CESifo WORKING PAPERS

7247
2018

September 2018

Racing With or Against the Machine? Evidence from Europe

Terry Gregory, Anna Salomons, Ulrich Zierahn

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 7247*
Category 14: Economics of Digitization

Racing With or Against the Machine? Evidence from Europe

Abstract

A fast-growing literature shows that digital technologies are displacing labor from routine tasks, raising concerns that labor is racing against the machine. We develop a task-based framework to estimate the aggregate labor demand and employment effects of routine-replacing technological change (RRTC), along with the underlying mechanisms. We show that while RRTC has indeed had strong displacement effects in the European Union between 1999 and 2010, it has simultaneously created new jobs through increased product demand, outweighing displacement effects and resulting in net employment growth. However, we also show that this finding depends on the distribution of gains from technological progress.

JEL-Codes: E240, J230, J240, O330.

Keywords: labor demand, employment, routine-replacing technological change, tasks, local demand spillovers.

Terry Gregory
Centre for European Economic Research (ZEW) Mannheim, L7, 1
Germany – 68161 Mannheim
gregory@zew.de

Anna Salomons
Utrecht University School of Economics
Kriekenpitplein 21-22
The Netherlands – 3584 EC Utrecht
a.m.salomons@uu.nl

Ulrich Zierahn
Centre for European Economic Research (ZEW) Mannheim, L7, 1
Germany – 68161 Mannheim
zierahn@zew.de

September 2018
Helpful comments by David Autor, Christian Dustmann, Bernd Fitzenberger, Maarten Goos, Frank Levy, and participants of the following workshops are gratefully acknowledged: ZEW & IAB conference on "Spatial Dimensions of the Labour Market"; 6th Economic Workshop at the IAAEU; TASKS-III conference on "Changing Tasks - Consequences for Inequality"; DFG & ZEW conference on "Occupations, Skills and the Labor Market"; KU Leuven workshop on "New Empirical Developments in Health and Labor Markets"; annual ESPE and ERSA conferences; as well as Manchester University, Trier University, Utrecht University, and ZEW labor market seminars. The authors gratefully acknowledge funding from the state Baden-Württemberg within the SEEK program; Salomons gratefully acknowledges funding from the Netherlands Organisation for Scientific Research.

1 Introduction

In recent years, rapid improvements in digital technologies such as information and communication technologies (ICT) and artificial intelligence (AI) have led to a lively public and scientific debate on the impact of automation on jobs. As highlighted by Acemoglu and Restrepo (2018a), this debate is permeated by a false dichotomy. On the one hand, there are alarmists, foremost in public press, arguing that automation will lead to the end of work. Their views are fueled by reports zooming in on the automation potential of existing jobs, claiming that large shares of U.S. and European jobs are at risk of being eliminated in coming decades (Bowles 2014; Frey and Osborne 2016).[1] On the other hand, there are economists arguing that technological revolutions of the past have not persistently reduced labor demand, and that there is no reason to believe that this time is different. Their views are reflected in canonical skill-biased technological change (SBTC) frameworks that assume technology is complementary to (skilled) workers, thus precluding labor displacement and, ultimately, ruling out the possibility that technological change may decrease labor demand and employment (see Acemoglu and Autor 2011; Acemoglu and Restrepo 2018b for a discussion and overview of this extensive literature).

Recent theoretical studies take a more nuanced view by considering that technological change may have both labor-replacing and labor-augmenting effects. In particular, the routine-replacing technological change (RRTC)[2] hypothesis adapts canonical frameworks by explicitly allowing for labor displacement. In particular, RRTC entails that digital technologies substitute for human labor in so-called routine tasks, which follow a set protocol, making them codifiable in software (see Autor et al. 2003). Using a rich theoretical framework rooted in this approach, Acemoglu and Restrepo (2018a,c) show that technological progress may lead to decreased labor demand (along with falling wages and employment), if positive forces spurred by e.g. productivity increases are not large enough to countervail negative labor displacement effects resulting from automation.[3] Other studies have considered the theoretical conditions for more extreme scenarios, including human obsolescence and labor immiseration (Benzell et al. 2016; Nordhaus

[1] Although Arntz et al. (2017) show that these narrow “feasibility studies” overstate the exposure of jobs to automation by ignoring the substantial variation in job tasks within occupations.

