Castro, G. Á. and D. B. R. Camarillo (2014). Determinants of tax revenue in OECD countries over the period 2001–2011. *Contaduría y administración 59*(3), 35–59.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2018). Adjusting to Robots: Worker-Level Evidence. Opportunity and Inclusive Growth Institute Working Papers 13, Federal Reserve Bank of Minneapolis.

Diamond, P. A. and J. A. Mirrlees (1971). Optimal taxation and public production i: Production efficiency. *The American economic review 61*(1), 8–27.

EUKLEMS (2019). EUKLEMS release 2019. Data extracted in Oct 2020.

European Commission (2020). Taxation trends in the European Union - Data for the EU Member States, Iceland and Norway: 2020 edition. Report, European Commission, DG for Taxation and Customs Union.

Frey, C. B. and M. A. Osborne (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change 114*, 254–280.

Gasteiger, E. and K. Prettner (2022). Automation, stagnation, and the implications of a robot tax. *Macroeconomic Dynamics 26*(1), 218–249.

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

Gregory, T., A. Salomons, and U. Zierahn (2018). Racing with or Against the Machine? Evidence from Europe. Technical report, CESifo Working Paper No. 7247.

Hawksworth, J., R. Berriman, and S. Goel (2018). Will robots really steal our jobs? An international analysis of the potential long term impact of automation. Report, PricewaterhouseCoopers.

Hettich, W. and S. L. Winer (2005). *Democratic choice and taxation: A theoretical and empirical analysis*. Cambridge University Press.

Hötte, K., M. Somers, and A. Theodorakopoulos (2022). Technology and jobs: A systematic literature review. arxiv preprint arxiv:2204.01296, Cornell University.

IFR (2020). International Foundation of Robotics. Proprietary data on Industrial robot Deliveries and Stocks.

Kiser, E. and S. M. Karceski (2017). Political economy of taxation. *Annual review of political science 20*, 75–92.

Korinek, A. and J. E. Stiglitz (2017). Artificial intelligence and its implications for income distribution and unemployment. NBER Working Paper No. 24174, National Bureau of Economic Research.

Kovacev, R. (2020). A Taxing Dilemma: Robot Taxes and the Challenges of Effective Taxation of AI, Automation and Robotics in the Fourth Industrial Revolution. The Ohio State Technology Law Journal, 16 Ohio State Technology L.J. 182.

Nedelkoska, L. and G. Quintini (2018). Automation, skills use and training. Technical report, OECD Social, Employment and Migration Working Papers No. 202.

OECD (2019). *Revenue Statistics 2019*. OECD Publishing, Paris.

OECD (2020). Global Revenue Statistics Database. Data extracted on 28 Oct 2020.

Rebelo, S., P. Teles, and J. Guerreiro (2019). Should Robots Be Taxed? Macroeconomis and Growth and Public Economics Discussion Paper DP 122238, Centre for Economic Policy Research.

Stehrer, R., A. Bykova, K. Jäger, O. Reiter, and M. Schwarzhappel (2019). Industry level growth and productivity data with special focus on intangible assets. Statistical Report 8, Vienna Institute for International Economic Studies.

Süssmuth, B., A. Irmen, B. Heer, et al. (2020). Taxation, Automation Capital, and the Functional Income Distribution. In *VfS Annual Conference 2020 (Virtual Conference): Gender Economics*, Number 224572. German Economic Association.

Webb, M. (2020). The impact of artificial intelligence on the labor market. Working paper, Department of Economics, Stanford University, Stanford, California.

Supplementary Online Appendix:* Automation and Taxation

Kerstin Hötte[1,2], Angelos Theodorakopoulos[3], Pantelis Koutroumpis[4†]

[1] *The Alan Turing Institute*
[2] *Institute for New Economic Thinking, University of Oxford*
[3] *Aston Business School, Aston University*
[4] *Oxford Martin School, University of Oxford*

May 2023

*This document provides relevant supporting material for online publication.

†Corresponding author: khotte@turing.ac.uk

The authors thankfully acknowledge the contribution of Martina Magli working on an early version of this project. Moreover, the authors are grateful for comments and feedback from their colleagues in the Oxford Martin Programme on Technological and Economic Change and the Future of Work. The authors acknowledge support from the European Union Horizon 2020 Research and Innovation programme under grant agreement No 822330 TECHNEQUALITY. A replication package for the results presented in this paper is available upon request. This paper previously circulated under the titles: “Does automation erode governments’ tax basis? An empirical assessment of tax revenues in Europe” and “Automation and taxation: An empirical assessment in Europe”.

A. Data construction

Overall, we combine different data sets at different aggregation levels with varying coverage in terms of countries, industries, and time. After merging the data as described below, we end up with two samples. The first sample is a country-level panel data set covering the whole economy, from agriculture to public sectors, for nineteen European countries during 1995-2016.[1]

The second sample is an industry-level panel data set covering only automation-intensive industries. We classify industries as automation-intensive when information on the use of robots exists, since the data coverage of industries is endogenous, i.e. only significant customers of industrial robots are reported (IFR, 2020). These data cover the same set of countries and years as the country-level data, excluding Portugal due to missing information. The industries classified as automation-intensive include: agriculture; mining and quarrying; ten manufacturing industries; electricity, gas, and water supply; construction; and education, research and development.[2]

A.1. Sources of tax revenue

Taxes are part of our country-level data and compiled on the basis of the Global Revenue Statistics Database of the OECD (2020). We use the OECD terminology to define the tax aggregates as follows:

- $T^l_{c,t}$—taxes on labor are the sum of *Social security contributions (2000)* and *Taxes on payroll and workforce (3000)*,
- $T^k_{c,t}$—taxes on capital are the sum of *Taxes on income, profits and capital gains (1000)* and *Taxes on property (4000)*,[3]
- and $T^y_{c,t}$—taxes on goods given by *Taxes on goods and services (5000)*,

[1] The sample is unbalanced since data are missing for: Lithuania, Latvia, and the United Kingdom during the base year, i.e. 1995; and Denmark, Portugal, Slovenia, and Slovakia for the period 1995-1999.

[2] The sample is unbalanced since certain country-industry-year combinations are missing. Generally, the industry and year coverage is rather limited for Eastern European countries i.e. Estonia, Lithuania, Latvia, Slovenia, and Slovakia. Details on the coverage are provided in the Appendix Table B.2.

[3] We include property taxes as part of capital taxes because: (1) they consist largely of taxes on corporate property; and (2) we interpret property as part of the productive capital that is used to provide economic services to final consumers. This interpretation also holds for the majority of private property taxes. For example, taxes on houses are one of the most significant parts of property taxes. Housing is a service consumed by households, even if private housing is not traded on the market. This interpretation is not applicable to other components of property taxes (e.g. taxes on gifts). However, tax revenues raised from these residual accounts are negligibly small. The total block of property taxes accounts on average for less than 2% of GDP. Checks excluding all *4000*-tax codes confirm that this does not alter the results.

where the numbers in parentheses indicate the tax code from the OECD tax classification system (OECD, 2019, A.1).[4]

To describe the impact on tax revenues, we use taxes measured in national currency. To put this in relation to production, we look at taxes measured as percentage of GDP. For an analysis on the structure of taxation, we use tax data measured as percentage of total taxation.

A.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). We use:

- LAB for $wL_{c,t} = \sum_{i \in I_c} w_{i,c,t} L_{i,c,t}$
- CAP for $rK_{c,t} = \sum_{i \in I_c} r_{i,c,t} K_{i,c,t}$
- and GO for $pQ_{c,t} = \sum_{i \in I_c} p_{i,c,t} Q_{i,c,t}$[5]

where $w_{i,c,t}$, $r_{i,c,t}$ and $p_{i,c,t}$, are computed by dividing the respective variables measured in values to their volumes.[6]

Automation may lead to industrial restructuring. To measure this, we construct two structural indicators using industry-level data. First, we compute the service sector market share: $Services_{c,t} = \frac{\sum_{i \in I_c^s} p_{i,c,t} Q_{i,c,t}}{\sum_{i \in I_c} p_{i,c,t} Q_{i,c,t}}$, where I_c^s is the set of service industries in c.[7] Second, we compute as a measure of industrial concentration the Hirschmann-Herfindahl index on the basis of industry shares in total production, i.e. $HHI_{c,t} = \sum_{i \in I_c} \left(\frac{p_{i,c,t} Q_{i,c,t}}{p_{c,t} Q_{c,t}} \right)^2$.

For an indicator of cross-industrial wage inequality, we use industry-level data on wages to calculate the country-level Gini coefficient as follows: $Gini^w_{c,t} = \frac{\sum_{i=1}^{I_c} (2i - I_c - 1) w_{i,c,t}}{I_c \sum_{i=1}^{I_c} w_{i,c,t}}$, where I_c are all industries in country c and i and is now the rank of industry-level wages in ascending order. Analogously, we compute $Gini^L_{c,t}$, which measures the distribution of

[4] In this analysis, we ignore residual taxes (*6000*) which, on average across OECD countries, account for approximately 0.2% of GDP and 0.6% of total taxation.

[5] LAB is computed as the compensation of employees in current prices of national currency in million times the ratio of total hours worked by persons engaged over total hours worked by employees, which assumes that in each industry the self-employed earn the same hourly wage as the employees. CAP is the capital compensation calculated as the value added minus labor compensation. Note that we use the value of the capital stock as a proxy for the rate of return to capital. GO is the gross output in current prices of national currency in million.

[6] Specifically, we source from EUKLEMS $L_{c,t} = \sum_{i \in I_c} L_{i,c,t}$, $K_{c,t} = \sum_{i \in I_c} K_{i,c,t}$ and $Q_{c,t} = \sum_{i \in I_c} Q_{i,c,t}$ as the number of hours worked in million (H_EMPE), the net capital stock volume of all assets in million (Kq_GFCF), and the gross output volume in million (GO_Q). Similarly, we construct country-level $w_{c,t}$, $r_{c,t}$ and $p_{c,t}$ by dividing the corresponding country-level aggregates in values by volumes $L_{c,t}$, $K_{c,t}$ and $Q_{c,t}$, respectively.

[7] We define service industries as NACE Rev. 2 (ISIC Rev. 4) 2-digit codes 45-99 or 1-digit codes G-U.

employment across industries. A higher level of $Gini^{w}_{c,t}$ ($Gini^{L}_{c,t}$) indicates a more unequal distribution of wage (labor) across industries.

To examine the impact of automation on productivity, we use industry-level data to calculate labor productivity $LProd_{c,t}$ as the share of gross output volumes over the total number of hours worked. We also estimate total factor productivity $TFP_{c,t}$ as the residual from an OLS regression of gross output volumes on a translog production function of volumes of capital, labor (hours worked) and material inputs (cf. Stehrer et al., 2019).

In the tax regressions, we additionally control for determinants of taxation identified in the literature (e.g. Castañeda Rodríguez, 2018; Castro and Camarillo, 2014). We include GDP growth and different indicators of public finances sourced from Eurostat (2020), such as: government consolidated gross debt as % of GDP ($Debt^{\%GDP}_{c,t}$); net government lending/borrowing as % of GDP ($Lending^{\%GDP}_{c,t}$); government interest payments on debt as % of GDP ($Interest^{\%GDP}_{c,t}$); and public gross fixed capital formation as % of GDP ($GovInv^{\%GDP}_{c,t}$). We capture the role of trade by including the period average exchange rate ($XRate_{c,t}$) from the OECD (2020) data set. Robustness checks including additional controls, such as corporate tax rates, and import and export rates are provided in E.3.

A.3. Measuring automation

We use two measures for automation calculated on the basis of: (1) the stock of the number of operational industrial robots; and (2) the capital stock of ICT, including computer software and databases.

The data on industrial robots is from the International Federation of Robotics (IFR) (IFR, 2020). An industrial robot is defined as "automatically controlled, reprogrammable, multipurpose manipulator [...] for industrial applications" (IFR, 2020).[8] The IFR provides data on deliveries and stocks of industrial robots at the industry level. Industrial robots are a measure of automation because they can readily replace humans in the execution of specific tasks (see Acemoglu and Restrepo, 2020; de Vries et al., 2020; Faber, 2020; Graetz and Michaels, 2018).

To measure the extent to which robots became part of an industry's production technology, we follow Graetz and Michaels (2018) to construct the *robot density* measure as the stock of the number of operational robots over the number of hours worked by human labor in industry i, i.e. $R_{i,c,t} = \frac{\#Robots_{i,c,t}}{L_{i,c,t}}$. For the country level analysis, we compute $R_{c,t} = \frac{\sum_{i \in I_c} \#Robots_{i,c,t}}{\sum_{i \in I_c} L_{i,c,t}}$.

