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Technequality

Understanding the relation between technological innovations and social inequality

Which governments will be most affected by automation
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Description of deliverable (100 words)

Deliverable 5.2 is looks into the effects of robot and ICT adoption across European countries for the period 1993-2016 using country, industry and firm level data. We describe the regional and national effects of automation technologies on the economy using their direct (replacement), indirect (reinstatement) and overall (real income) contributions .

Which governments will be most affected by automation?*

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1. Introduction

Research suggests that the diffusion of automation technologies may have disruptive effects on the labor market when tasks formerly performed by human labor are replaced by machines [Brynjolfsson and McAfee, 2014, Acemoglu and Restrepo, 2019, Frey and Osborne, 2017]. Technological advancements may make whole business models obsolete, as we have observed throughout technological history [Frey, 2019, Brynjolfsson et al., 2017]. However, the effects of automation may be complex, as second order effects such as new technological opportunities and productivity gains enable the reinstatement of new jobs within and across industries. Furthermore, productivity gains may also lead to decreasing prices and higher wages when machines complement labor. Both may result in higher levels of real income which in turn could be a driver of increasing demand, output expansion, and new jobs created [Hötte et al., 2021, Bessen, 2019, Acemoglu and Restrepo, 2018]. It is also well documented that the effects may be very heterogeneous across different occupations and industries [Autor et al., 2020].

In this report, we looked at local effects asking: Which local and national governments will be most affected by automation technology diffusion? What are the implications of automation technology diffusion for fiscal revenues? These are the guiding questions of this report.

To do so, we estimated the effects of automation technology diffusion on local labor demand by firms in industries exposed to these technologies and on corporate taxes paid by these firms. To explore potentially interesting patterns of heterogeneity across regions, we illustrate the results both at the national (country) and sub-national (regional NUTS 2) level. The focus on corporate taxes, i.e. taxes on the profits of a firm, is a natural choice given the absence of alternative detailed datasets that would allow for both a multi-country analysis and a more complete representation of fiscal revenues at the granular level across regions. While corporate taxes capture only a rather specific category of fiscal taxes they can be seen as a first preliminary exploration on whether interesting associations between automation and fiscal revenues would arise at the regional level. One potential way to think about this is automation affecting the structure of production though various channels that would in turn be reflected on shifts in profits, and thus taxes payed by the firms. However, for a more complete understanding of automation-driven shifts in regional fiscal taxes, payroll, social security contributions and other potentially relevant fiscal tax sources need to be considered.

In the analysis, we distinguish between two different types of automation technologies: robots and information and communications technology (ICT). We consider robots as an indicator for the automation of manual tasks, while ICT could complement or substitute cognitive tasks.

We observe that the impact of automation varies considerably across regions (sub-national level) and countries (national level). More specifically, on top of cross-country heterogeneity, for some countries, like the United Kingdom, Greece, and Germany we also observe a very high within-country heterogeneity of the results. In Italy, we find opposite effects for robots and ICT, with robots showing a positive and ICT a strongly negative association with employment and taxation. This heterogeneity highlights the potential underlying differences in the degree upon which regional economies adapt to technological change, and thus the extent to which local economies respond vis-á-vis the presence of existing regional-level policies in place.

The results provide insights about a potential channel of how automation technology diffusion interacts with fiscal revenues, namely the direct impact of automation on the corporate tax payments made by firms being active in automation-intensive industries. However, more research is needed to gain a better understanding of the second order effects in terms of labor reinstatement and changes in real income, as these are also expected to influence fiscal revenues.

In the next section of this report, a short introduction to the mechanisms that drive regional heterogeneity is given. Section 3 introduces the methods and data. Section 4 and 5 present the results at the national and regional NUTS 2 level. Section 6 offers a short discussion and 7 concludes.