[2] Sometimes also referred to as routine-biased technological change (RBTC).

[3] This partially mirrors the theoretical results in Autor and Dorn (2013) and Goos et al. (2014), who show that the effect of RRTC on the employment share of routine jobs depends on the relative sizes of the elasticity of substitution between inputs in production and the elasticity of substitution in consumption between different goods and services. This is a departure from canonical SBTC models which consider a single final consumption good, thus abstracting from such adjustments in the composition of product demand (e.g. see Card and Lemieux 2001; Katz and Murphy 1992).

2015; Sachs et al. 2015; Susskind 2017). The common thread in this literature is that the aggregate effect of technological progress on jobs is shown to be theoretically ambiguous (see also Caselli and Manning 2018). To determine whether labor is racing with or against the machine therefore ultimately requires empirically testing the existence of both these labor-displacing and countervailing forces, and determining their relative sizes: this paper aims to tackle these questions.

In particular, we investigate how routine-replacing technologies impact economy-wide labor demand and employment by developing and estimating an empirically tractable framework. This task-based framework builds on Autor and Dorn (2013) and Goos et al. (2014), and incorporates three main channels through which RRTC affects labor demand. Firstly, RRTC reduces labor demand through *substitution effects*, as declining capital costs incentivize firms in the high-tech tradable sector to substitute capital for routine labor inputs, and to restructure production processes towards routine tasks. Secondly, RRTC induces additional labor demand by increasing product demand, as declining capital costs reduce the prices of tradables – we call this the *product demand effect*. Thirdly, *product demand spillovers* also create additional labor demand: the increase in product demand raises incomes, which is partially spent on low-tech non-tradables, raising local labor demand. We further investigate how these spillovers depend on the allocation of gains from technological progress by considering the role of non-wage income in producing these spillovers, inspired by a theoretical literature emphasizing this channel (Benzell et al. 2016; Freeman 2015; Sachs et al. 2015). The first of these three forces acts to reduce labor demand, whereas the latter two go in the opposite direction. As such, the net labor demand effect of RRTC is theoretically ambiguous. For each of these three labor demand channels, we also model the resulting labor supply responses: this allows us to obtain predictions for changes in employment. We use data over 1999-2010 for 238 regions across 27 European countries to construct an empirical estimate of the economy-wide effect of RRTC on labor demand and employment for Europe as a whole. Rather than only identifying the net impact, we also use our model to decompose these economy-wide effects into the three labor demand channels outlined above.

This contributes to the literature in several ways. Firstly, ours is the first estimate of the effect of routine-replacing technologies on economy-wide labor demand and employment.[4] As

[4]A large literature surveyed in Acemoglu and Autor (2011) has studied the *relative* labor demand changes resulting from RRTC, but has so far ignored the absolute labor demand and employment effects which lie at the heart of the current debate on whether labor is racing with or against the machine.

outlined in Autor et al. (2003), routine-task replacement is the very nature of digital technology, making this especially relevant to study. Our approach complements work which has either taken a more narrow view by considering industrial robotics in isolation (Acemoglu and Restrepo 2017; Chiacchio et al. 2018; Dauth et al. 2017; Graetz and Michaels 2018), or a wider view by considering all increases in Total Factor Productivity (TFP) irrespective of their source (Autor and Salomons 2018).