For the construction of the stock of the number of operational robots in each industry ($\#Robots_{i,c,t}$), we closely follow Graetz and Michaels (2018) using data from IFR (2020).

[8] This definition follows the ISO norm 8373 (see https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

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). This procedure is the same as the one used in EUKLEMS to compute the stock of ICT capital which is the other key mode of automation considered in our analysis.

In particular, we set the first year (1993 in the IFR dataset) value of our robot stock measure equal to the corresponding estimate of the robot stock provided by the IFR.[9] For all subsequent years, we construct the stock of the number of robots based on deliveries using the perpetual inventory method and assuming a depreciation rate of 10%.

As a second automation indicator, we use the *ICT density* measured as net ICT capital stock per hour worked $L_{i,c,t}$. The data on ICT capital is taken from EUKLEMS (2019) as the sum of net capital stock volumes of computing equipment (Kq_IT), communications equipment (Kq_CT), and computer software and databases (Kq_Soft_DB). It includes both tangible (hardware) and intangible (databases and software) ICTs.

The coverage of industries differs for data on robots and ICT. Data on ICT covers the whole economy, except for all industries in Portugal and certain industries and/or years in Eastern European countries. Robot data are also available for more countries than those in the ICT data set, but reported only for the following industries: agriculture; mining and quarrying; ten manufacturing industry groups; electricity, gas and water supply; construction; and education, research and development (see Appendix Table B.2). These two automation measures are computed both at the country-year and country-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 include these two types of automation to potentially account for two different AT types. Robots and ICTs can be distinguished by the type of task they can execute: robots are designed to perform manual tasks, while ICT has a stronger link to cognitive tasks. While robots are pure ATs that execute a clearly defined task previously performed by humans, it is less clear whether this also applies to ICTs. ICTs can be flexibly applied for many different tasks and, to some extent, these tasks do not have a clear analogue in the range of tasks that can be executed by humans.

In our analysis, we introduce both diffusion measures simultaneously and as an interaction term. Robot-ICT interaction captures complementarities between the two ATs or otherwise stated the depth of automation, i.e. the extent to which both manual and cognitive tasks are performed by machinery. Concerns about multicollinearity can be

[9] To estimate robot stocks, the IFR assumes that a robot has twelve years of service life. As in Graetz and Michaels (2018), while we prefer to use a measure of the robot stock that is based on more conventional assumptions about depreciation, we must rely on the IFR estimates to initialize our series of robot stocks.

ruled out since we find a very low correlation between both measures (with a correlation coefficient of 22% for all countries in the sample).

A major concern is over the potential endogeneity of the diffusion measures. While we study the impact of AT diffusion on the economy, the causality can run vice-versa, and thus AT adoption could be contingent on economic dynamics. For instance, a well documented macroeconomic regularity is that investment cycles are positively correlated with cyclical boosts and busts in the economy (Anzoategui et al., 2019; Stock and Watson, 1999). In our analyses, while we control for gross capital formation which captures the cyclicality of general investments, AT-specific investments could still follow a different trend. To cope with endogeneity of this sort, we apply a series of robustness checks, including the use of lagged ($t-1$) diffusion measures and exploring two types of IV regressions. For the latter, we experiment with: (1) an internal IV strategy using deeper lags (up to $t-3$) of the AT measures as instruments; and (2) an external IV strategy, whereby we use data on global trade in robots and ICT products to construct external instruments for AT adoption (see Appendix Section D).

B. Additional Tables and Figures

Table B.1: List of NACE Rev.2 (ISIC Rev.4) industry groups in industry level data.

Industry aggregation:		
EUKLEMS	IFR	Description of industries in IFR dataset
01t03	01t03	A-B-Agriculture, forestry, fishing
05t09	05t09	C-Mining and quarrying
10t12	10t12	10-12-Food and beverages
13t15	13t15	13-15-Textiles
16t18	16	16-Wood and furniture
16t18	17t18	17-18-Paper
19t21	19t20	20-21-other chemical products n.e.c.
19t21	21	19-Pharmaceuticals, cosmetics
22t23	22	22-Rubber and plastic products (non-automotive)
22t23	23	23-Glass, ceramics, stone, mineral products (non-auto
24t25	24	24-Basic metals
24t25	25	25-Metal products (non-automotive)
26t27	26t27	26-27-Electrical/electronics
28	28	28-Industrial machinery
29t30	29	29-Automotive
29t30	30	30-Other vehicles
31t33	32	91-All other manufacturing branches
35t39	35t39	E-Electricity, gas, water supply
41t43	41t43	F-Construction
85	85	P-Education/research/development
Rest	Rest	90-All other non-manufacturing branches

Notes: EUKLEMS and IFR refer to the aggregation of NACE Rev.2 (ISIC Rev.4) 2-digit industries considered in the EUKLEMS and IFR data set, respectively. The industry level analysis in this paper is based on the more aggregate EUKLEMS industry aggregation.

Table B.2: Time period coverage of each country industry pair in the industry level sample.

	Industry groups based on ISIC Rev.4 (NACE Rev.2) 2-digit codes used in the industry-level sample														
Country	01t03	05t09	10t12	13t15	16t18	19t21	22t23	24t25	26t27	28	29t30	31t33	35t39	41t43	85
AT	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
BE	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
CZ	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
DE	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
DK	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
EE	2000-2016	2000-2016	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2000-2016	2000-2016	2000-2016
ES	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
FI	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
FR	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
GR	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
IT	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
LT	1995-2016	1995-2016	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1995-2016	1995-2016	1995-2016
LV	1995-2016	2000-2016	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2000-2016	1995-2016	2000-2016
NL	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
SE	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016
SI	2000-2016	2000-2016	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2000-2016	2000-2016	2000-2016
SK	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
UK	2007-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016	1995-2016

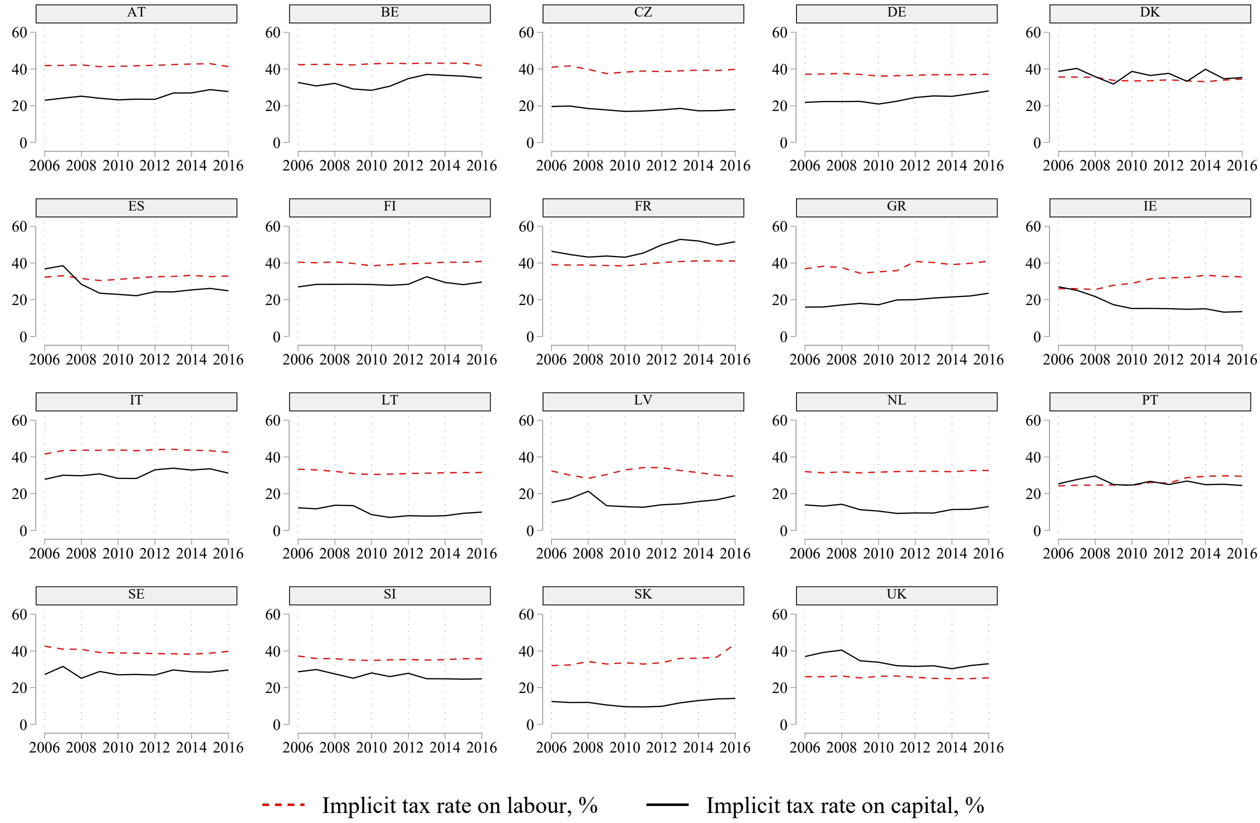
Notes: This table presents the year coverage across countries and industries for the industry level sample used in the analysis. Industries refer to groupings of NACE Rev.2 (ISIC Rev.4) 2-digit industry codes and are discussed in detail in Table B.1.

Table B.3: Descriptive statistics

	% of GDP				% of total tax			Production			GDP	Services		% of GDP				Gini	
	T	T^l	T^k	T^y	T^l	T^k	T^y	wL	rK	pQ	$growth$	pQ	HHI	$Debt$	$Interest$	$Lending$	$GovInv$	w	L
Mean	36	12	13	12	32	35	32	530	330	1830	2.3	57	.13	63	2.8	-3	3.5	.16	.51
St.Dev.	5.8	4.2	5.2	1.5	10	10	5.2	578	414	2212	3.5	6.8	.026	34	1.8	3.7	1	.049	.029
Min	23	.29	4.6	6.9	.6	17	23	2.5	1.7	8.7	-15	41	.082	8.5	.4	-32	1.5	.081	.41
Median	35	12	12	11	33	32	31	209	120	715	2.3	57	.13	58	2.6	-2.6	3.6	.15	.51
Max	49	19	33	16	45	69	44	2307	1978	10831	25	71	.19	181	11	6.9	7.7	.4	.6

Notes: This table shows the main descriptives (mean, standard deviation, minimum, median, maximum) of the core variables included in the regression analyses covering all nineteen European countries during the period 1995-2016. Further information about the data is provided in the main article (see Section 4).

Figure B.1: Evolution of implicit taxes on labor and capital



Notes: These figures show the evolution of implicit tax rates on labor and capital in whole Europe and for the subsets of Eastern Northern and Southern European countries as defined in the text. The data are downloaded from the European Commission's tax database (European Commission, 2020a). See also European Commission (2020b).

C. Further determinants of taxation

Here, we briefly outline other determinants of taxation that are included in the regressions but not discussed in the main text. These regressors are motivated by the literature on taxation and cover: GDP growth; the market share of services $Services_{c,t}$; public finance related indicators (debt, interest payments and deficit); measures for industrial concentration $HHI_{c,t}$; the exchange rate $XRate_{c,t}$ (i.e. US$ per Euro) as proxy for trade; and public investments $GovInvest_{c,t}^{\%GDP}$.

Labor taxes in absolute terms, in relation to GDP and as share in total taxation exhibit a positive correlation with the service share. This pattern holds for both sub-periods pre- and post-2008. High indebtedness and higher deficits are positively related to taxes in absolute terms and measured in percentage GDP. Net lending as percentage GDP is positively correlated with all taxes except from labor taxes, which are negatively related to deficits.

We find a higher exchange rate $XRate_{c,t}$ to be negatively related to taxes on capital, goods and in total, measured in absolute terms and as percentage of GDP. We also observe a higher exchange rate to be positively related to the relative tax contribution of labor at the cost of taxes on capital.[10]

[10]Note that the exchange rate varies across European countries only in the time dimension, since the EU's Exchange Rate Mechanism aims to keep exchange rate fluctuations between the Euro and other European currencies flat (see also https://stats.oecd.org/glossary/detail.asp?ID=3055). Hence, $XRate_{c,t}$ captures the competitiveness of European countries on global markets but can not be interpreted as an indicator of within-European trade.