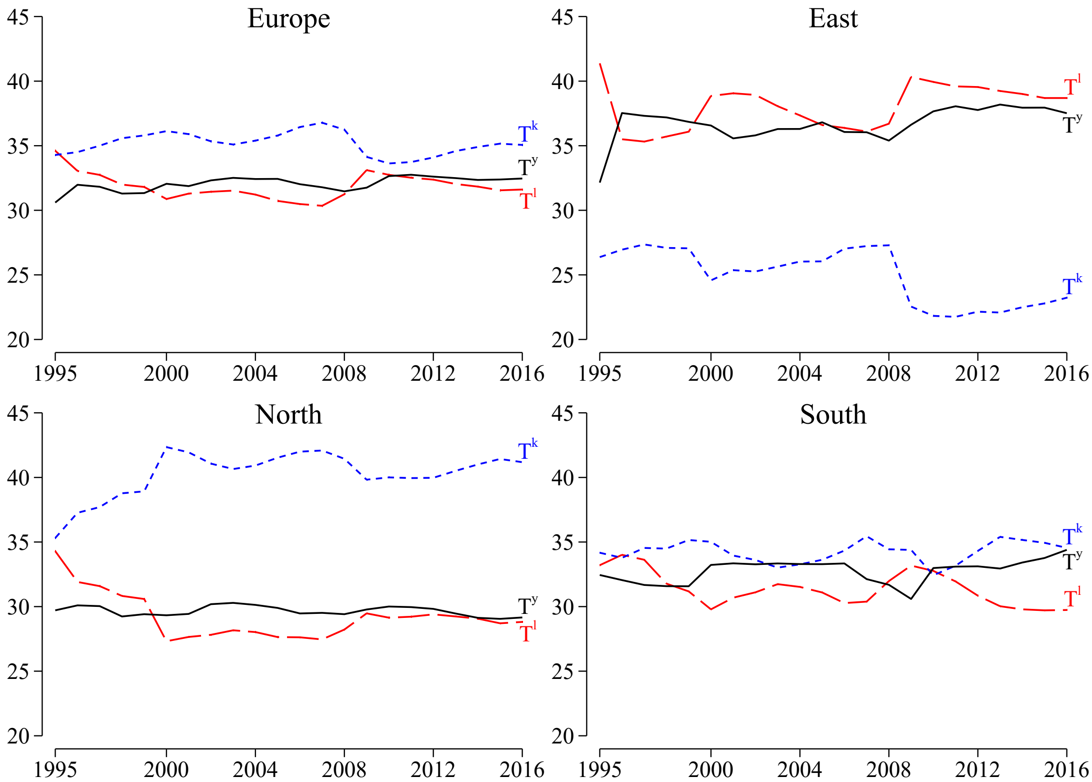
2. Sources of regional heterogeneity

Regionally, the effects of automation are especially heterogeneous across countries and sub-national regions. While some occupations are easy to automate and certain business models become obsolete, others are augmented when automation technologies become available [Autor et al., 2003]. This increases productivity in these jobs and creates new opportunities of economic activity [Acemoglu and Restrepo, 2018, Blanas et al., 2019, Bessen, 2019]. Some industries rely more heavily on jobs that are at a high risk to automation while others can be expected to expand if new technological opportunities emerge. As regions differ by their industrial structure, the effects of automation on employment, productivity, and output are regionally diverse. The effects in automation technology adopting industries also have spillover effects on other sectors when disposable income changes or new technological opportunities attract workers from other regions.

Evaluating the fiscal impact of automation diffusion is challenging given the heterogeneity and complexity of tax systems. Aggregate fiscal revenues are composed of taxes from different sources, such as labor, capital, and consumption. National tax systems also differ by the structure of taxation, i.e. whether taxes are levied at the local, regional, or national level [OECD, 2019].

Figure 1 shows how the structure of taxation varies across different European regions. The structure of taxation is measured by tax revenues charged on labor, capital, or goods as a share of total tax revenues. While Northern European countries receive the largest share (above 40%) of their fiscal revenues from the taxation of capital, Eastern countries rely more heavily on taxes on labor and goods with only 25% of their revenues coming from capital. The figure also highlights the impact of the financial crisis which was associated with a steep kink in the share of tax revenues coming from capital. Hence, for fiscal revenues it matters to which extent governments rely on taxes from different sources and how the economy is affected, as the impact of economic shocks may be asymmetric across types of tax revenues.

Figure 1: Structure of taxation - average across Europe and regional groups



Notes: T^l, T^k and T^y is the country group average tax on labor, capital, and goods, respectively, as % of total taxation. The sample includes 19 European countries for the period 1995-2016 which covers three regional groups: East (CZ, LT, LV, SI, and SK); North (AT, BE, DE, DK, FI, FR, IE, NL, SE and UK); and South (ES, GR, IT, and PT). Data from [OECD, 2020, Hötte et al., 2021].

3. How to study regional automation impacts?

A Europe-wide analysis of fiscal impacts at the regional level is subject to data limitations. Ideally, we would have data that provides a direct link between local economic activity and tax revenues from different sources. But this data does not exist and we can only draw a partial picture of the potential effects of automation diffusion of fiscal revenues. To that end, we restrict the analysis to the impact of automation on corporate taxation, being aware that this is only one part of aggregate taxes on capital.

Due to data limitations, we do not study the impact on tax revenues charged on labor and we also neglect spillover effects to other non-automating industries, for example induced by changing consumption patterns when local wealth levels change in response to automation. By applying the categorization scheme of automation impacts into replacement, reinstatement, and real-income effects that was introduced in Hötte et al. [2021], we can say that this analysis only covers the impact of the replacement effect on taxes levied on firms in those industries most exposed to automation. As such, we do not capture more complex second order effects when jobs are created in non-automating industries or changes in wealth levels lead to an expansion or decline in aggregate output.

This analysis relies on firm level data provided by Bureau van Dijk Electronic Publishing [2020a] (herein BvDEP) to study the nexus between regional patterns of automation, labor demand, and corporate tax payments at the country (NUTS0) and regional (NUTS2) level. Even though we can only draw only a partial picture of the economic reality, the findings suggest that the impacts of automation are diverse at the granular level. For governments, this understanding is of particular interest because — dependent on the country-specific structure of tax administration — locally raised taxes can be decisive to ensure the financing of essential public infrastructure.

The BvDEP dataset includes financial statements of firms sourced from national registries harmonized to ensure cross-country comparability. Details on our data pre-processing are available in the Appendix B.

The firm level data does not provide information on automation technology diffusion and thus we combine it with industry level data on the adoption of industrial robots from the International Federation of Robotics [IFR, 2020] and the use of ICT capital from EUKLEMS [2019]. From the first dataset we measure robot adoption based on the number of operational industrial robots, while from the latter we capture both tangible (hardware) and intangible (databases and software) ICTs by summing the net capital stock volumes of computing equipment, communications equipment, and computer software and databases. We expect these two technology-groups to reflect two distinct automation technologies since they can be differentiated by the type of task they can perform. Specifically, robots are designed to execute manual tasks, while ICTs are more closely related to cognitive tasks. Specifically, robots execute a clearly defined task previously performed by humans, while ICTs can be flexibly applied to many different tasks which most likely do not have a clear analogue in the range of tasks executed by humans. As such, it is fair to assume that these two measures of automation capturing different automation technologies.[1]

For easier interpretation and comparability, we use standardized (z-scaled) measures for robot and ICT diffusion, called robot- and ICT-density.[2] Firms are classified by NACE Rev.2 (ISIC Rev.4) 2-digit industry codes which are used to merge the firm level data with the industry level measures on robot- and ICT-intensity. The sample includes 15 industry groups summarized in Table A.1 in the Appendix.[3]

We restricted the sample of firms to those located in countries and sub-national regions for which industry level data on robot and ICT adoption exists. As we made separate analyses for the impact of robots or taxes on labor market and corporate tax revenues, we adapt the sample size for each of these analyses to achieve the maximal amount of information in the data. An overview of the data coverage is provided in Appendix A.