Moreover, we do not only study the net impact of RRTC on labor demand and employment, but also empirically quantify the relevance of the underlying transmission channels derived from our framework. As such, we study both the labor-displacing and countervailing effects of RRTC highlighted in the theoretical literature in an empirically tractable manner. This is in contrast to the existing empirical literature which uses reduced-form approaches to inform on these employment effects. However, empirically quantifying the relevance of the underlying transmission channels is important both because these channels are the key distinguishing features of modern theoretical frameworks of technological change, and because their relative sizes inform about the conditions under which labor demand and employment are likely to rise or decline as a result of RRTC. This matters even more because reduced-form estimates have so far not produced a strong consensus: Acemoglu and Restrepo (2017) and Chiacchio et al. (2018) find robustly negative employment effects, whereas positive or weakly positive effects are found by others (Autor and Salomons 2018; Dauth et al. 2017; Graetz and Michaels 2018). Our approach of separately identifying these channels helps shed light on how the net effect of technological change on jobs comes about. In doing so, we build a bridge between reduced form empirical work which studies net employment effects while remaining largely silent on the underlying mechanisms, and theoretical contributions which highlight mechanisms but do not speak to their relative sizes with empirical evidence.

Our results indicate that the net labor demand and employment effects of routine-replacing technological change over the past decade have been positive, suggesting that labor has been racing with rather than against the machine in aggregate. However, this does not imply an absence of labor displacement. Indeed, decomposing net labor demand and employment changes into the three separate channels reveals a substantial decrease in labor demand and employment resulting from the substitution of capital for labor. Nevertheless, the product demand effect and its spillovers to the non-tradable sector are large enough to overcompensate this substitution effect for the countries and time period we study. Overall, these findings validate the recent literature's approach of modeling technological change as having labor-displacing effects, but also stress the importance of considering countervailing product demand responses. Lastly, we show that these estimates hinge critically on rising non-wage income feeding back into local product demand: if only wage income is taken into account, the total labor demand effects are found to be only half as large. This highlights that the allocation of the gains from technological progress matters for whether labor is racing with or against the machine.

The remainder of this paper is organized as follows. Section 2 presents our theoretical framework for analyzing the employment effect of RRTC as well as the decomposition of this effect into the three channels outlined above. Our empirical strategy for identifying the parameters of this framework is outlined in Section 2.7. Section 3 describes the data and presents our parameter estimates. Section 4 outlines and discusses our results, and Section 5 concludes.

2 Framework

In this section, we present a stylized task-based framework for understanding how labor races with or against the machine: specifically, we examine how RRTC affects labor demand and employment. We do this by modeling how firms' production processes shift towards capital inputs in the face of RRTC, leading to subsequent output price changes as well as a spatial reallocation of output and jobs.

We build on Goos et al. (2014) and distinguish tradable and non-tradable goods in order to model the spatial reallocation of labor demand resulting from RRTC.[5] This extension serves three purposes. Firstly, it allows us to consider the transmission channel of local labor demand spillovers, which a related economic geography literature (see Moretti 2011) indicates to be potentially important.[6] Secondly, this spatial framework captures the technology-induced component of interregional trade.[7] Since we will estimate this framework using regional data

[5] The model in Goos et al. (2014) neither contains a spatial dimension nor differentiates sectors by their tradability. A similar theoretical distinction between tradable and non-tradable goods is made in Autor and Dorn (2013), although our set-up differs from theirs in that we assume that trade between regions is costly.

[6] According to this literature, technological change creates high-tech jobs which, in turn, generate additional employment through local demand spillovers. Reduced-form empirical estimates indeed provide evidence for the existence of such spillovers for both the U.S. (Moretti 2010; Moretti and Thulin 2013) and Europe (Goos et al. 2015).

[7] Our framework does not account for any employment effects of *exogenously* decreasing trade barriers. Previous work has shown that one such exogenous change, the accession of China to the WTO, has had an economically sizable impact on employment in U.S. (Autor et al. 2013; Caliendo et al. 2015) and German regions (Dauth et al. 2014). However, these effects were also found not to be strongly correlated with the employment effects of RRTC at the regional or occupational level, or across time (Autor et al. 2015).

from 27 European countries, we expect to empirically capture the most important part of such technology-induced trade: intra-EU27 trade makes up roughly 70 percent of total European trade (WTO 2012). Finally, this approach allows us to later exploit spatial variation in regions' exposure to RRTC for empirically identifying the parameters of our model.[8]