Table C.4: Taxation and the structure of production

	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)	(0.737)	(0.327)	(0.471)	(0.146)	(0.516)	(0.774)	(0.731)
$ICT_{c,t}$	-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)	(0.493)	(0.293)	(0.450)	(0.261)	(0.821)	(0.837)	(0.683)
$R*ICT_{c,t}$	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)	(0.249)	(0.317)	(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)	(0.500)	(0.238)	(0.766)	(0.895)	(0.783)
$D*ICT_{c,t}$	-0.011	-0.169	-0.072	0.040	-0.165	0.558	-1.149	0.427	1.638	-2.978*	0.782
	(0.028)	(0.190)	(0.073)	(0.061)	(0.896)	(0.652)	(0.860)	(0.388)	(1.598)	(1.681)	(1.463)
$D*R*ICT_{c,t}$	-0.007	0.017	-0.025	-0.002	-0.470	-0.027	-0.594	0.151	0.273	-0.553	0.883
	(0.022)	(0.083)	(0.049)	(0.030)	(0.853)	(0.428)	(0.619)	(0.189)	(0.821)	(0.957)	(0.987)
$wL_{c,t}$	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)	(0.179)	(0.089)	(0.117)	(0.075)	(0.200)	(0.207)	(0.196)
$pQ_{c,t}$	0.463**	-0.201	0.589*	0.430**							
	(0.200)	(0.524)	(0.334)	(0.153)							
$GDPgrowth_{c,t}$	-0.000	-0.002	0.001	0.001	-0.025	-0.036*	-0.002	0.014	-0.079*	0.008	0.061*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.047)	(0.021)	(0.022)	(0.015)	(0.042)	(0.037)	(0.032)
$Services_{c,t}$	0.000	-0.005	-0.009	-0.008	-0.052	0.150	-0.157	-0.044	0.528**	-0.420	-0.160
	(0.003)	(0.018)	(0.010)	(0.005)	(0.138)	(0.091)	(0.116)	(0.044)	(0.217)	(0.253)	(0.149)
$HHI_{c,t}$	-1.002*	0.030	-2.327**	-2.531***	-30.313	18.475	-34.978**	-13.810	76.537**	-56.711	-16.825
	(0.504)	(1.789)	(0.954)	(0.878)	(20.020)	(14.914)	(12.216)	(9.282)	(35.001)	(32.821)	(28.772)
$Debt^{\%GDP}_{c,t}$	0.001*	0.001	0.002*	0.002***	0.040**	0.003	0.018	0.020***	-0.027*	0.012	0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.018)	(0.008)	(0.011)	(0.004)	(0.014)	(0.021)	(0.013)
$Interest^{\%GDP}_{c,t}$	-0.005	-0.001	-0.004	-0.008	-0.097	-0.091	0.052	-0.059	-0.035	0.225	0.193
	(0.006)	(0.012)	(0.011)	(0.006)	(0.242)	(0.127)	(0.139)	(0.037)	(0.272)	(0.288)	(0.213)
$Lending^{\%GDP}_{c,t}$	0.004**	-0.002	0.006**	0.002	0.104**	0.011	0.076**	0.017*	-0.048	0.100*	-0.068*
	(0.001)	(0.003)	(0.003)	(0.002)	(0.038)	(0.014)	(0.035)	(0.010)	(0.042)	(0.057)	(0.035)
$GovInv^{\%GDP}_{c,t}$	0.001	0.006	0.006	-0.011	0.056	0.074	0.047	-0.065	0.112	0.112	-0.268
	(0.005)	(0.009)	(0.009)	(0.008)	(0.153)	(0.070)	(0.102)	(0.056)	(0.137)	(0.185)	(0.162)
$XRate_{c,t}$	-0.004***	-0.003	-0.009***	-0.004*	-0.125***	0.001	-0.116***	-0.010	0.145**	-0.196***	0.088***
	(0.001)	(0.006)	(0.003)	(0.002)	(0.033)	(0.028)	(0.028)	(0.010)	(0.063)	(0.059)	(0.019)
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. All regressions use country level data for nineteen European countries during 1995-2016 and include: GDP growth ($GDPgrowth_{c,t}$), gross output share of service industries in the total economy ($Services_{c,t}$); Herfindahl-Hirschman Index computed based on the gross output shares of macro-sectors ($HHI_{c,t}$); government consolidated gross debt as % of GDP ($Debt^{\%GDP}_{c,t}$); government interest payable as % of GDP ($Interest^{\%GDP}_{c,t}$); net government lending/borrowing as % of GDP ($Lending^{\%GDP}_{c,t}$); gross fixed capital formation as % of GDP ($GovInv^{\%GDP}_{c,t}$); period average exchange rate ($XRate_{c,t}$); and country (c) and year (t) fixed effects that are further interacted with D. 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.

D. Coping with endogenous automation

As explained in Section 6.1, one major concern to the robustness of our results arises from potential endogeneity of AT diffusion. Ideally, we would like to measure the pure impact of technological progress in ATs as an exogenous driver of AT diffusion to see how technological change affects the economy and public revenues. But we can only observe patterns of AT adoption which can endogenously dependent on economic dynamics.

To cope with these concerns, we use three different types of robustness checks relying on lagged data and IVs. Here, we present the results of these robustness checks.

In Section D.1, we used robot and ICT density from $t-1$ instead of contemporaneous diffusion measures as explanatory variables. In Section D.2, we used an IV approach. In particular, deeper lags from $t-1$, $t-2$ and $t-3$ are used as explanatory variables on the first stage to instrument contemporaneous AT diffusion. Below the tables with the results, we report statistics to test for under-, weak- and over-identification of the IV approach. The estimates of the coefficients of this approach are consistent with the results presented in the main text.

Another IV approach is shown in Section D.3. Here, we use robot and ICT products imports by all countries in the world except c as in instrument for robot and ICT diffusion in country c. This approach is inspired by Blanas et al. (2019) and follows the idea that AT imports to other countries should be driven by technological advances in ATs, but are entirely exogenous from the economic dynamics in country c. Again, we obtain qualitatively consistent point estimates for the coefficients, but the validity tests indicate a weak explanatory power at the first stage.

Summing up, the lag-based and both IV approaches to cope with the endogeneity of AT diffusion measures support our analysis qualitatively, but the trade-based IV approach suffers from the weakness of instruments.[11]

[11] We have also experimented with alternative external IV approaches to construct Bartik-style IVs, but we ran into similar issues in terms of the validity of instrument validity.

D.1. Using lagged $(t-1)$ measures of ATs as controls

Table D.5: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t-1}$	-0.000	-0.002	0.014	-0.014	0.032	0.034	0.197	-0.199	-0.054	0.528	-0.759
	(0.017)	(0.027)	(0.048)	(0.028)	(0.786)	(0.336)	(0.511)	(0.162)	(0.600)	(0.844)	(0.771)
$ICT_{c,t-1}$	-0.026	0.040	-0.038	-0.068	-0.139	0.140	-0.135	-0.144	0.370	-0.168	-0.037
	(0.018)	(0.067)	(0.047)	(0.044)	(0.583)	(0.384)	(0.571)	(0.252)	(1.093)	(1.077)	(0.812)
$R*ICT_{c,t-1}$	0.013	-0.014	0.034	0.024	0.247	-0.183	0.362*	0.068	-0.535	0.462	-0.074
	(0.009)	(0.023)	(0.023)	(0.019)	(0.288)	(0.139)	(0.205)	(0.111)	(0.328)	(0.367)	(0.297)
$D*R_{c,t-1}$	-0.075***	-0.106**	-0.126**	-0.024	-1.191	-0.310	-1.285*	0.404	0.413	-2.717**	2.123***
	(0.025)	(0.047)	(0.049)	(0.060)	(0.810)	(0.283)	(0.641)	(0.255)	(0.825)	(1.078)	(0.691)
$D*ICT_{c,t-1}$	0.038**	0.026	0.068	0.062	0.487	-0.068	0.589	-0.034	-0.517	0.955	-0.598
	(0.018)	(0.056)	(0.052)	(0.043)	(0.708)	(0.433)	(0.691)	(0.228)	(1.114)	(1.173)	(0.863)
$D*R*ICT_{c,t-1}$	-0.041**	-0.052	-0.119***	-0.005	-1.236	0.095	-1.767***	0.436**	1.285	-2.959***	1.865**
	(0.019)	(0.067)	(0.037)	(0.033)	(0.765)	(0.409)	(0.601)	(0.158)	(0.767)	(0.821)	(0.723)
$wL_{c,t}$	0.444***	0.657***	0.409	0.477***	-0.446**	-0.002	0.150	-0.594***	0.429*	0.919***	-1.359***
	(0.118)	(0.227)	(0.246)	(0.067)	(0.200)	(0.092)	(0.145)	(0.094)	(0.244)	(0.281)	(0.219)
$rK_{c,t}$	0.008	0.193	-0.002	0.025	-0.641***	-0.085	0.069	-0.625***	0.353	0.858***	-1.253***
	(0.074)	(0.205)	(0.125)	(0.092)	(0.179)	(0.087)	(0.123)	(0.079)	(0.219)	(0.214)	(0.207)
N	380	380	380	380	380	380	380	380	380	380	380

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. 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 computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table D.6: The replacement effect

	ln $wL_{i,c,t}$	ln $w_{i,c,t}$	ln $L_{i,c,t}$	ln $rK_{i,c,t}$	ln $r_{i,c,t}$	ln $K_{i,c,t}$
$R_{i,c,t-1}$	-0.024	0.013	-0.036*	-0.025	-0.003	-0.016
	(0.023)	(0.010)	(0.018)	(0.047)	(0.003)	(0.018)
$ICT_{i,c,t-1}$	-0.015	0.007	-0.022	-0.015	-0.008**	-0.022
	(0.015)	(0.007)	(0.015)	(0.059)	(0.003)	(0.030)
$R * ICT_{i,c,t-1}$	-0.009	-0.000	-0.009	0.023	-0.002*	0.007
	(0.006)	(0.003)	(0.006)	(0.015)	(0.001)	(0.006)
$D * R_{i,c,t-1}$	0.014	0.006	0.008	-0.064	0.001	0.040
	(0.038)	(0.013)	(0.037)	(0.092)	(0.007)	(0.029)
$D * ICT_{i,c,t-1}$	0.053***	-0.001	0.054***	-0.013	0.011	0.066*
	(0.016)	(0.011)	(0.014)	(0.074)	(0.016)	(0.035)
$D * R * ICT_{i,c,t-1}$	0.015	0.000	0.014	-0.087	0.000	0.005
	(0.013)	(0.005)	(0.013)	(0.052)	(0.005)	(0.017)
N	4668	4668	4668	4619	4578	4578

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. All regressions use industry level data for nineteen European countries during 1995-2016 for the set of industries susceptible to automation, and include: country-industry (*ci*); country-year (*ct*); and industry-year (*it*) fixed effects that are further interacted with D. 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.

Table D.7: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t-1}$	-0.046	0.025	-0.063	-0.010	-1.581***	0.008
	(0.034)	(0.022)	(0.040)	(0.024)	(0.475)	(0.007)
$ICT_{c,t-1}$	-0.049	0.046	0.040	0.077	2.181***	0.015
	(0.030)	(0.029)	(0.028)	(0.049)	(0.737)	(0.009)
$R * ICT_{c,t-1}$	0.007	-0.018	-0.040**	-0.028	-0.502	0.000
	(0.015)	(0.012)	(0.018)	(0.027)	(0.331)	(0.005)
$D * R_{c,t-1}$	-0.140*	-0.066	-0.029	-0.076*	0.074	0.002
	(0.069)	(0.039)	(0.062)	(0.038)	(0.767)	(0.015)
$D * ICT_{c,t-1}$	0.099**	-0.035*	-0.018	-0.063	-2.387**	-0.015*
	(0.042)	(0.019)	(0.033)	(0.042)	(0.870)	(0.007)
$D * R * ICT_{c,t-1}$	-0.130	-0.008	-0.015	0.011	1.048	-0.002
	(0.095)	(0.042)	(0.048)	(0.019)	(1.179)	(0.008)
N	380	380	380	380	380	380

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table D.8: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL + rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t-1}$	-0.017	-0.034	-0.029	-0.010	0.072**	-0.039	0.018	0.022	-0.015
	(0.047)	(0.034)	(0.034)	(0.034)	(0.033)	(0.030)	(0.030)	(0.025)	(0.017)
$ICT_{c,t-1}$	-0.011	0.126*	0.043	0.029	0.009	-0.014	-0.026	-0.005	0.005
	(0.028)	(0.062)	(0.038)	(0.031)	(0.019)	(0.024)	(0.030)	(0.016)	(0.011)
$R * ICT_{c,t-1}$	-0.001	-0.062*	-0.027	-0.026	0.008	0.002	0.014	-0.007	0.001
	(0.020)	(0.036)	(0.025)	(0.023)	(0.015)	(0.010)	(0.018)	(0.011)	(0.004)
$D * R_{c,t-1}$	-0.220***	-0.164***	-0.198***	-0.176**	-0.154***	-0.107***	-0.076	-0.082**	0.021
	(0.074)	(0.052)	(0.058)	(0.061)	(0.049)	(0.026)	(0.050)	(0.035)	(0.017)
$D * ICT_{c,t-1}$	0.057**	-0.070	0.006	0.023	0.010	0.025	0.042*	0.004	-0.031***
	(0.024)	(0.047)	(0.026)	(0.022)	(0.017)	(0.019)	(0.024)	(0.012)	(0.009)
$D * R * ICT_{c,t-1}$	-0.101**	-0.064*	-0.082**	-0.100**	-0.049*	-0.014	-0.055	0.009	0.084**
	(0.038)	(0.034)	(0.029)	(0.036)	(0.023)	(0.024)	(0.051)	(0.040)	(0.038)
N	380	380	380	380	296	296	296	296	296