Finally, we linked the firm level data to the location of economic activity trough the NUTS version 2016 regional classification codes which cover 281 regions at NUTS 2 and 1348 regions at NUTS 3 level [Eurostat, 2020]. The sample used in our analysis for the effects of robot (ICT) intensity covers 24 (18) NUTS 0 and 273 (227) NUTS 2 regions. For

[1] From an empirical perspective, we find a very low correlation (20%) between these two measures which rules out potential multicollinearity concerns.

[2] Note that robot and ICT density measures are expressed over the total number of hours worked by human labor in each industry.

[3] An alternative possibly interesting dimension to explore would be at the occupation level, similar to the level at which automation risk measures are commonly computed in the literature. However, this is not straightforward to apply since it would be not necessarily intuitive and straightforward to classify industrial robots for certain occupations, e.g. managers where the number would be expected to be zero by default, and that no known datasets for ICT exist at the industry-occupation level, at least for such a large panel of countries that we explore in this report.

more details over the summary statistics of the firm level sample and variables considered, see Appendix Table A.4.

The firm level data that we use is considered to be one of the best available firm level data sets, but is also known to be biased towards larger sized firms due to a lower stringency in the reporting obligations for small firms [Bajgar et al., 2020, Kalemli-Ozcan et al., 2015]. The sample covers around 60% of economic activity in terms of employment in the 15 automation-intensive industries in our sample (see Appendix Table A.2).[4]

A note must be said about the representativeness of the firm level corporate income taxes relative to the economy wide capital and corporate income taxes. At the country level, corporate taxes on income, profits, and capital gains (variable code 1200 in OECD [2019] data set) represent only 22% of total capital taxes, on average across sample-countries (see Appendix Table A.3). When we focus on the firm level samples we see that, on average, they represent around 20% of the economy-wide corporate taxes on income, profits, and capital gains (see Appendix Table A.3). This gap is mainly due to the fact that the firm level sample is a limited sub-set of the fifteen industries where industrial robots diffuse and does not represent the whole economy. However, even if we observed firm level data for the whole economy, the sample would remain underrepresented, in line with the results from above on the coverage on employment. Overall, while the firm level data is helpful in uncovering interesting underlying heterogeneity, it should be kept in mind that the results capture a rather limited part of the aggregate effects and that there is a risk that the lack of representativeness also affects the type and extent of heterogeneity that can be uncovered.

3.1. Methods

Using regression analyses, we estimated the impact of robot $R_{i,t}$ and $ICT_{i,t}$ intensity in industry i in time t on labor demand $L_{f,r,i,t}$, and corporate tax payment $T^{\pi}_{f,r,i,t}$ of firm f located in region r. To illustrate the effects, we estimated for each country the following specification

$$Y_{f,r,t} \sim \beta^{x}_{r} \cdot \mathbb{1}(r,i)_f \cdot X_{i,t} + \epsilon_{r,f,t} \tag{1}$$

where $Y_{f,r,t} \in \{T^{\pi}_{f,r,t}, L_{f,r,t}\}$, $X_{i,t} \in \{R_{i,t}, ICT_{i,t}\}$ and $i \in I_c$. $\mathbb{1}(r,i)_f$ is a firm-specific dummy variable that equals one if firm f is located in region r and with primary economic activity in industry i.[5] All regressions include firm and NUTS 0 or NUTS 2-region-year FE and are weighted by the base-sample-year share of each industry's number of hours worked to country-wide hours worked. Standard errors are multi-way clustered at the industry, region, and year level.

Note that we combined data from different levels of aggregation merging industry-country level data on automation with firm level data containing the region where the firm is reported. This enabled us to map the industry-country level to the more disaggregate NUTS 2 region level dimension. Since we do not directly observe the allocation of robot- and ICT-intensity across regions, our empirical strategy relies on the assumption that all

[4] For similar evidence see Bormans and Theodorakopoulos [2020].

[5] Since we drop firms reporting consolidated accounts, we accounted for any double counting that could possibly arise from subsidiary firms integrating their statements to the national of international head-quarter. However, we cannot control for such a possibility for multi-plant firms, due to the absence of data at such granular level.

industries in a country are homogeneously exposed to automation technology diffusion, irrespective of the region.

In the next section, we illustrated the effects of ICT and robot adoption at the regional level drawing maps that show the estimated effect β_r^x on corporate tax payments and on their local labor demand. Different color codes indicate the size and direction of the expected impact.

4. Automation impacts at the country level

In Figure 2, we show the impact of robots and ICT diffusion on national labor markets and corporate taxes paid by the firms in the 15 automation-adopting industries during the period 2008-2016. Note that the estimation sample covers post-financial and EU-crisis periods during which countries, regions and firms have shown different economic responses. However, the firm and region-year specific fixed effects in the estimations capture any crises-driven differential responses that could be driving the results at those dimensions.