In particular, our framework consists of $i = 1, 2, \ldots, I$ regions, where each region has a non-tradable and a tradable sector.[9] Firms produce tradable goods and services by combining a set of occupational tasks which are themselves produced by combining labor and technological capital. Hence, we differentiate labor by tasks or occupations and thus indirectly consider skill or qualification differences as long as they correspond to occupational differences. RRTC is modeled as exogenously declining costs of capital in routine tasks relative to non-routine tasks, which can alternatively be interpreted as increasing productivity of capital in routine tasks relative to non-routine tasks. Non-tradable goods and services, on the other hand, are produced using only labor. Assuming that only tradables use capital in production implies that technological change directly affects the tradable sector whereas the non-tradable sector is affected only indirectly through local spillovers, as in Autor and Dorn (2013). This is rooted in the empirical observation that tradables, such as business services, are more ICT-intense and have seen faster ICT-adoption than non-tradables such as personal services (see Table 7 in Appendix A.4.1).

2.1 Production of tradables

The production structure in the tradable sector g is depicted in Figure 1. Regional firms in the tradable sector produce a variety c_i^g that can be traded across regions. We assume monopolistic competition between the firms so that prices are a constant markup over marginal costs.[10] The production of tradables requires a set of different tasks $T_j, j = 1, 2, \ldots, J$, which differ in their routine intensity: the more routine the task is, the easier it is to automate. These tasks are combined to produce tradable output Y_i^g with a Constant Elasticity of Substitution (CES) production technology, $Y_i^g = \left[\sum_{j=1}^{J} (\beta_{ij} T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$, where $\eta > 0$ is the elasticity of substitution between tasks, reflecting to what extent firms may substitute one task for another. The term

[8]Figure 8 in the Appendix shows that regions are differently routine-intense in terms of their employment, so that they are differently exposed to RRTC.

[9]The empirical classification we implement to distinguish tradables from non-tradables is reported in Table 1 from Section 3.

[10]c_i^g refers to the regional goods bundle, which is a CES bundle of the varieties produced by the firms residing in region i. Firms within the same region are identical and thus charge the same price. For illustrative purposes, we present the model at the level of regions.

β_{ij} captures region i's efficiency in performing task j. As in Goos et al. (2014), each task itself is performed by a combination of human labor and machines (technological capital). We assume a Cobb-Douglas (CD) production technology, $T_{ij} = (N^g_{ij})^\kappa (K_{ij})^{1-\kappa}$, where the production of tasks depends on labor from occupation j N^g_j, task-specific capital inputs K_j, and the share of labor in the costs of producing a task, $0 < \kappa < 1$.[11]

Firms minimize the costs of producing Y^g_i, which leads to the regional task demand,

$$T_{ij} = Y^g_i \beta^{1-\eta}_{ij} \left(\frac{c^I_i}{w^\kappa_{ij} r^{1-\kappa}_j} \right)^\eta, \tag{1}$$

which rises in tradable production Y^g_i, in the efficiency of that task β_{ij}, and in the ratio of marginal costs c^I_i relative to the task-specific costs $w^\kappa_{ij} r^{1-\kappa}_j$, to the extent that tasks can be substituted (η). In this setting, we then think of RRTC as a decline in the costs of technological capital in routine tasks relative to non-routine tasks. Equation (1) shows that, as relative capital costs for routine tasks decrease, firms start shifting their tradable production towards these tasks.

Firms minimize the costs of producing T_{ij}, which leads to regions' occupational employment,

$$N^g_{ij} = T_{ij} \left(\frac{r_j}{w_j} \frac{\kappa}{1-\kappa} \right)^{1-\kappa}, \tag{2}$$

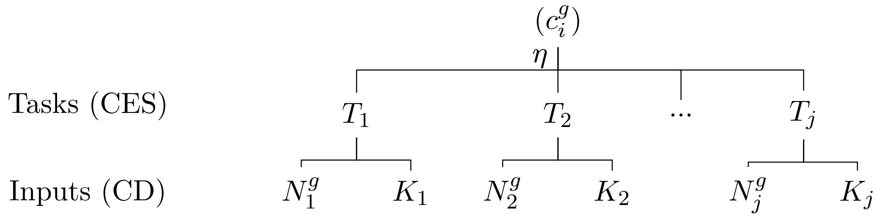
which increases in the demand for tasks in that region T_{ij} as well as in task-specific capital costs r_j relative to occupational wages w_j. From Equation (2) it can be seen that occupational employment decreases with falling capital costs for routine tasks, reflecting that firms substitute capital for human labor in routine tasks. Note that, although labor and capital are p-substitutes in the production of tasks in our framework, they can be either gross complements or gross substitutes.