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

D.2. Using deeper lags ($t-1$, $t-2$, $t-3$) of AT measures as IV

Table D.9: Taxation and automation

	Taxes in ln of nat. currency				Taxes as % of GDP				Taxes as % of total tax		
	$\ln T_{c,t}$	$\ln T^l_{c,t}$	$\ln T^k_{c,t}$	$\ln T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	-0.014	0.004	-0.012	-0.031	0.256	0.188	0.035	0.033	-0.041	-0.568	-0.285
	(0.014)	(0.037)	(0.040)	(0.021)	(0.522)	(0.276)	(0.396)	(0.173)	(0.658)	(0.943)	(0.571)
$ICT_{c,t}$	-0.095*	0.390	-0.163*	-0.254**	1.203	2.164	-0.706	-0.254	3.566	-4.806**	0.209
	(0.055)	(0.340)	(0.089)	(0.127)	(2.827)	(2.069)	(1.252)	(0.449)	(2.819)	(2.385)	(1.937)
$R * ICT_{c,t}$	0.038**	-0.110	0.080**	0.082**	-0.145	-0.799	0.595	0.059	-1.511*	2.127**	-0.280
	(0.018)	(0.102)	(0.032)	(0.037)	(0.913)	(0.663)	(0.426)	(0.151)	(0.905)	(0.833)	(0.655)
$D * R_{c,t}$	-0.050***	-0.104**	-0.097**	0.011	-1.167*	-0.463	-1.006**	0.303	0.124	-1.710*	1.718***
	(0.019)	(0.048)	(0.045)	(0.029)	(0.605)	(0.326)	(0.456)	(0.204)	(0.808)	(1.007)	(0.634)
$D * ICT_{c,t}$	0.052	-0.547	0.045	0.225*	-1.846	-1.571	-0.664	0.389	-1.467	1.688	0.467
	(0.053)	(0.399)	(0.091)	(0.134)	(2.841)	(2.096)	(1.304)	(0.477)	(2.903)	(2.522)	(1.998)
$D * R * ICT_{c,t}$	-0.029	0.131	-0.065	-0.059	0.030	0.653	-0.792	0.169	1.283	-2.131**	1.041
	(0.021)	(0.129)	(0.040)	(0.046)	(1.155)	(0.814)	(0.552)	(0.186)	(1.107)	(1.009)	(0.778)
$wL_{c,t}$	0.444***	0.937***	0.394***	0.435***	-0.446***	-0.020	0.158*	-0.583***	0.407**	0.887***	-1.316***
	(0.084)	(0.259)	(0.138)	(0.116)	(0.108)	(0.068)	(0.085)	(0.050)	(0.166)	(0.200)	(0.145)
$rK_{c,t}$	0.010	0.139	-0.033	0.064	-0.658***	-0.109*	0.056	-0.605***	0.322**	0.805***	-1.197***
	(0.051)	(0.138)	(0.097)	(0.073)	(0.104)	(0.066)	(0.078)	(0.046)	(0.156)	(0.180)	(0.137)
Under-F	12.8	12.8	12.8	12.8	12.5	12.5	12.5	12.5	12.5	12.5	12.5
Under-p	.077	.077	.077	.077	.0867	.0867	.0867	.0867	.0867	.0867	.0867
Weak-CD F	7.8	7.8	7.8	7.8	7.09	7.09	7.09	7.09	7.09	7.09	7.09
Weak-KP rk F	1.32	1.32	1.32	1.32	1.01	1.01	1.01	1.01	1.01	1.01	1.01
Over-Hansen J	5.08	9.56	2.33	10.9	3.58	9.48	2.3	4.6	8.52	2.1	1.5
Over-Hansen J p	.533	.144	.887	.0922	.733	.148	.89	.596	.202	.91	.959
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. 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 computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table D.10: The replacement effect

	ln $wL_{i,c,t}$	ln $w_{i,c,t}$	ln $L_{i,c,t}$	ln $rK_{i,c,t}$	ln $r_{i,c,t}$	ln $K_{i,c,t}$
$R_{i,c,t}$	0.001	0.015	-0.014	-0.029	0.005	0.000
	(0.029)	(0.010)	(0.025)	(0.068)	(0.005)	(0.022)
$ICT_{i,c,t}$	-0.008	0.010	-0.017	-0.039	-0.008	-0.041
	(0.021)	(0.010)	(0.020)	(0.060)	(0.015)	(0.040)
$R * ICT_{i,c,t}$	-0.010**	0.001	-0.011**	0.023*	-0.002*	0.007
	(0.005)	(0.002)	(0.005)	(0.013)	(0.001)	(0.005)
$D * R_{i,c,t}$	-0.009	0.007	-0.016	0.035	-0.007	0.029
	(0.030)	(0.011)	(0.026)	(0.071)	(0.007)	(0.023)
$D * ICT_{i,c,t}$	0.046**	-0.002	0.048**	0.041	0.010	0.087**
	(0.023)	(0.011)	(0.022)	(0.062)	(0.019)	(0.042)
$D * R * ICT_{i,c,t}$	0.015**	0.001	0.014*	-0.028	0.001	0.009
	(0.007)	(0.004)	(0.007)	(0.022)	(0.003)	(0.009)
Under-F	41.2	41.2	41.2	41.5	41.2	41.2
Under-p	7.29e-07	7.29e-07	7.29e-07	6.43e-07	7.32e-07	7.32e-07
Weak-CD F	324	324	324	320	318	318
Weak-KP rk F	11	11	11	11.1	11	11
Over-Hansen J	4.43	12	10.6	7.09	7.62	5.79
Over-Hansen J p	.619	.0631	.101	.313	.267	.448
N	4897	4897	4897	4842	4802	4802

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. All regressions use industry level data for nineteen European countries during 1995-2016 for the set of industries susceptible to automation, and include: country-industry (ci); country-year (ct); and industry-year (it) fixed effects that are further interacted with D. 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.

Table D.11: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.100***	0.002	-0.115***	-0.041	-0.848*	0.007
	(0.033)	(0.021)	(0.035)	(0.026)	(0.496)	(0.009)
$ICT_{c,t}$	-0.015	-0.058	0.005	0.019	2.741**	0.032
	(0.092)	(0.071)	(0.081)	(0.073)	(1.289)	(0.029)
$R * ICT_{c,t}$	-0.010	0.028	-0.024	0.001	-0.585	-0.006
	(0.034)	(0.022)	(0.028)	(0.025)	(0.411)	(0.010)
$D * R_{c,t}$	-0.125***	-0.039	-0.016	-0.049*	-0.477	0.008
	(0.039)	(0.026)	(0.039)	(0.029)	(0.592)	(0.012)
$D * ICT_{c,t}$	0.345***	-0.119*	0.123	-0.103	-5.016***	-0.008
	(0.088)	(0.070)	(0.080)	(0.075)	(1.440)	(0.029)
$D * R * ICT_{c,t}$	-0.227***	0.036	-0.059**	0.036	1.972***	-0.006
	(0.038)	(0.023)	(0.030)	(0.029)	(0.544)	(0.011)
Under-F	13.9	13.9	13.9	13.9	13.9	13.9
Under-p	.0536	.0536	.0536	.0536	.0536	.0536
Weak-CD F	7.95	7.95	7.95	7.95	7.95	7.95
Weak-KP rk F	1.17	1.17	1.17	1.17	1.17	1.17
Over-Hansen J	11.2	7.26	6.39	11.9	15.8	11.7
Over-Hansen J p	.0815	.298	.381	.0647	.0146	.0686
N	395	395	395	395	395	395

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table D.12: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL+rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t}$	-0.084*	-0.131**	-0.108**	-0.091**	0.046**	-0.047**	-0.001	0.012	-0.007
	(0.045)	(0.059)	(0.046)	(0.045)	(0.022)	(0.022)	(0.020)	(0.020)	(0.011)
$ICT_{c,t}$	-0.061	-0.066	-0.064	-0.087	-0.001	0.025	-0.001	-0.034	0.035
	(0.112)	(0.138)	(0.118)	(0.119)	(0.051)	(0.056)	(0.043)	(0.050)	(0.032)
$R*ICT_{c,t}$	0.021	0.023	0.020	0.021	0.012	-0.012	-0.003	0.003	-0.007
	(0.041)	(0.047)	(0.042)	(0.042)	(0.021)	(0.023)	(0.018)	(0.019)	(0.012)
$D*R_{c,t}$	-0.187***	-0.084	-0.147***	-0.114**	-0.124***	-0.110***	-0.044*	-0.052**	0.019
	(0.053)	(0.064)	(0.053)	(0.052)	(0.027)	(0.023)	(0.023)	(0.024)	(0.012)
$D*ICT_{c,t}$	0.175	-0.057	0.080	0.143	0.031	-0.019	0.171***	0.029	-0.139***
	(0.111)	(0.142)	(0.118)	(0.122)	(0.057)	(0.058)	(0.048)	(0.060)	(0.036)
$D*R*ICT_{c,t}$	-0.141***	-0.062	-0.104**	-0.140***	-0.063**	-0.025	-0.112***	-0.027	0.099***
	(0.046)	(0.055)	(0.048)	(0.048)	(0.027)	(0.033)	(0.024)	(0.030)	(0.020)
Under-F	13.9	13.9	13.9	13.9	13.2	13.2	13.2	13.2	13.2
Under-p	.0538	.0538	.0538	.0538	.0663	.0663	.0663	.0663	.0663
Weak-CD F	8	8	8	8	5.98	5.98	5.98	5.98	5.98
Weak-KP rk F	1.19	1.19	1.19	1.19	1.1	1.1	1.1	1.1	1.1
Over-Hansen J	10.4	9.61	11.4	12.7	8.63	6.12	10.1	8.07	3.7
Over-Hansen J p	.108	.142	.076	.0484	.196	.41	.119	.233	.717
N	395	395	395	395	309	309	309	309	309

Notes: $*\ p<0.05$, $**\ p<0.01$, $***\ p<0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

D.3. Using trade data on imports of robot and ICT products to construct external IVs for the AT measures

Table D.13: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	0.005	0.004	0.031	-0.005	0.401	0.032	0.396	-0.027	-0.677	0.838	-0.632
	(0.013)	(0.028)	(0.044)	(0.021)	(0.482)	(0.258)	(0.378)	(0.141)	(0.730)	(0.872)	(0.510)
$ICT_{c,t}$	-0.048	0.149	-0.072	-0.122**	-0.183	-0.344	0.292	-0.131	0.119	-0.701	0.948
	(0.034)	(0.104)	(0.069)	(0.061)	(1.162)	(0.558)	(0.931)	(0.380)	(1.305)	(1.484)	(1.287)
$R * ICT_{c,t}$	0.017	-0.033	0.038	0.031	0.192	-0.017	0.204	0.005	-0.350	0.619	-0.493
	(0.011)	(0.029)	(0.024)	(0.019)	(0.389)	(0.188)	(0.287)	(0.131)	(0.450)	(0.493)	(0.437)
$D * R_{c,t}$	-0.071***	-0.094**	-0.143***	-0.019	-1.294**	-0.269	-1.392***	0.367**	0.830	-3.226***	2.079***
	(0.018)	(0.042)	(0.054)	(0.029)	(0.593)	(0.299)	(0.513)	(0.177)	(0.928)	(1.087)	(0.595)
$D * ICT_{c,t}$	0.010	-0.295*	-0.037	0.095	-0.317	1.030	-1.609	0.262	1.996	-2.272	-0.363
	(0.041)	(0.178)	(0.088)	(0.071)	(1.427)	(0.696)	(1.147)	(0.434)	(1.646)	(1.910)	(1.555)
$D * R * ICT_{c,t}$	-0.012	0.052	-0.033	-0.014	-0.395	-0.168	-0.453	0.226	0.151	-0.783	1.317**
	(0.019)	(0.059)	(0.041)	(0.029)	(0.694)	(0.323)	(0.514)	(0.182)	(0.738)	(0.873)	(0.617)
$wL_{c,t}$	0.455***	0.909***	0.417***	0.458***	-0.426***	0.013	0.146*	-0.585***	0.451***	0.836***	-1.326***
	(0.084)	(0.248)	(0.134)	(0.120)	(0.110)	(0.068)	(0.084)	(0.048)	(0.162)	(0.194)	(0.147)
$rK_{c,t}$	0.016	0.187	-0.018	0.057	-0.627***	-0.062	0.044	-0.608***	0.377**	0.753***	-1.217***
	(0.051)	(0.124)	(0.094)	(0.070)	(0.103)	(0.064)	(0.076)	(0.044)	(0.153)	(0.173)	(0.139)
Under-F	52.4	52.4	52.4	52.4	55.5	55.5	55.5	55.5	55.5	55.5	55.5
Under-p	0.999	0.999	0.999	0.999	.999	.999	.999	.999	.999	.999	.999
Weak-CD F	1.44	1.44	1.44	1.44	1.32	1.32	1.32	1.32	1.32	1.32	1.32
Weak-KP rk F	.876	.876	.876	.876	.868	.868	.868	.868	.868	.868	.868
Over-Hansen J	136	111	123	157	153	138	134	132	129	125	139
Over-Hansen J p	.002	.0914	.016	.0000276	.0000751	.00133	.00302	.00386	.00673	.012	.00105
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. 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 computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table D.14: The reinstatement effect