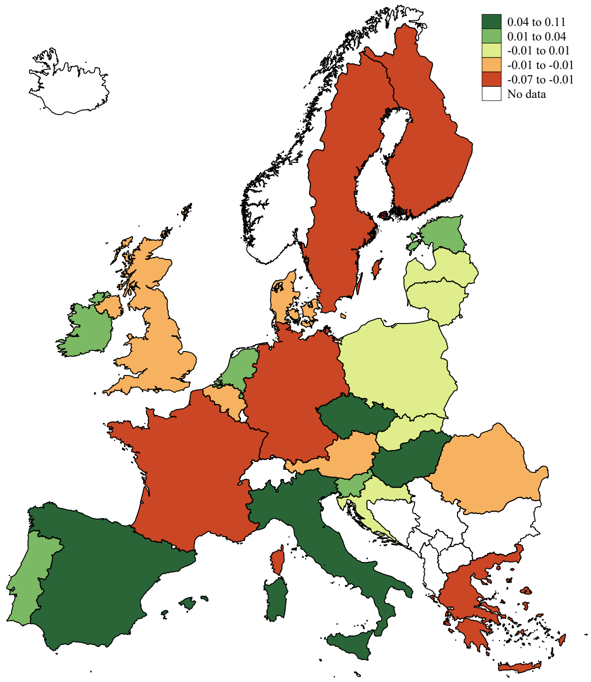
The two figures on top (Figure 2a and 2b) show the impact of robot and ICT diffusion on employment in the firms covered by our sample, and the bottom figures (2c and 2d) show the analogue for corporate tax revenues. The color codes indicate the direction and the scale of the effect. For example, the green color in Figure 2a indicates that the diffusion of robots was associated with an increase in employment. Red color is associated with a negative impact, and yellow color indicates that there is no effect.

The results suggest a diverse set of effects. During the period of study, we find that the diffusion of industrial robots (Figure 2a) shows significantly heterogeneous effects on labor demand in different countries. For example, in Norway, Sweden, Germany, and Greece the adoption of industrial robots during 2008-2016 was associated with a decline for labor in robot adopting industries while we observe a rising demand for labor in Spain, Italy, Czech Republic, and Hungary. Other countries appear to be rather moderately affected.

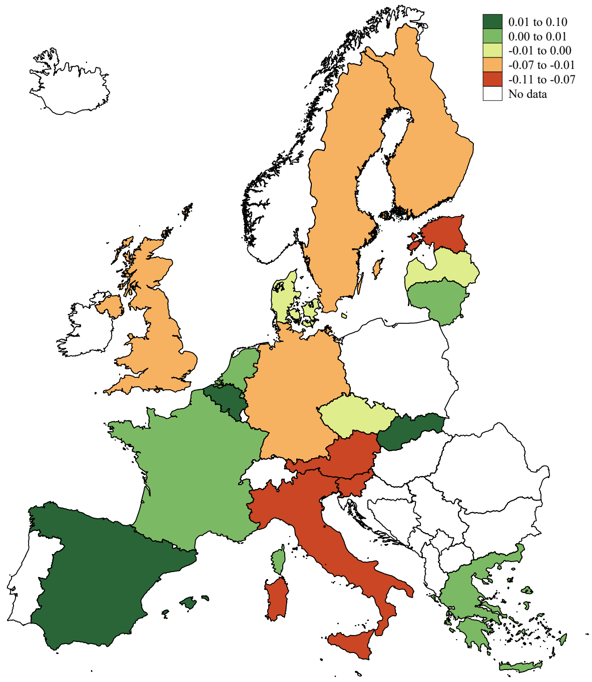
For many countries, we find that the impact on corporate tax revenues is positively correlated with the impact on labor. For example, in Spain, Italy, and Czech Republic the positive impact on employment was accompanied by a rise in corporate tax payments. In other countries like Germany, Greece, Finland, and Sweden, the strong decline in the demand for labor coincided with a decreasing tax revenues. Most other countries are rather moderately affected but show a similar pattern of correlation. However, the figure shows that this pattern of correlation does not always hold: France experienced a decrease in labor but a strong increase in corporate taxation.

In some of the countries where we observe negative impacts of robot diffusion on taxes and labor, show the opposite effect for ICT. For example, Italy exerts the most positive effects of robots on labor demand and taxation, but exhibits strong negative impacts of ICT on both labor and corporate taxation.

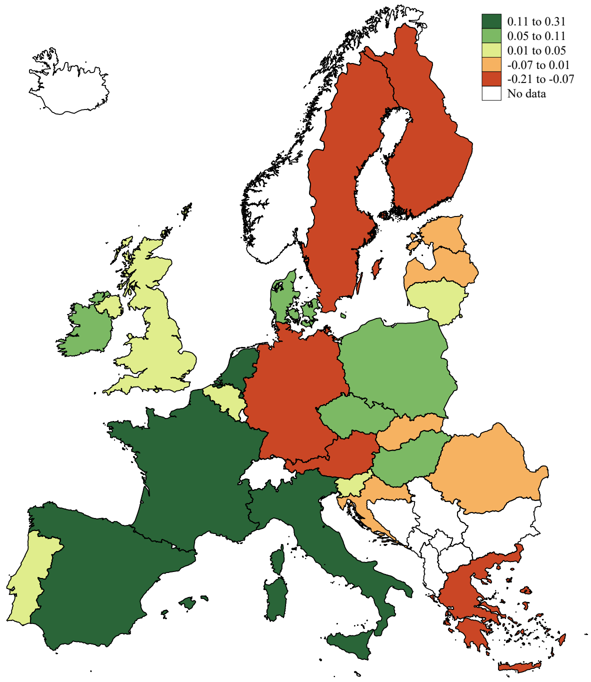
In Spain, we find positive effects of both types of automation technologies: Both robots and ICT show a positive impact on labor and taxes. Conversely, we note only negative effects for Sweden. Again, we find that the relationship between labor market and tax effects is not homogeneous. For example, for the UK, we observe negative automation effects of both robots and ICT on labor, but for both technologies we find that corporate tax revenues increase.