Substitution effects. RRTC affects employment through substitution effects, where workers are replaced by machines in the production of routine tasks (direct positive relationship between r_j and N^g_{ij} in Equation 2).[12] This effect is further reinforced as firms shift their production technology towards routine task inputs (indirect negative relationship between r_j and N^g_{ij} working

[11] Note that, as in Goos et al. (2014), we equate tasks and occupations (both denoted by subscript j).

[12] Note that this substitution effect covers both substitution of capital for labor in routine-intensive jobs, as well as rising labor demand in non-routine-intensive jobs.

Figure 1: Regional production



through T_{ij} in Equation 2).[13] Overall, these two substitution effects lead to a decline in employment. The size of the negative employment effect rises in the substitutability between tasks in tradables production (η) and is more pronounced in regions with a higher initial share of routine tasks.

2.2 Consumption

The product demand structure is depicted in Figure 2. We assume that the utility of households depends on the consumption of tradables C_g and non-tradables C_s and follows a CD utility function: $U = C_g^{\mu} C_s^{1-\mu}$, where $0 < \mu < 1$ is the expenditure share of tradables.[14] Non-tradables are consumed locally, and are – without loss of generalizability – assumed to be homogeneous. Tradables are composed of varieties c_i^g produced by the regional firms and are consumed by households from all regions. We assume that preferences for tradables follow a CES utility function, $C_g = \left[\sum_{i=1}^{I} (c_i^g)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, where $\sigma > 0$ is the elasticity of substitution between regional bundles of tradables. As such, σ reflects to what extent consumers can replace local bundles with bundles from other regions. The regional bundles of tradables are, in turn, composed of the regional firms' varieties. For illustrative purposes, we present the model at the level of regions.[15]

Individuals maximize utility by optimizing the composition of regional bundles, which leads to the demand for regional tradables,

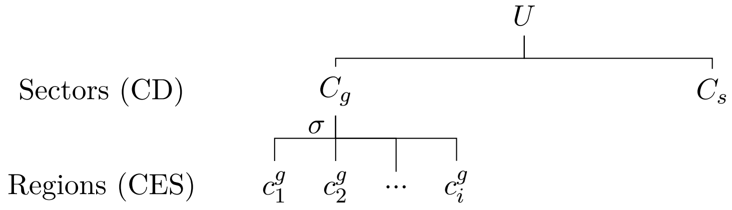
$$c_i^g = \left(\frac{\tau_{ii'} p_i^g}{P^g}\right)^{-\sigma} \mu \frac{I}{P^g}, \tag{3}$$

[13]Note that this substitution effect corresponds to the canonical factor-augmenting view of technological change: changing relative prices (or productivities) of labor and capital induce substitution between capital- and labor-intensive tasks. As highlighted by Acemoglu and Restrepo (2018a,c), this effect alone is unable to explain key features of automation technologies. We therefore take into account direct capital-labor substitution through our first substitution effect.

[14]By relying on CD utility, we assume homothetic preferences and thus assume that technology-induced price declines of tradables do not affect the expenditure shares of tradables and non-tradables. In an extended version of our model (available on request) we introduce non-homothetic preferences, relaxing the restriction that $\delta_2 = 1$ in empirical Equation 13. However, empirically, non-homothetic preferences have been found to have only small effects on relative task demand (Autor and Dorn, 2013; Goos et al., 2014) so we do not pursue this extension further.

[15]The firm-level relaxes our model by allowing σ to be smaller than one.