	$\ln w_{c,t}$	$\ln L_{c,t}$	$\ln r_{c,t}$	$\ln K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.066***	0.034**	-0.059**	0.005	-1.740***	0.006
	(0.025)	(0.014)	(0.023)	(0.016)	(0.512)	(0.007)
$ICT_{c,t}$	-0.133*	-0.005	-0.028	0.014	1.943	0.048*
	(0.078)	(0.053)	(0.074)	(0.069)	(1.244)	(0.028)
$R * ICT_{c,t}$	0.022	0.001	-0.020	-0.009	-0.161	-0.008
	(0.027)	(0.016)	(0.022)	(0.024)	(0.475)	(0.008)
$D * R_{c,t}$	-0.158***	-0.072***	-0.074**	-0.097***	0.459	0.008
	(0.037)	(0.021)	(0.030)	(0.022)	(0.632)	(0.010)
$D * ICT_{c,t}$	0.459***	-0.167***	0.153**	-0.096	-4.260***	-0.025
	(0.082)	(0.058)	(0.076)	(0.069)	(1.289)	(0.028)
$D * R * ICT_{c,t}$	-0.257***	0.058***	-0.063**	0.043*	1.613***	-0.003
	(0.038)	(0.019)	(0.027)	(0.026)	(0.570)	(0.009)
Under-F	50.5	50.5	50.5	50.5	50.5	50.5
Under-p	0.999	0.999	0.999	0.999	0.999	0.999
Weak-CD F	1.28	1.28	1.28	1.28	1.28	1.28
Weak-KP rk F	.658	.658	.658	.658	.658	.658
Over-Hansen J	149	123	155	142	130	136
Over-Hansen J p	.000168	.017	.000044	.00067	.0059	.00194
N	395	395	395	395	395	395

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table D.15: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL + rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t}$	-0.028	-0.003	-0.021	0.005	0.077***	-0.037**	0.023	0.025	-0.013
	(0.036)	(0.033)	(0.028)	(0.028)	(0.019)	(0.017)	(0.019)	(0.016)	(0.008)
$ICT_{c,t}$	-0.106	0.061	-0.036	-0.041	-0.000	-0.013	-0.034	-0.048	-0.010
	(0.105)	(0.101)	(0.094)	(0.096)	(0.040)	(0.044)	(0.034)	(0.041)	(0.021)
$R * ICT_{c,t}$	0.024	-0.028	-0.001	-0.006	0.011	-0.004	0.009	0.008	0.008
	(0.035)	(0.037)	(0.032)	(0.032)	(0.017)	(0.018)	(0.015)	(0.016)	(0.008)
$D * R_{c,t}$	-0.245***	-0.218***	-0.238***	-0.215***	-0.155***	-0.120***	-0.068***	-0.065***	0.025**
	(0.045)	(0.044)	(0.038)	(0.038)	(0.024)	(0.022)	(0.023)	(0.024)	(0.011)
$D * ICT_{c,t}$	0.218*	-0.185*	0.052	0.096	0.030	0.019	0.202***	0.042	-0.094***
	(0.112)	(0.111)	(0.103)	(0.105)	(0.044)	(0.052)	(0.036)	(0.046)	(0.026)
$D * R * ICT_{c,t}$	-0.145***	-0.016	-0.086**	-0.117***	-0.062***	-0.035	-0.122***	-0.031	0.085***
	(0.044)	(0.048)	(0.043)	(0.043)	(0.023)	(0.032)	(0.021)	(0.026)	(0.016)
Under-F	50.1	50.1	50.1	50.1	46.6	46.6	46.6	46.6	46.6
Under-p	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
Weak-CD F	1.3	1.3	1.3	1.3	1.65	1.65	1.65	1.65	1.65
Weak-KP rk F	.657	.657	.657	.657	.906	.906	.906	.906	.906
Over-Hansen J	147	148	148	151	156	116	137	127	113
Over-Hansen J p	.000221	.000213	.000187	.000104	.0000342	.0482	.00158	.00923	.0683
N	395	395	395	395	309	309	309	309	309

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

E. Taxes, trade and income distribution

In this section, we provide the results from a series of robustness checks. First, we make sure that our results are not driven by changes in the tax system. Unfortunately, comprehensive data that covers the whole range of different taxes that is consistent across our sample of countries and covers a reasonable number of years is not available. We are only able to proxy tax reforms using data on corporate taxation that cover a smaller period of time but all countries in our sample. We use two different data sources.

In E.1, we repeat all baseline country level regressions and include as an additional control the corporate tax rate ($CRT_{c,t}$) sourced from KPMG.[12] This data are only available between 2003-2016. Next, in E.2 we repeat all baseline country level regressions and include, as an additional control, the effective tax rate ($ETR_{c,t}$) sourced from Eurostat.[13] The ETR variable is only available between 2006-2016.

Another concern 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 percentage of GDP sourced from the OECD National Accounts Database.[14] Results are shown in Table E.3.

Furthermore, to explore the nexus between distribution and taxation, we examine the progressiveness of taxation in Table E.4. To do so, we rely on the same empirical specification used to understand the determinants of taxation, but now our regressions include, as an additional control, the Gini coefficient measuring cross-industry wage inequality ($Gini^{w}_{c,t}$) sourced from Eurostat.

Finally, we also test whether the attribution of capital taxes within the broad categories from OECD might affect our results. In particular we test whether the exclusion of the OECD tax category 1100 "taxes on income, profits and capital gains of individuals" from the taxes on capital T^k changes the interpretation of our findings (assuming that these are neither capital nor labor taxes in the strict sense of their origin). The results are presented in E.5 where we find similar results as in our baseline but the share of taxes as a percent of total taxes and GDP drops significantly due to this omission.

[12] The data were sourced from the KPMG website: https://home.kpmg/xx/en/home/services/tax/tax-tools-and-resources/tax-rates-online.html

[13] This is the Effective Average Tax Rate (ETR) for large corporations in non-financial sector, computed at corporate level, for average asset composition and funding sources, using the Devereux/Griffith methodology. The data are available in Eurostat: https://ec.europa.eu/taxation_customs/business/economic-analysis-taxation/data-taxation_en

[14] Find data in OECD: https://stats.oecd.org/viewhtml.aspx?datasetcode=NAAG&lang=en#

E.1. Controlling for changes in corporate taxation using KPMG data

Table E.16: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	-0.009	0.016	0.010	-0.041	0.001	0.235	0.097	-0.331*	0.684	0.369	-1.012
	(0.017)	(0.027)	(0.045)	(0.026)	(0.571)	(0.422)	(0.422)	(0.181)	(0.804)	(0.829)	(0.711)
$ICT_{c,t}$	-0.007	-0.029	-0.002	-0.013	0.168	-0.133	0.074	0.227*	-1.179	0.413	0.754
	(0.021)	(0.046)	(0.034)	(0.052)	(0.389)	(0.446)	(0.304)	(0.124)	(0.850)	(0.668)	(0.468)
$R * ICT_{c,t}$	0.002	0.023	0.008	-0.007	0.071	-0.053	0.223	-0.099	0.273	0.012	-0.327
	(0.013)	(0.027)	(0.022)	(0.027)	(0.413)	(0.237)	(0.369)	(0.073)	(0.341)	(0.456)	(0.307)
$D * R_{c,t}$	-0.141***	-0.133*	0.031	-0.145	0.078	-0.585	0.050	0.614	-1.364	-0.570	2.136
	(0.045)	(0.072)	(0.106)	(0.130)	(1.077)	(0.974)	(1.075)	(0.619)	(2.736)	(2.522)	(1.450)
$D * ICT_{c,t}$	0.130***	0.048	-0.060	0.270***	0.682	1.444*	-0.942	0.179	4.262**	-2.678	-1.603
	(0.033)	(0.104)	(0.069)	(0.086)	(1.358)	(0.711)	(0.813)	(0.681)	(1.830)	(1.679)	(1.135)
$D * R * ICT_{c,t}$	-0.092***	-0.100***	-0.089	-0.076*	-1.775**	-0.993***	-1.028	0.246	-1.422	-0.967	2.592***
	(0.023)	(0.032)	(0.066)	(0.039)	(0.782)	(0.310)	(1.057)	(0.345)	(1.042)	(1.414)	(0.824)
$wL_{c,t}$	0.438***	0.353*	0.512**	0.500***	-0.608***	0.027	0.075	-0.710***	0.626**	0.983**	-1.628***
	(0.066)	(0.169)	(0.235)	(0.080)	(0.164)	(0.063)	(0.165)	(0.082)	(0.251)	(0.405)	(0.260)
$rK_{c,t}$	0.032	0.179	0.154	-0.176**	-0.671***	0.007	0.053	-0.731***	0.668***	0.932***	-1.608***
	(0.054)	(0.110)	(0.129)	(0.074)	(0.129)	(0.039)	(0.129)	(0.084)	(0.187)	(0.278)	(0.247)
N	266	266	266	266	266	266	266	266	266	266	266

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. All regressions use country level data for nineteen European countries during 2003-2016 and include: GDP growth, gross output share of service industries in the total economy; Herfindahl-Hirschman Index computed 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; corporate tax rate; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table E.17: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.050	0.031*	-0.041	-0.007	-1.847***	0.008
	(0.030)	(0.016)	(0.025)	(0.021)	(0.371)	(0.005)
$ICT_{c,t}$	-0.028	-0.000	0.025	0.060	3.036***	0.011
	(0.043)	(0.028)	(0.037)	(0.040)	(1.002)	(0.008)
$R * ICT_{c,t}$	-0.010	0.008	-0.026	-0.014	-1.023	0.003
	(0.019)	(0.014)	(0.019)	(0.023)	(0.650)	(0.005)
$D * R_{c,t}$	-0.416**	-0.200***	-0.320**	-0.192*	-0.210	0.025
	(0.143)	(0.032)	(0.125)	(0.094)	(1.675)	(0.043)
$D * ICT_{c,t}$	0.096	-0.027	-0.027	-0.001	-1.238	-0.031
	(0.119)	(0.060)	(0.075)	(0.141)	(3.669)	(0.018)
$D * R * ICT_{c,t}$	-0.077	-0.018	0.029	-0.051	0.766	0.006
	(0.058)	(0.031)	(0.044)	(0.083)	(1.007)	(0.009)
N	266	266	266	266	266	266

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the reinstatement effect for nineteen European countries during the period 2003-2016. 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; corporate tax rate; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table E.18: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL+rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t}$	-0.005	-0.027	-0.019	0.001	0.076***	-0.031**	0.028	0.038**	-0.001
	(0.034)	(0.033)	(0.020)	(0.025)	(0.024)	(0.014)	(0.027)	(0.017)	(0.010)
$ICT_{c,t}$	-0.013	0.082	0.028	0.016	0.006	-0.003	-0.005	0.006	0.003
	(0.060)	(0.047)	(0.048)	(0.060)	(0.033)	(0.037)	(0.028)	(0.020)	(0.007)
$R * ICT_{c,t}$	0.008	-0.031	-0.012	-0.012	0.011	-0.004	0.002	-0.009	0.010*
	(0.031)	(0.029)	(0.027)	(0.032)	(0.019)	(0.021)	(0.016)	(0.010)	(0.005)
$D * R_{c,t}$	-0.691***	-0.345*	-0.568**	-0.517**	-0.237*	-0.350*	-0.035	-0.149	-0.049
	(0.221)	(0.186)	(0.200)	(0.206)	(0.122)	(0.166)	(0.121)	(0.094)	(0.043)
$D * ICT_{c,t}$	0.198	0.053	0.151	0.216	0.136	0.100	0.137	0.172***	-0.071
	(0.179)	(0.182)	(0.180)	(0.151)	(0.103)	(0.082)	(0.091)	(0.048)	(0.059)
$D * R * ICT_{c,t}$	-0.139	-0.123	-0.124	-0.142	-0.145*	-0.047	-0.115*	-0.102**	-0.002
	(0.094)	(0.103)	(0.103)	(0.093)	(0.072)	(0.047)	(0.056)	(0.044)	(0.030)
N	266	266	266	266	210	210	210	210	210