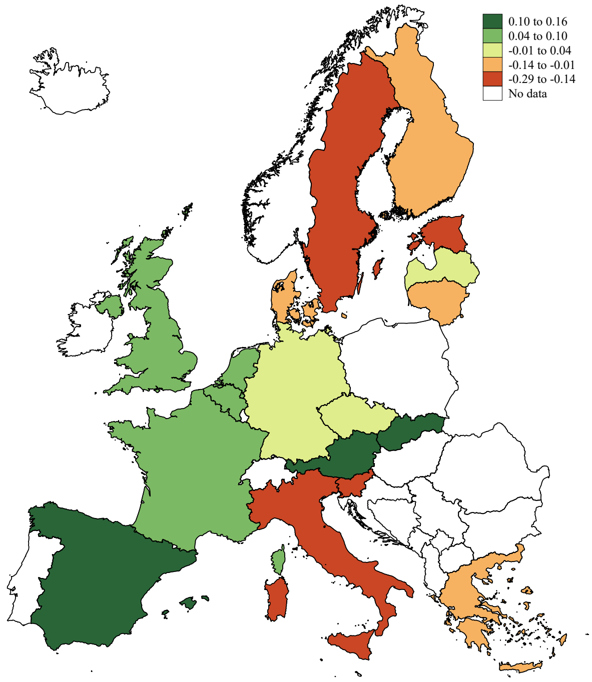
(a) Labor & robots



(b) Labor & ICT



(c) Taxes & robots



(d) Taxes & ICT

Figure 2: automation at the national level (NUTS0 regions)

Source: Author's calculations based on Orbis Global, IFR and EUKLEMS data sets.

Notes: Each map presents the point estimates from regressing for each country separately the ln of the firm level corporate income tax ($Taxes$) and number of employees (L), respectively, on the industry level robot (R) or ICT intensity. All regressions include firm and NUTS3 version 2016-region-year fixed effects and are weighted using the same weights as in the industry level analysis, i.e. base-sample-year share of each industry's number of hours worked to country-wide hours worked. The estimated effects are plotted with 2 shades of green and red for two groups of positive and negative values, respectively, with the darker colors representing stronger effects. Regions with no data are left blank.

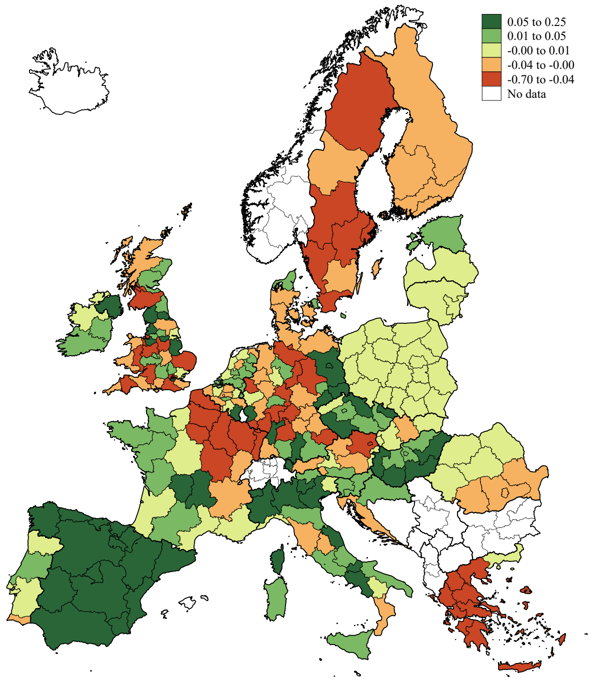
5. Automation impacts in NUTS-2 regions

Next, we zoom in and explore the relationship between automation technology diffusion, employment and corporate tax payments at the sub-national NUTS 2 level. We apply the same method as for the national level and show the results in Figure 3. The figures on top (Figure 3a and 3b) show the impact of automation on the employment of firms in automation-adopting industries in our sample, and the figures on the bottom (3c and 3d) illustrate the impact on corporate taxes.

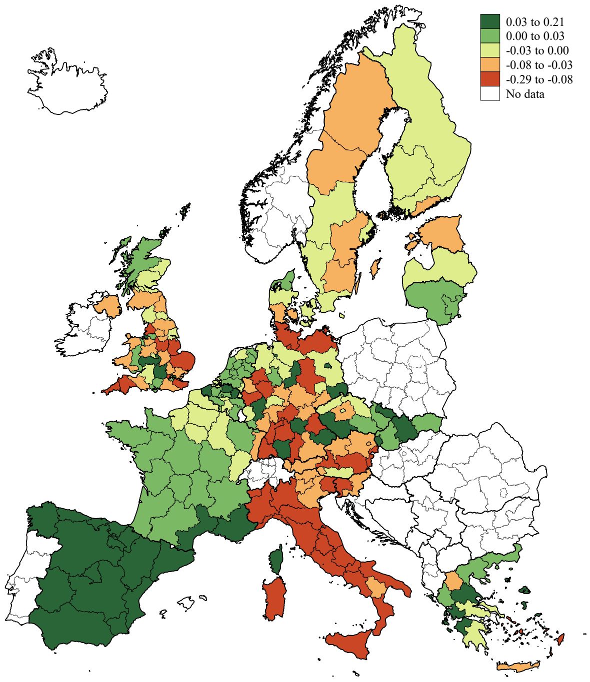
The results at the NUTS 2 level also show that it may be insufficient to look at aggregate country level data when trying to understand the impact of automation. For example in France, we observed at the country level a negative impact of robots on employment. Zooming in, we can see that the negative employment effect only holds for the eastern part of France while we observe positive effects in the western part. Interestingly, the effect on corporate tax payments is positive even in those regions that experience a decline in employment.