Figure 2: Product demand



where P^g is an aggregated price index and p_i^g are local producer prices in the tradable sector. $\tau_{ii'}$ are iceberg trade costs between the exporting i and importing i' region. Equation 3 shows that consumption of tradables rises with households' real income $\frac{I}{P^g}$ and with the share of income spent on these tradables μ. Moreover, consumption of tradables decreases in the relative price for these goods and services $\frac{p_i^g}{P^g}$ to the extent that consumers can switch to tradables produced by other regions (σ).[16]

Product demand effect. This consumption structure provides us with the second channel through which RRTC affects employment. The substitution of capital for labor (see substitution effects) allows firms to reduce costs, which lowers the output prices of tradables. Product demand for tradables rises as a result of lower output prices (negative relationship between $\frac{p_i^g}{P^g}$ and c_i^g in Equation 3), leading to higher production and income, inducing additional employment in the tradable sector. This product demand effect of RRTC thus raises employment.[17] The effect increases in the substitutability between goods bundles, σ, and is stronger in regions with a higher initial share of routine tasks.

2.3 Non-tradable sector

Firms in the non-tradable sector produce homogeneous goods and services using labor inputs, only. As outlined at the beginning of this section, this reflects the limited substitution possibilities between technological capital and labor in the production of non-tradables. The production function for non-tradables in region i is $C_i^s = \alpha_s L_i^s$, where labor input L_i^s is a CES-aggregate of task-specific labor inputs and α_s is the productivity of labor. We further assume the labor

[16]The elasticity of substitution in production (between tasks) η and the elasticity of substitution in consumption (between regional goods bundles) σ determine whether labor and capital in the tradable sector are gross complements or substitutes. This can be shown by deriving the cross-elasticity of unconditional labor demand with respect to capital costs. Our parameter estimates from Table 5 suggest that capital and labor are gross complements.

[17]The counterpart to our product demand effect is the productivity effect in the Acemoglu and Restrepo (2018a,c) framework. A major distinction, however, is that our product demand effect does not contain spillovers to other sectors, which we instead model separately in Section 2.3. The sum of our product demand and spillover effects is thus similar to the productivity effect in Acemoglu and Restrepo (2018a,c).

aggregate L_i^s to be performed by occupations $j = 1,..,J$, $L_i^s = \left[\sum_{j=1}^{J}(\beta_{ij}^s N_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ with $\eta > 0$.

Firms minimize the costs of producing non-tradables C_i^s by minimizing the cost of obtaining the labor aggregate L_i^s. Occupational employment in the non-tradable sector is then given by

$$N_{ij}^s = (1-\mu)\beta_{ij}^{1-\eta}\left(\frac{w_j}{w_i^s}\right)^{-\eta}\frac{I_i}{w_i^s}. \tag{4}$$

Employment generally decreases with wages in the non-trabable sector w_i^s and increases with local income I_i. Occupational employment in non-tradables rises with regions' efficiency in performing tasks (β_{ij}^s) and declines with occupational wages w_j relative to regional wages w_i^s to the extent that tasks can be substituted (η). RRTC thus affects employment in Equation 4 only indirectly through its effect on local income.

Local income I_i is composed of the sum of income in the non-tradable and tradable sectors. The former consists of labor income, only, whereas the latter consists of labor income and firm profits, which we can rewrite as sales minus capital costs, $I_i = w_i^s L_i^s + p_i^g Y_i^g - \sum_{j=1}^{J} r_j K_j$.[18] Defining $\phi_{1-K} = p_i^g - \sum_{j=1}^{J} r_j K_{ij}/Y_i^g$ as the disposable income resulting from tradable sales per unit of real output, we can express local income as follows:

$$I_i = w_i^s L_i^s + \phi_{1-K} Y_i^g \tag{5}$$

RRTC thus affects local income and, hence, employment in the non-tradable sector positively by increasing output Y_i^g. Note that RRTC has two opposing effects on ϕ_{1-K}: falling capital costs r_j imply falling production costs and thus more disposable income per unit of output, although falling prices (i.e. lower nominal sales) due to falling capital costs counteract this effect.