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 2003-2016. Labor productivity 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. 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; corporate tax rate; period average exchange rate; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

E.2. Controlling for changes in corporate taxation using Eurostat data

Table E.19: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	-0.008	-0.011	0.020	-0.052	0.278	0.263	0.237	-0.206	0.115	0.502	-0.976
	(0.020)	(0.024)	(0.048)	(0.032)	(0.610)	(0.429)	(0.406)	(0.204)	(0.906)	(0.749)	(0.631)
$ICT_{c,t}$	0.015	-0.017	0.019	0.016	0.270	-0.124	0.177	0.163	-0.865	0.646	0.587
	(0.031)	(0.041)	(0.033)	(0.055)	(0.481)	(0.557)	(0.465)	(0.157)	(1.162)	(0.871)	(0.531)
$R * ICT_{c,t}$	-0.012	0.008	-0.001	-0.030	0.055	-0.064	0.237	-0.091	0.090	-0.068	-0.326
	(0.020)	(0.025)	(0.032)	(0.031)	(0.591)	(0.324)	(0.592)	(0.110)	(0.708)	(0.690)	(0.434)
$D * R_{c,t}$	-0.055	-0.013	0.118	0.123	-0.534	-2.532**	1.446	-0.027	-0.292	4.263	1.298
	(0.080)	(0.016)	(0.160)	(0.136)	(2.331)	(0.899)	(1.474)	(0.087)	(0.300)	(2.817)	(2.344)
$D * ICT_{c,t}$	0.151	0.017	-0.026	0.244**	-2.045	1.247	-1.356	-0.145	0.927***	-0.269	-3.934
	(0.094)	(0.015)	(0.203)	(0.106)	(3.483)	(1.033)	(3.048)	(0.086)	(0.319)	(3.734)	(3.391)
$D * R * ICT_{c,t}$	-0.147	-0.002	-0.229	-0.086	-2.272	0.054	-3.939**	0.044	-1.623***	-6.526**	5.233**
	(0.089)	(0.038)	(0.172)	(0.077)	(1.927)	(0.490)	(1.312)	(0.128)	(0.551)	(2.732)	(2.011)
$wL_{c,t}$	0.415***	0.135	0.561**	0.380***	-0.658***	0.026	0.092	-0.811***	0.333	1.098**	-1.756***
	(0.059)	(0.224)	(0.231)	(0.098)	(0.161)	(0.068)	(0.190)	(0.061)	(0.463)	(0.488)	(0.323)
$rK_{c,t}$	0.035	0.157	0.162	-0.218**	-0.705***	0.006	0.065	-0.803***	0.455	1.019**	-1.696***
	(0.054)	(0.145)	(0.107)	(0.074)	(0.124)	(0.034)	(0.148)	(0.068)	(0.363)	(0.335)	(0.295)
N	209	209	209	209	209	209	209	209	209	209	209

Notes: $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. All regressions use country level data for nineteen European countries during 2006-2016 and include: GDP growth, gross output share of service industries in the total economy; Herfindahl-Hirschman Index computed 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; effective tax rate; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table E.20: The reinstatement effect

	$\ln w_{c,t}$	$\ln L_{c,t}$	$\ln r_{c,t}$	$\ln K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.035	0.018	-0.035	-0.006	-1.583**	0.009*
	(0.028)	(0.018)	(0.023)	(0.023)	(0.523)	(0.004)
$ICT_{c,t}$	0.006	0.005	0.036	0.100*	1.979	0.007
	(0.025)	(0.036)	(0.039)	(0.045)	(1.144)	(0.007)
$R*ICT_{c,t}$	-0.031*	-0.001	-0.038	-0.033	-0.534	0.007
	(0.017)	(0.022)	(0.025)	(0.031)	(0.655)	(0.005)
$D*R_{c,t}$	-0.261	-0.146***	-0.174	-0.097	-2.667	0.090
	(0.165)	(0.039)	(0.098)	(0.098)	(3.001)	(0.054)
$D*ICT_{c,t}$	0.179*	0.097	0.071	0.109	-0.633	-0.017
	(0.091)	(0.092)	(0.099)	(0.113)	(1.727)	(0.030)
$D*R*ICT_{c,t}$	-0.040	-0.075**	0.084	-0.127*	0.342	-0.011
	(0.051)	(0.029)	(0.062)	(0.057)	(1.228)	(0.014)
N	209	209	209	209	209	209

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the reinstatement effect for nineteen European countries during the period 2006-2016. 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); effective tax rate; period average exchange rate; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table E.21: The real income effect

	$\ln wL_{c,t}$	$\ln rK_{c,t}$	$\ln (wL+rK)_{c,t}$	$\ln pQ_{c,t}$	$\ln Q_{c,t}$	$\ln p_{c,t}$	$\ln LProd_{c,t}$	$\ln KProd_{c,t}$	$\ln TFP_{c,t}$
$R_{c,t}$	-0.009	-0.034	-0.024	-0.006	0.069***	-0.034**	0.030	0.043***	-0.003
	(0.031)	(0.039)	(0.024)	(0.025)	(0.021)	(0.012)	(0.022)	(0.013)	(0.010)
$ICT_{c,t}$	0.043	0.123*	0.079*	0.067	0.050**	0.023	0.021	0.028**	0.021***
	(0.037)	(0.061)	(0.039)	(0.055)	(0.019)	(0.025)	(0.018)	(0.009)	(0.003)
$R*ICT_{c,t}$	-0.028	-0.057	-0.046	-0.046	-0.013	-0.024	-0.012	-0.017*	-0.001
	(0.030)	(0.037)	(0.028)	(0.034)	(0.019)	(0.016)	(0.013)	(0.008)	(0.009)
$D*R_{c,t}$	-0.384*	-0.245	-0.326	-0.178	-0.063	-0.142	0.046	0.060	-0.031
	(0.197)	(0.204)	(0.191)	(0.171)	(0.102)	(0.124)	(0.094)	(0.077)	(0.018)
$D*ICT_{c,t}$	0.282**	0.306**	0.317***	0.336***	0.185*	0.096*	0.144*	0.039	-0.061
	(0.118)	(0.135)	(0.083)	(0.089)	(0.099)	(0.053)	(0.069)	(0.058)	(0.047)
$D*R*ICT_{c,t}$	-0.162**	-0.268***	-0.181**	-0.171**	-0.220***	-0.014	-0.119**	-0.010	-0.017
	(0.055)	(0.077)	(0.066)	(0.071)	(0.055)	(0.024)	(0.051)	(0.074)	(0.015)
N	209	209	209	209	165	165	165	165	165

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 2006-2016. Labor productivity 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. 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; effective tax rate; period average exchange rate; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

E.3. Controlling for trade

Table E.22: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	0.003	0.014	0.012	-0.018	0.185	0.209	0.170	-0.195	0.280	0.304	-0.878
	(0.017)	(0.033)	(0.047)	(0.025)	(0.770)	(0.344)	(0.488)	(0.130)	(0.570)	(0.811)	(0.738)
$ICT_{c,t}$	-0.030*	0.032	-0.040	-0.079*	-0.387	0.135	-0.164	-0.357	0.611	-0.038	-0.307
	(0.016)	(0.049)	(0.048)	(0.038)	(0.524)	(0.316)	(0.479)	(0.232)	(0.899)	(0.904)	(0.624)
$R * ICT_{c,t}$	0.014*	0.000	0.032	0.027	0.307	-0.169	0.348	0.128	-0.573**	0.415	0.032
	(0.008)	(0.019)	(0.023)	(0.016)	(0.267)	(0.119)	(0.205)	(0.083)	(0.266)	(0.357)	(0.237)
$D * R_{c,t}$	-0.069***	-0.092	-0.134**	-0.002	-1.068	-0.461	-1.154**	0.547**	-0.166	-2.694**	2.354***
	(0.021)	(0.065)	(0.060)	(0.050)	(0.675)	(0.371)	(0.512)	(0.211)	(0.885)	(0.947)	(0.759)
$D * ICT_{c,t}$	-0.011	-0.167	-0.075	0.043	-0.166	0.564	-1.177	0.447	1.727	-3.099*	0.846
	(0.029)	(0.187)	(0.078)	(0.057)	(0.901)	(0.664)	(0.872)	(0.386)	(1.670)	(1.704)	(1.435)
$D * R * ICT_{c,t}$	-0.007	0.016	-0.023	-0.003	-0.468	-0.042	-0.555	0.129	0.119	-0.385	0.811
	(0.022)	(0.083)	(0.051)	(0.030)	(0.853)	(0.432)	(0.626)	(0.201)	(0.872)	(1.003)	(1.035)
$wL_{c,t}$	0.430***	0.789**	0.443	0.437***	-0.424**	0.011	0.144	-0.580***	0.486**	0.792***	-1.302***
	(0.134)	(0.306)	(0.291)	(0.056)	(0.196)	(0.095)	(0.136)	(0.081)	(0.210)	(0.246)	(0.186)
$rK_{c,t}$	-0.017	0.098	0.003	0.004	-0.627***	-0.067	0.045	-0.605***	0.402*	0.712***	-1.191***
	(0.087)	(0.154)	(0.163)	(0.109)	(0.180)	(0.091)	(0.112)	(0.071)	(0.197)	(0.188)	(0.181)
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. 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 computed 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; imports as % of GDP; exports as % of GDP; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table E.23: The reinstatement effect

	$\ln w_{c,t}$	$\ln L_{c,t}$	$\ln r_{c,t}$	$\ln K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.041	0.053***	-0.027	-0.013	-0.250	0.012**
	(0.027)	(0.018)	(0.030)	(0.024)	(0.542)	(0.006)
$ICT_{c,t}$	-0.010	0.011	0.057	0.068*	1.826**	0.005
	(0.038)	(0.023)	(0.039)	(0.034)	(0.654)	(0.012)
$R * ICT_{c,t}$	-0.012	0.001	-0.045**	-0.016	-0.370	0.002
	(0.013)	(0.009)	(0.016)	(0.017)	(0.281)	(0.005)
$D * R_{c,t}$	-0.187**	-0.097***	-0.112***	-0.081*	-1.162	0.001
	(0.066)	(0.032)	(0.037)	(0.039)	(0.858)	(0.015)
$D * ICT_{c,t}$	0.329***	-0.173***	0.092	-0.172**	-3.178***	0.024
	(0.096)	(0.028)	(0.075)	(0.076)	(1.000)	(0.019)
$D * R * ICT_{c,t}$	-0.218***	0.052***	-0.056	0.069	1.044	-0.017
	(0.062)	(0.012)	(0.038)	(0.040)	(0.623)	(0.011)
N	395	395	395	395	395	395

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. 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); imports as % of GDP; exports as % of GDP; period average exchange rate; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table E.24: The real income effect

	$\ln wL_{c,t}$	$\ln rK_{c,t}$	$\ln (wL + rK)_{c,t}$	$\ln pQ_{c,t}$	$\ln Q_{c,t}$	$\ln p_{c,t}$	$\ln LProd_{c,t}$	$\ln KProd_{c,t}$	$\ln TFP_{c,t}$
$R_{c,t}$	0.014	-0.048	-0.018	-0.000	0.071**	-0.015	-0.005	0.035*	-0.001
	(0.037)	(0.054)	(0.034)	(0.030)	(0.027)	(0.018)	(0.023)	(0.019)	(0.011)
$ICT_{c,t}$	0.009	0.125**	0.055	0.039	0.022	0.003	0.013	-0.005	0.001
	(0.049)	(0.047)	(0.044)	(0.039)	(0.020)	(0.030)	(0.027)	(0.025)	(0.016)
$R * ICT_{c,t}$	-0.007	-0.045*	-0.023	-0.023	0.003	-0.004	-0.005	-0.006	0.004
	(0.016)	(0.025)	(0.019)	(0.017)	(0.010)	(0.010)	(0.012)	(0.010)	(0.006)
$D * R_{c,t}$	-0.297***	-0.170**	-0.246***	-0.216***	-0.147***	-0.141***	-0.036	-0.074**	0.013
	(0.075)	(0.073)	(0.062)	(0.063)	(0.040)	(0.024)	(0.030)	(0.034)	(0.015)
$D * ICT_{c,t}$	0.106	-0.275**	-0.051	0.000	0.005	0.010	0.136***	0.006	-0.098***
	(0.088)	(0.126)	(0.100)	(0.094)	(0.036)	(0.046)	(0.041)	(0.029)	(0.021)
$D * R * ICT_{c,t}$	-0.117**	0.022	-0.055	-0.087	-0.046**	-0.036	-0.085**	-0.019	0.082***
	(0.047)	(0.058)	(0.052)	(0.055)	(0.020)	(0.038)	(0.033)	(0.022)	(0.016)
N	395	395	395	395	309	309	309	309	309