Comparing the countries, we find that the degree of regional heterogeneity in the effects differs across countries but also across technology types (robots or ICT). For example, in Austria, Greece, Germany, and the United Kingdom, the effects are quite heterogeneous across regions: some areas experience an increase in employment and corporate tax payments while others show a steep decline. In other countries like France, Spain, and Italy, the effects are relatively homogeneous across regions. Interestingly, for some countries, whether or not the effects are homogeneous depends on the technology type: For example, Swedish regions show homogeneously a negative association between robot diffusion and employment and corporate tax payments, while the impact of ICT differs across regions. While the northern part of Sweden does not show any strong effects, the south of Sweden shows a strong decline in corporate tax payments.

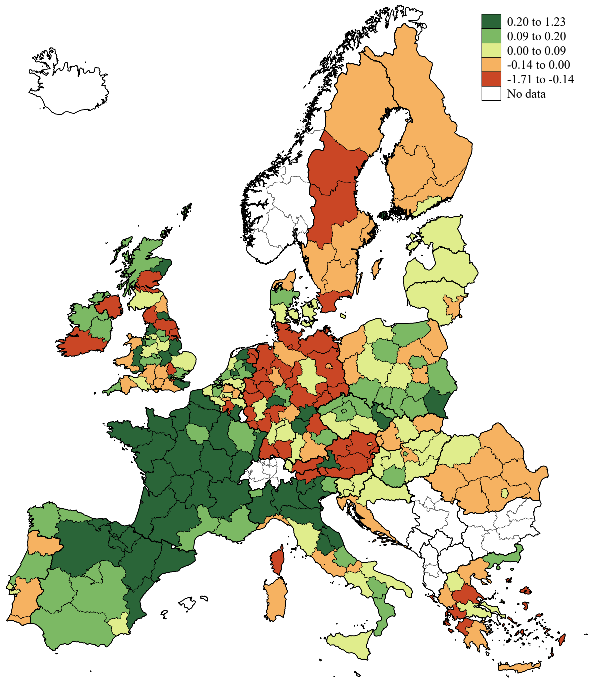
Generally and in line with findings at the country level, we observe a positive correlation between the impact of automation technology diffusion on labor and taxes in most regions. Comparing the Figures on top (2a and 2b) with those on the bottom (2c and 2d), we can see, in most regions, an increase in corporate tax payments when automation technologies are associated with positive employment effects, and we observe the opposite if the impact is negative. Again, we find few exceptions where negative employment effects coincide with an increase in corporate tax payments. For example, in Alentejo (Portugal, PT18) or Corse (France, FR83) we observe positive employment effects of robots but a decline in corporate tax payments. Also in parts of Ireland and many regions of the UK, we find a negative correlation between the effect of robots on labor and corporate tax payments as we can see in the opposite color coding in these regions comparing Figure 2a and 2d.



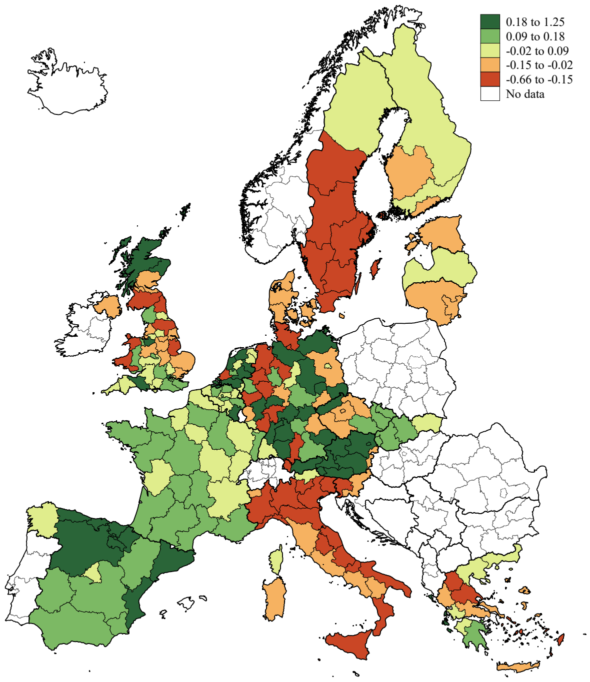
(a) Labor & robots



(b) Labor & ICT



(c) Taxes & robots



(d) Taxes & ICT

Figure 3: automation at the sub-national level (NUTS2 regions)

Source: Author's calculations based on Orbis Global, IFR and EUKLEMS data sets.

Notes: Each map presents the point estimates from regressing for each country separately the ln of the firm level corporate income tax ($Taxes$) and number of employees (L), respectively, on the industry level robot (R) or ICT intensity interacted with a full set of NUTS2 version 2016-regional dummies. All regressions include firm and NUTS2 version 2016-region-year fixed effects and are weighted using the same weights as in the industry level analysis, i.e. base-sample-year share of each industry's number of hours worked to country-wide hours worked. The estimated effects are plotted with 2 shades of green and red for two groups of positive and negative values, respectively, with the darker colors representing stronger effects. Regions with no data are left blank.

6. Discussion

The empirical observations show that the relationship between automation technology diffusion and taxation is not straightforward. The ambiguous patterns of correlation between automation and corporate tax revenues indicate that it may be insufficient to solely focus on labor market effects when trying to understand the impact of automation technology on taxation. However, it should be kept in mind that there is a high variation in the data coverage across countries.

The firms captured in our dataset differ by the extent to which the data is representative for the whole industry in the respective country. For example, for Estonia and Greece, the firm level data on employment in the 15 industries covered by our analysis accounts for only less than 10% of employment as it would be measured by country level accounts in EUKLEMS which are representative of the employment activity in these sectors. Contrarily, in other countries like Sweden, Netherlands, and Finland these industries are well represented with more than 90% of industry level employment covered. This may result from different industrial structures in these countries as the Orbis data is biased towards larger sized firms that fall under more stringent financial reporting requirements. A poor coverage indicates that the automation-intensive industries studied in this analysis are characterized by smaller sized firms which may be differently affected by automation than large firms [Atasoy et al., 2016]. Differences in the industrial structure may also indicate that these industries differ by their importance for the national economy, and thus, for fiscal revenues.