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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. 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; imports as % of GDP; exports as % of GDP; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

E.4. The progressiveness of taxation

Table E.25: Taxation and the structure of economic production

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	0.005	0.015	0.014	-0.012	0.239	0.197	0.180	-0.137	0.220	0.299	-0.801
	(0.016)	(0.032)	(0.046)	(0.024)	(0.766)	(0.360)	(0.474)	(0.149)	(0.604)	(0.776)	(0.793)
$ICT_{c,t}$	-0.030**	0.034	-0.045	-0.075*	-0.385	0.128	-0.187	-0.326	0.626	-0.132	-0.219
	(0.013)	(0.050)	(0.044)	(0.040)	(0.506)	(0.286)	(0.465)	(0.261)	(0.809)	(0.873)	(0.665)
$R * ICT_{c,t}$	0.016**	-0.001	0.040*	0.025	0.334	-0.155	0.386*	0.103	-0.582**	0.540	-0.075
	(0.007)	(0.016)	(0.021)	(0.015)	(0.256)	(0.110)	(0.198)	(0.094)	(0.256)	(0.343)	(0.223)
$D * R_{c,t}$	-0.067***	-0.096	-0.118**	-0.012	-1.108	-0.444	-1.146**	0.481*	-0.114	-2.634**	2.233**
	(0.020)	(0.060)	(0.055)	(0.049)	(0.692)	(0.369)	(0.524)	(0.241)	(0.819)	(0.976)	(0.858)
$D * ICT_{c,t}$	-0.007	-0.164	-0.063	0.043	-0.075	0.589	-1.088	0.424	1.683	-2.823*	0.644
	(0.026)	(0.190)	(0.071)	(0.059)	(0.900)	(0.673)	(0.834)	(0.390)	(1.628)	(1.571)	(1.482)
$D * R * ICT_{c,t}$	-0.006	0.018	-0.024	-0.001	-0.522	-0.045	-0.629	0.152	0.247	-0.643	0.963
	(0.021)	(0.081)	(0.048)	(0.029)	(0.835)	(0.432)	(0.606)	(0.188)	(0.852)	(0.930)	(0.980)
$wL_{c,t}$	0.403***	0.841**	0.306	0.426***	-0.412*	0.010	0.161	-0.583***	0.451*	0.849***	-1.331***
	(0.118)	(0.359)	(0.222)	(0.084)	(0.209)	(0.097)	(0.154)	(0.086)	(0.226)	(0.290)	(0.203)
$rK_{c,t}$	-0.012	0.195	-0.084	0.026	-0.611***	-0.064	0.060	-0.608***	0.391*	0.759***	-1.223***
	(0.079)	(0.210)	(0.121)	(0.106)	(0.194)	(0.096)	(0.131)	(0.076)	(0.216)	(0.230)	(0.212)
$Gini^w_{c,t}$	-0.265***	-0.295	-0.540**	-0.164	-3.860	-1.350	-2.645	0.134	-1.931	-6.679	5.923
	(0.076)	(0.326)	(0.236)	(0.192)	(3.044)	(2.774)	(2.812)	(1.911)	(7.875)	(6.260)	(6.322)
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. 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 computed 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; Gini index from the industry level distribution of hourly wage ($Gini^w_{c,t}$); and country (c) and year (t) fixed effects. 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.

E.5. Excluding OECD group 1100 "taxes on income, profits and capital gains of individuals" from capital taxes

Table E.26: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	-0.001	0.012	0.012	-0.014	0.143	0.176	0.102	-0.135	0.190	0.089	-0.710
	(0.013)	(0.031)	(0.053)	(0.024)	(0.503)	(0.327)	(0.183)	(0.146)	(0.516)	(0.273)	(0.731)
$ICT_{c,t}$	-0.030	0.034	0.052	-0.075*	-0.065	0.126	0.134	-0.326	0.624	0.811	-0.213
	(0.023)	(0.050)	(0.090)	(0.040)	(0.461)	(0.293)	(0.302)	(0.261)	(0.821)	(0.742)	(0.683)
$R * ICT_{c,t}$	0.006	-0.003	-0.013	0.024	-0.076	-0.164	-0.016	0.104	-0.594**	-0.311	-0.038
	(0.010)	(0.016)	(0.032)	(0.016)	(0.208)	(0.108)	(0.103)	(0.092)	(0.249)	(0.252)	(0.224)
$D * R_{c,t}$	-0.049*	-0.098	-0.081	-0.013	-0.386	-0.428	-0.438	0.480*	-0.091	-1.007*	2.163**
	(0.026)	(0.061)	(0.087)	(0.050)	(0.521)	(0.340)	(0.257)	(0.238)	(0.766)	(0.557)	(0.783)
$D * ICT_{c,t}$	0.007	-0.169	-0.224	0.040	0.237	0.558	-0.748	0.427	1.638	-2.297	0.782
	(0.036)	(0.190)	(0.157)	(0.061)	(0.720)	(0.652)	(0.567)	(0.388)	(1.598)	(1.421)	(1.463)
$D * R * ICT_{c,t}$	0.004	0.017	0.034	-0.002	0.174	-0.027	0.050	0.151	0.273	0.253	0.883
	(0.021)	(0.083)	(0.093)	(0.030)	(0.582)	(0.428)	(0.336)	(0.189)	(0.821)	(0.783)	(0.987)
$wL_{c,t}$	0.453***	0.899**	0.616	0.459***	-0.570***	0.006	0.006	-0.583***	0.445*	0.160	-1.313***
	(0.133)	(0.340)	(0.422)	(0.056)	(0.156)	(0.093)	(0.098)	(0.086)	(0.218)	(0.285)	(0.200)
$rK_{c,t}$	0.003	0.218	-0.041	0.039	-0.707***	-0.069	-0.031	-0.607***	0.383*	0.121	-1.198***
	(0.092)	(0.209)	(0.225)	(0.101)	(0.154)	(0.089)	(0.091)	(0.075)	(0.200)	(0.245)	(0.196)
N	395	395	395	395	395	395	395	395	395	395	395

Notes: $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$. All regressions use country level data for the same nineteen European countries excluding Germany (DE) during 1995-2016 and include: GDP growth, gross output share of service industries in the total economy; Herfindahl-Hirschman Index computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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. Taxes on capital T^k exclude the OECD tax category 1100 "taxes on income, profits and capital gains of individuals". Standard errors are two-way clustered at the country and year level.

F. Controlling for outlier countries

In this section, we examine whether the baseline results are driven by countries or regions that exhibit exceptionally high rates of robot adoption, such as Germany or, more generally, Western Europe. Results presented below remain robust across subsamples of countries.

F.1. Baseline results with interaction dummy for Western European countries (AT, BE, DE, DK, ES, FI, FR, GR, IE, IT, NL, PT, SE, UK). Rest is: CZ, LT, LV, SI, SK

Table F.27: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	-0.020	-0.077*	0.121	-0.061*	-0.169	-0.652	0.810*	-0.327***	-1.899	3.080*	-0.912*
	(0.013)	(0.041)	(0.078)	(0.030)	(0.275)	(0.424)	(0.455)	(0.100)	(1.545)	(1.603)	(0.491)
$ICT_{c,t}$	-0.020	0.204	-0.076	-0.058	-0.240	0.901	-0.655	-0.486*	2.683	-1.827	-1.336
	(0.044)	(0.186)	(0.046)	(0.053)	(1.397)	(0.977)	(0.825)	(0.265)	(1.846)	(1.602)	(1.125)
$R * ICT_{c,t}$	0.018	-0.048	0.039**	0.041***	0.265	-0.271	0.308*	0.228***	-1.071**	0.668	0.438
	(0.012)	(0.044)	(0.016)	(0.014)	(0.333)	(0.218)	(0.177)	(0.057)	(0.440)	(0.387)	(0.256)
$D * R_{c,t}$	0.003	0.068	-0.112	0.042	0.346	0.381	-0.520	0.485***	1.015	-3.155	1.257*
	(0.015)	(0.050)	(0.079)	(0.035)	(0.477)	(0.423)	(0.654)	(0.140)	(1.600)	(1.888)	(0.659)
$D * ICT_{c,t}$	-0.038	-0.590	-0.071	0.095	-1.743	-0.909	-2.374***	1.541***	-2.560	-2.227	5.013***
	(0.045)	(0.452)	(0.065)	(0.081)	(1.379)	(1.158)	(0.697)	(0.518)	(2.545)	(2.375)	(1.050)
$D * R * ICT_{c,t}$	-0.000	0.215	0.015	-0.053	0.230	0.027	0.837***	-0.634**	0.734	0.990	-1.642***
	(0.019)	(0.174)	(0.025)	(0.036)	(0.562)	(0.407)	(0.229)	(0.249)	(0.828)	(0.660)	(0.461)
N	394	394	394	394	394	394	394	394	394	394	394

Notes: $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. 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 computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table F.28: The replacement effect

	ln $wL_{i,c,t}$	ln $w_{i,c,t}$	ln $L_{i,c,t}$	ln $rK_{i,c,t}$	ln $r_{i,c,t}$	ln $K_{i,c,t}$
$R_{i,c,t}$	-0.061	0.141	-0.202***	0.162	0.010	-0.114
	(0.101)	(0.090)	(0.063)	(0.103)	(0.011)	(0.120)
$ICT_{i,c,t}$	0.005	0.009	-0.004	0.038	-0.012***	0.033
	(0.030)	(0.034)	(0.020)	(0.032)	(0.004)	(0.030)
$R * ICT_{i,c,t}$	-0.057	0.063	-0.120***	0.026	0.012**	-0.078
	(0.045)	(0.044)	(0.024)	(0.047)	(0.004)	(0.046)
$D * R_{i,c,t}$	0.051	-0.121	0.172**	-0.196*	-0.021	0.142
	(0.105)	(0.090)	(0.068)	(0.104)	(0.013)	(0.123)
$D * ICT_{i,c,t}$	-0.000	-0.006	0.006	-0.021	0.013	-0.026
	(0.033)	(0.034)	(0.023)	(0.037)	(0.011)	(0.034)
$D * R * ICT_{i,c,t}$	0.055	-0.058	0.113***	-0.021	-0.016***	0.090*
	(0.045)	(0.044)	(0.025)	(0.049)	(0.005)	(0.046)
N	4848	4848	4848	4793	4753	4753

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. All regressions use industry level data for nineteen European countries during 1995-2016 for the set of industries susceptible to automation, and include: country-industry (ci); country-year (ct); and industry-year (it) fixed effects that are further interacted with D. 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.

Table F.29: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^{w}_{c,t}$
$R_{c,t}$	-0.183***	0.053**	-0.107*	-0.002	0.137	0.075**
	(0.046)	(0.019)	(0.061)	(0.055)	(0.451)	(0.033)
$ICT_{c,t}$	0.097	-0.098*	0.158**	-0.161*	-4.488***	-0.001
	(0.081)	(0.053)	(0.061)	(0.083)	(1.506)	(0.053)
$R * ICT_{c,t}$	-0.032	0.031*	-0.053*	0.035	0.709*	-0.003
	(0.023)	(0.015)	(0.026)	(0.025)	(0.407)	(0.014)
$D * R_{c,t}$	0.087	-0.100***	0.010	-0.077	-1.199*	-0.057
	(0.052)	(0.023)	(0.067)	(0.065)	(0.593)	(0.036)
$D * ICT_{c,t}$	0.104	0.039	-0.164	0.296*	6.004**	0.026
	(0.098)	(0.085)	(0.126)	(0.144)	(2.420)	(0.067)
$D * R * ICT_{c,t}$	-0.056	-0.013	0.065	-0.104	-0.801	-0.002
	(0.041)	(0.038)	(0.066)	(0.060)	(1.078)	(0.026)
N	394	394	394	394	394	394

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table F.30: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL+rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t}$	-0.130***	-0.105*	-0.120***	-0.115**	0.067	-0.152***	-0.015	0.017	-0.014
	(0.041)	(0.060)	(0.041)	(0.047)	(0.041)	(0.021)	(0.038)	(0.031)	(0.019)
$ICT_{c,t}$	0.005	-0.229**	-0.105	-0.033	-0.005	-0.185***	0.024	-0.164**	-0.182***
	(0.060)	(0.088)	(0.064)	(0.100)	(0.052)	(0.034)	(0.035)	(0.057)	(0.041)
$R*ICT_{c,t}$	-0.003	0.053	0.024	0.009	0.002	0.061***	-0.022	0.032*	0.052***
	(0.024)	(0.033)	(0.026)	(0.036)	(0.016)	(0.017)	(0.014)	(0.017)	(0.015)
$D*R_{c,t}$	-0.014	-0.020	-0.027	-0.004	-0.093**	0.107***	0.022	-0.010	0.027
	(0.055)	(0.102)	(0.069)	(0.069)	(0.043)	(0.026)	(0.038)	(0.039)	(0.023)
$D*ICT_{c,t}$	0.136	0.238	0.204	0.144	0.031	0.213***	0.073	0.193**	0.191***
	(0.112)	(0.163)	(0.126)	(0.154)	(0.102)	(0.045)	(0.077)	(0.080)	(0.062)
$D*R*ICT_{c,t}$	-0.068	-0.079	-0.085	-0.084	-0.023	-0.071***	-0.033	-0.068*	-0.050**
	(0.060)	(0.074)	(0.064)	(0.069)	(0.050)	(0.022)	(0.041)	(0.032)	(0.021)
N	394	394	394	394	308	308	308	308	308

Notes: $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. Regression results to test the real income effect for nineteen European countries during the period 1995-2016. Labor productivity 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. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

F.2. Excluding Germany (DE) from sample

Table F.31: Taxation and automation

	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$T^y_{c,t}$	$T_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$	$T^l_{c,t}$	$T^k_{c,t}$	$T^y_{c,t}$
$R_{c,t}$	0.004	0.015	-0.004	0.009	0.165	0.155	0.043	-0.033	0.191	0.101	-0.382
	(0.013)	(0.031)	(0.039)	(0.020)	(0.609)	(0.304)	(0.407)	(0.120)	(0.557)	(0.760)	(0.652)
$ICT_{c,t}$	-0.037**	0.035	-0.061	-0.087*	-0.559	0.171	-0.342	-0.388	0.842	-0.465	-0.245
	(0.017)	(0.055)	(0.047)	(0.044)	(0.554)	(0.294)	(0.465)	(0.284)	(0.812)	(0.854)	(0.704)
$R * ICT_{c,t}$	0.013*	-0.002	0.033*	0.019	0.284	-0.135	0.333**	0.085	-0.504**	0.485*	-0.044
	(0.007)	(0.014)	(0.016)	(0.012)	(0.214)	(0.086)	(0.149)	(0.071)	(0.178)	(0.248)	(0.169)
$D * R_{c,t}$	-0.078***	-0.119	-0.085	-0.084*	-1.141	-0.505	-0.774	0.137	-0.486	-2.225	1.197
	(0.019)	(0.073)	(0.057)	(0.043)	(0.700)	(0.471)	(0.698)	(0.264)	(1.230)	(1.588)	(1.005)
$D * ICT_{c,t}$	0.007	-0.155	-0.068	0.087	0.152	0.668	-1.078	0.562	1.799	-2.647	0.944
	(0.030)	(0.192)	(0.090)	(0.076)	(1.013)	(0.709)	(1.052)	(0.459)	(1.774)	(2.084)	(1.568)
$D * R * ICT_{c,t}$	-0.011	0.006	-0.017	-0.018	-0.452	-0.059	-0.457	0.064	0.136	-0.520	0.586
	(0.016)	(0.065)	(0.041)	(0.027)	(0.650)	(0.308)	(0.515)	(0.169)	(0.669)	(0.860)	(0.762)
$wL_{c,t}$	0.440***	0.877**	0.382	0.462***	-0.396*	0.005	0.162	-0.563***	0.422*	0.863***	-1.281***
	(0.125)	(0.334)	(0.261)	(0.053)	(0.199)	(0.096)	(0.141)	(0.089)	(0.230)	(0.291)	(0.198)
$rK_{c,t}$	0.012	0.222	-0.071	0.080	-0.599***	-0.066	0.053	-0.586***	0.374*	0.761***	-1.161***
	(0.081)	(0.211)	(0.124)	(0.105)	(0.182)	(0.090)	(0.114)	(0.078)	(0.203)	(0.214)	(0.193)
N	373	373	373	373	373	373	373	373	373	373	373

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $* * * \ p < 0.001$. All regressions use country level data for the same nineteen European countries used in the baseline sample excluding Germany (DE) during 1995-2016 and include: GDP growth, gross output share of service industries in the total economy; Herfindahl-Hirschman Index computed 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; and country (c) and year (t) fixed effects that are further interacted with D. 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.

Table F.32: The replacement effect

	$\ln wL_{i,c,t}$	$\ln w_{i,c,t}$	$\ln L_{i,c,t}$	$\ln rK_{i,c,t}$	$\ln r_{i,c,t}$	$\ln K_{i,c,t}$
$R_{i,c,t}$	-0.025	0.009	-0.033**	-0.012	-0.003	-0.018
	(0.018)	(0.008)	(0.015)	(0.029)	(0.002)	(0.011)
$ICT_{i,c,t}$	-0.026	0.012	-0.037*	-0.097	-0.005	-0.033
	(0.020)	(0.008)	(0.020)	(0.074)	(0.004)	(0.040)
$R * ICT_{i,c,t}$	-0.006	0.000	-0.006	0.013	-0.002**	0.008
	(0.005)	(0.002)	(0.005)	(0.012)	(0.001)	(0.005)
$D * R_{i,c,t}$	-0.014	0.008	-0.022	-0.038	-0.004	0.028
	(0.029)	(0.012)	(0.032)	(0.053)	(0.006)	(0.025)
$D * ICT_{i,c,t}$	0.071***	-0.004	0.075***	0.121	0.008	0.081*
	(0.021)	(0.010)	(0.018)	(0.072)	(0.015)	(0.043)
$D * R * ICT_{i,c,t}$	0.016	0.002	0.014	-0.006	0.002	0.008
	(0.012)	(0.004)	(0.012)	(0.032)	(0.005)	(0.016)
N	4567	4567	4567	4519	4472	4472

Notes: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. All regressions use country level data for the same nineteen European countries used in the baseline sample excluding Germany (DE) during 1995-2016 for the set of industries susceptible to automation, and include: country-industry (*ci*); country-year (*ct*); and industry-year (*it*) fixed effects that are further interacted with D. 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.

Table F.33: The reinstatement effect

	ln $w_{c,t}$	ln $L_{c,t}$	ln $r_{c,t}$	ln $K_{c,t}$	$Services_{c,t}$	$Gini^w_{c,t}$
$R_{c,t}$	-0.024	0.022	-0.046	0.006	-0.931**	0.004
	(0.025)	(0.014)	(0.028)	(0.016)	(0.363)	(0.006)
$ICT_{c,t}$	-0.003	0.028	0.084**	0.066	2.675***	0.009
	(0.038)	(0.029)	(0.038)	(0.040)	(0.647)	(0.011)
$R * ICT_{c,t}$	-0.011	-0.002	-0.038**	-0.013	-0.406*	0.001
	(0.010)	(0.007)	(0.014)	(0.014)	(0.221)	(0.004)
$D * R_{c,t}$	-0.224***	-0.009	-0.014	-0.112**	0.084	0.019
	(0.075)	(0.050)	(0.060)	(0.046)	(0.857)	(0.021)
$D * ICT_{c,t}$	0.402***	-0.234***	0.039	-0.144*	-5.237***	0.013
	(0.099)	(0.036)	(0.064)	(0.070)	(1.054)	(0.019)
$D * R * ICT_{c,t}$	-0.185***	0.055***	-0.023	0.036	1.506**	-0.009
	(0.048)	(0.009)	(0.024)	(0.028)	(0.547)	(0.008)
N	373	373	373	373	373	373

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the reinstatement effect forthe same nineteen European countries used in the baseline sample excluding Germany (DE) 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

Table F.34: The real income effect

	ln $wL_{c,t}$	ln $rK_{c,t}$	ln $(wL + rK)_{c,t}$	ln $pQ_{c,t}$	ln $Q_{c,t}$	ln $p_{c,t}$	ln $LProd_{c,t}$	ln $KProd_{c,t}$	ln $TFP_{c,t}$
$R_{c,t}$	-0.001	-0.017	-0.011	0.006	0.058**	-0.023	0.019	0.015	-0.011
	(0.035)	(0.023)	(0.025)	(0.025)	(0.026)	(0.019)	(0.025)	(0.018)	(0.009)
$ICT_{c,t}$	0.028	0.111**	0.061	0.048	0.022	0.011	-0.001	0.001	0.004
	(0.055)	(0.042)	(0.047)	(0.051)	(0.027)	(0.031)	(0.033)	(0.023)	(0.014)
$R * ICT_{c,t}$	-0.007	-0.031	-0.017	-0.018	0.003	-0.002	-0.001	-0.004	0.004
	(0.014)	(0.019)	(0.016)	(0.016)	(0.009)	(0.008)	(0.012)	(0.008)	(0.004)
$D * R_{c,t}$	-0.244**	-0.143	-0.209**	-0.168*	-0.110*	-0.115**	-0.070	-0.009	0.006
	(0.087)	(0.083)	(0.082)	(0.082)	(0.060)	(0.050)	(0.045)	(0.036)	(0.022)
$D * ICT_{c,t}$	0.116	-0.237*	-0.027	0.025	0.014	0.003	0.200***	-0.018	-0.124***
	(0.091)	(0.120)	(0.104)	(0.106)	(0.039)	(0.067)	(0.042)	(0.045)	(0.029)
$D * R * ICT_{c,t}$	-0.093**	-0.001	-0.053	-0.078*	-0.043**	-0.026	-0.090***	-0.008	0.069***
	(0.038)	(0.046)	(0.042)	(0.044)	(0.019)	(0.035)	(0.026)	(0.024)	(0.017)
N	373	373	373	373	287	287	287	287	287

Notes: $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. Regression results to test the real income effect for the same nineteen European countries used in the baseline sample excluding Germany (DE) during the period 1995-2016. Labor productivity 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. 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; and country (c) and year (t) fixed effects that are further interacted with D. Standard errors are two-way clustered at the country and year level.

References

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Adarov, A., R. Stehrer, et al. (2019). Tangible and Intangible Assets in the Growth Performance of the EU, Japan and the US. Research Report 442, Vienna Institute for International Economic Studies.

Anzoategui, D., D. Comin, M. Gertler, and J. Martinez (2019). Endogenous technology adoption and R&D as sources of business cycle persistence. *American Economic Journal: Macroeconomics 11*(3), 67–110.

Blanas, S., G. Gancia, and S. Y. T. Lee (2019). Who is afraid of machines? *Economic Policy*.

Castañeda Rodríguez, V. M. (2018). Tax determinants revisited. An unbalanced data panel analysis. *Journal of Applied Economics 21*(1), 1–24.

Castro, G. Á. and D. B. R. Camarillo (2014). Determinants of tax revenue in OECD countries over the period 2001–2011. *Contaduría y administración 59*(3), 35–59.

de Vries, G. J., E. Gentile, S. Miroudot, and K. M. Wacker (2020). The rise of robots and the fall of routine jobs. *Labour Economics 66*, 101885.

EUKLEMS (2019). EUKLEMS release 2019. Data extracted in Oct 2020.

European Commission (2020a). Data on Taxation, Implicit tax rates. Data extracted in April 2021.

European Commission (2020b). Taxation trends in the European Union - Data for the EU Member States, Iceland and Norway: 2020 edition. Report, European Commission, DG for Taxation and Customs Union.

Eurostat (2020). Eurostat Data on Government deficit and debt. Data extracted on 22 Oct 2020.

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

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

IFR (2020). International Foundation of Robotics. Proprietary data on Industrial robot Deliveries and Stocks.

IFR (2020). WR Industrial Robots 2020 - Sources & Methods. World Robotics Data manual, International Foundation of Robotics.

OECD (2019). *Revenue Statistics 2019*. OECD Publishing, Paris.

OECD (2020). Global Revenue Statistics Database. Data extracted on 28 Oct 2020.

Stehrer, R., A. Bykova, K. Jäger, O. Reiter, and M. Schwarzhappel (2019). Industry level growth and productivity data with special focus on intangible assets. Statistical Report 8, Vienna Institute for International Economic Studies.

Stock, J. H. and M. W. Watson (1999). Chapter 1 - Business cycle fluctuations in US macroeconomic time series. In *Handbook of macroeconomics*, Volume 1 Part A, pp. 3–64. Elsevier.