As already noted above, the results shown in this report show only a limited fraction of the potential impact that automation may have on fiscal revenues. The data only includes firms from industries for which data on industrial robot adoption is available. As argued in Hötte et al. [2021], these industries can be understood as most exposed to automation technology diffusion because the availability of data correlates with whether or not these industries are significant users of robots. Further, and more importantly, we only cover corporate tax payments which represent a rather small fraction of fiscal revenues. The effects of automation on taxation are complex and all second and third order effects, such as labor reinstatement in non-automating industries or changes in regional output in response to automation-induced changes in real income, were not captured by this analysis due to data limitations at the regional level. A comprehensive assessment of the existence of these effects at the aggregate level and their interaction with taxation was made in Hötte et al. [2021].

Another aspect that was not covered, but remains relevant to understand, is the impact of automation on taxation at the local level, are cross-regional dependencies in terms of economic spillovers when prices for goods change, but also in terms of labor migration when the local employment conditions change in response to automation. The analysis made in this study only captures the demand for labor by a small subset of firms, the development of which does not necessarily coincide with employment rates when the population or the industrial structure change.

The key message from this study is that regional heterogeneity matters. This does not only hold in terms of whether or not the employment effects of automation are positive or negative, but it also holds for the relationship between employment and corporate tax payments.

7. Wrapping up and concluding remarks

Which local and national governments will be most affected by automation technology diffusion? Our results highlight that regional diversity matters: Many regions in Spain and France benefit from both, robots and ICT. Italy benefits from robots, but suffers from ICT. In Scandinavian countries, we find rather negative or weak effects. Countries like Germany and Greece show a strong pattern of regional diversity, i.e. strong negative effects in some regions, but strong positive effects in other.

Even though this analysis only reports conditional correlations and is subject to severe data limitations, the insights about regional heterogeneity are important. We also find that it may be relevant which type of automation technology is considered: some regions benefit from the diffusion of robots but show the opposite effect for ICT. The results underline the importance of regional structural funds that help to address these patterns of diversity and support regions to cope with structural and economic change which could be driven by different types of technological change.

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A. Data

Table A.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 A.2: Representativeness of employment in Orbis vs. EUKLEMS data

Country	(1)	(2)	(3)	(4)	(5)
	Total employment			Employment share %	
	EUKLEMS	R-sample	ICT-sample	R-sample	ICT-sample
AT	1,254,090	932,795	932,795	74.38	74.38
BE	1,130,893	784,687	784,687	69.39	69.39
CZ	2,080,420	1,283,846	1,283,846	61.71	61.71
DE	12,381,000	8,997,709	8,997,709	72.67	72.67
DK	733,000	297,891	297,891	40.64	40.64
EE	241,000	57,452	10,524	23.84	4.37
ES	4,787,000	1,572,781	1,572,781	32.86	32.86
FI	705,900	824,132	824,132	116.75	116.75
FR	6,386,000	1,508,347	1,508,347	23.62	23.62
GR	777,160	49,835	49,835	6.41	6.41
HR	545,340	291,881	N/A	53.52	N/A
HU	1,495,220	536,044	N/A	35.85	N/A
IE	472,790	677,391	N/A	143.28	N/A
IT	6,534,000	4,614,803	4,614,803	70.63	70.63
LT	495,570	482,602	294,167	97.38	59.36
LV	291,860	113,203	113,203	38.79	38.79
NL	1,654,000	1,610,159	1,610,159	97.35	97.35
PL	5,863,800	1,313,027	N/A	22.39	N/A
PT	1,389,160	598,185	N/A	43.06	N/A
RO	2,907,400	1,470,350	N/A	50.57	N/A
SE	1,489,000	1,352,279	1,352,279	90.82	90.82
SI	325,680	155,516	53,275	47.75	16.36
SK	821,310	436,482	436,482	53.14	53.14
UK	6,433,010	4,806,876	4,806,876	74.72	74.72
Mean	2,549,775	1,448,678	1,641,322	60.06	55.78

Notes: Columns (1), (2) and (3) show the total number of employees in EUKLEMS, R-sample and ICT-sample, respectively, for each country in the last sample period, i.e. 2016. R- and ICT-sample refer to the firm level Orbis sample when robot- and ICT-density is reported, respectively. Columns (4) and (5) report the employment shares in % covered by the firm level sample relative to the aggregate data in EUKLEMS, i.e. the ratio of (2) over (1) and (3) over (1), respectively. All samples cover the same 15 industry-groupings used in the analysis and discussed in detail in Appendix Table A.1.

Table A.3: Representativeness of corporate taxes in Orbis firm level samples vs. OECD country level data.

Country	(1)	(2)	(3)	(4)	(5)
	Aggregate Tax			Tax share (Sample Tax/$T_c^{k,corp}$)%	
	T_c^k	$T_c^{k,corp}$	$T_c^k/T_c^{k,corp}$	R-sample	ICT-sample
AT	44	8	19.18	N/A	N/A
BE	81	15	18.03	39.61	39.61
CZ	385	179	46.40	0.16	0.16
DE	410	62	15.23	N/A	N/A
DK	641	60	9.32	7.62	7.62
EE	2	0	21.88	4.37	4.12
ES	133	25	18.97	35.34	35.34
FI	36	5	13.33	30.52	30.52
FR	331	45	13.70	19.10	19.10
GR	21	4	20.43	3.16	3.16
HU	3,076	831	27.02	0.10	N/A
IE	31	7	23.56	1.06	N/A
IT	275	36	13.19	27.11	27.11
LT	2	1	27.26	3.90	N/A
LV	2	0	18.61	N/A	N/A
NL	85	24	27.96	7.32	7.32
PL	150	34	22.81	6.84	N/A
PT	21	6	27.49	35.85	N/A
SE	744	121	16.20	1.36	1.36
SI	3	1	21.35	1.31	N/A
SK	6	3	46.77	31.92	31.92
UK	311	53	17.12	56.61	56.61
Mean	309	69	22.08	16.49	20.30

Notes: Column (1) shows the total tax on capital T^k in billions of national currency for each country in the last sample period, i.e. 2016. Column (2) is a sub-category of column (1) capturing corporate taxes on income, profits and capital gains $T^{k,corp}$ (with variable code 1200 in OECD [2019] data set). Column (3) is the ratio of (1) over (2) in %. Columns (4) and (5) capture the share of total taxes reported in the R- and ICT-sample used in the analysis, respectively, over (2) in %. R- and ICT-sample refer to the firm level Orbis sample when robot- and ICT-density is reported, respectively. The aggregate taxes cover the whole economy while the firm level samples cover the 15 industry-groupings discussed in detail in Appendix Table A.1.

Table A.4: Summary statistics for firm level sample

	R-sample		ICT-sample	
	$L_{f,i,t}$	$T^{\dagger}_{f,i,t}$	$L_{f,i,t}$	$T^{\dagger}_{f,i,t}$
Mean	23	321	26	409
St.Dev.	838	30,453	985	35,244
Min	1	.001	1	.001
Median	4	5.2	3	8
Max	855,492	24,474,986	855,492	24,474,986
# Observations	16,261,216	8,095,653	11,391,818	6,019,433
# Firms	4,385,360	1,964,694	3,245,827	1,478,475
# Countries	24	24	18	18
# NUTS2 regions	273	273	227	227
# NUTS3 regions	1,310	1,314	1,119	1,123

Notes: † refers to values in thousands for the Mean, St.Dev., Min, Median, and Max. This table presents the summary statistics on the firm level corporate income tax ($T_{f,i,t}$) and number of employees ($L_{f,i,t}$) for 2 different samples. R- and ICT-sample refer to samples with non-missing values of industry level robot- and ICT-intensity, respectively. The ICT-sample covers the following 18 countries: AT; BE; CZ; DE; DK; EE; ES; FI; FR; GR; IT; LT; LV; NL; SE; SI; SK; and UK, while the R-sample covers 6 additional countries: HR; HU; IE; PL; PT; and RO. Both samples cover the same set of 15 industry groups included in the industry level analysis—for more details see Appendix Table A.1.

B. Methods

We rely on the proprietary firm level data set Amadeus, the European counterpart of Orbis-Global, which is a product of Bureau van Dijk Electronic Publishing [2020a] (BvDEP). The underlying data are firms' financial statements sourced from various national registries (e.g. statistical agencies) and standardized by BvDEP for cross-country comparability.[6]

The data is balance sheet information of firms in those European countries where the industry level information on the adoption of industrial robots or use of ICT capital exists for the period 2008-2016. To cover the largest set of regions across EU as possible, we examine the effects of robot and ICT diffusion separately and, thus, rely on the maximal amount of information available across data sets. More precisely, the sample used to analyze the impact of ICT-intensity ($ICT_{i,t}$) covers the same set of countries and industries used in the country and industry level analysis from above. The sample used to analyze the impact of robot-intensity ($R_{i,t}$) also includes the following set of countries: Croatia (HR); Hungary (HU); Ireland (IE); Poland (PL); Portugal (PT); and Romania (RO).

For each firm in the data set we retain those reporting strictly positive firm-year values on the number of employees or taxes payed. The latter refers to income tax expenses

[6] For more details over the standardization procedure, see the correspondence tables used for each country by Bureau van Dijk Electronic Publishing [2020b]. For the initial data cleaning and preparation procedure we follow Kalemli-Ozcan et al. [2015]. Specifically, we drop firms reporting consolidated accounts, i.e. C1 and C2 codes and, if duplicate, the rest is kept based on the presence of annual reports over local registry filling. We also use annual records over quarters and late calendar months over early months.

of the reporting period plus any net deferred tax expenses/income between the current and the previous reporting period. Conclusions drawn from this analysis are limited to a rather specific category of fiscal taxes, i.e. corporate income taxes.

Each firm's primary production activity is based on the NACE Rev.2 (ISIC Rev.4) 2-digit industry code used to merge with the industry level measures on robot- and ICT-intensity. The sample includes the same set of 15 industry groups covered in the industry level sample (see Appendix Table A.1 for a detailed description of the industry codes). Finally, we link firms to the location of economic activity trough the NUTS version 2016 regional classification codes which across the EU and UK cover 281 regions at NUTS 2 and 1348 regions at NUTS 3 level [Eurostat, 2020]. The sample used in our analysis for the effects of robot (ICT) intensity covers 273 (227) NUTS 2 and 1314 (1127) NUTS 3 regions. For more details over the summary statistics of the firm level sample and variables considered, see Appendix Table A.4.

Orbis-Global is widely accepted as one of the best available options in terms of the richness of balance sheet information and cross-country comparability at the expense of incomplete coverage for smaller-sized firms with simplified financial reporting obligations [Bajgar et al., 2020, Kalemli-Ozcan et al., 2015]. Thus, while a large number of micro firms remain unrecorded, the sample manages to cover around 60% of economic activity in terms of employment, on average (see Appendix Table A.2).[7]

[7] For similar evidence see Bormans and Theodorakopoulos [2020].