Product demand spillover effect. This framework leads to the third channel through which RRTC impacts employment. In particular, RRTC leads to higher production (see product demand effect), which results in additional income among local households (positive relationship between $\phi_{1-K}Y_i^g$ and I_i in Equation 5). This induces a product demand spillover effect as the additional local income is partly spent on local non-tradables (positive relationship between I_i and N_{ij}^s in Equation 4), creating additional production and employment in the local economy.

[18] We assume that there is a competitive K-sector that produces K_j with real resource costs r_j and zero profits, such that capital costs play no role for consumption.

These spillovers are larger in regions with a higher initial share of routine tasks.

However, note that the product demand spillover effect is only unambiguously positive if firm owners are located in the region of production, such that additional firm profits arising from RRTC are spent locally. This may not be realistic if firms are, for instance, owned by non-EU residents. In the empirical investigation, we therefore compare two alternative scenarios, where either (1) all income from the tradables sector is spent locally and we assume that the income generated per unit of output, ϕ_{1-K}, stays constant, or (2) all non-wage income is consumed abroad, i.e. regional income consists only of wage income. Derivations on the labor demand and employment effects under the second assumption can be found in Appendix A.2.

2.4 Labor supply

We follow Acemoglu and Restrepo (2017) and specify the supply of labor as follows:

$$N_{ij}^{g} = \bar{N}_{ij}^{g} {w_{ij}^{g}}^{\epsilon} \quad \text{and} \quad N_{ij}^{s} = \bar{N}_{ij}^{s} {w_{ij}^{s}}^{\epsilon}, \tag{6}$$

This specification implies that $\epsilon > 0$ is the wage elasticity of labor supply. We do not directly model movements of workers between occupations, sectors and regions. However, this mobility is implicitly included in ϵ, meaning that ϵ measures both labor supply at the intensive and extensive margins, and workers' mobility between labor market segments. We do not directly model workers mobility due to lack of adequate data at the EU level.

2.5 Labor demand and product demand equations

Combining Equations (1) and (2) from the production of tradables as well as Equations (4) and (5) from the production of non-tradables, we can derive the following labor demand equations for the tradable (g) and non-tradable (s) sector:[19]

[19] See Appendix A.1 for details on these derivations.

$$
\begin{aligned}
\log N_{ij}^{g} =& \log Y_i^g + (1-\eta)\log\beta_{ij} + \eta\log c_i^I + (1-\kappa)\log\frac{\kappa}{1-\kappa} \\
&+(1-\eta)(1-\kappa)\log r_j - [(1-\kappa)+\kappa\eta]\log w_j \qquad (7) \\
\log N_{ij}^{s} =& \log Y_i^g + (1-\eta^s)\log\beta_{ij}^s + (\eta^s-1)\log w_i^s + \log\frac{1-\mu}{\mu} \\
&-\eta^s\log w_j + \log\phi_{1-K} \qquad (8)
\end{aligned}
$$

Note that we cannot observe task-specific capital costs r_j. In order to nevertheless empirically incorporate a relative decline in capital costs for routine relative to non-routine tasks, we follow the literature (starting with Autor et al. 2003) and replace log capital costs by $\gamma_R R_j \times t$, where R_j is the time-constant Routine Task Intensity (RTI) of occupation j interacted with a linear time trend t. The occupational RTI thereby rises in its routine task job content and declines in its non-routine task content. The term $\gamma_R < 0$ reflects the theoretical prediction that routine intensive occupations (tasks) are more susceptible to technological substitution compared to non-routine occupations. Note that RRTC in our framework need not only be viewed as a relative decline in capital costs for routine relative to non-routine tasks, but can also be interpreted as a relative increase in the productivity of capital for routine relative to non-routine tasks.

Given space-dependent transport costs, we can derive the product demand equation for the tradable sector from Equation (3),

$$
\log Y_i^g = \log\mu - \sigma\log\frac{p_i^g}{P^g} + \log\sum_{i'=1}^{I}\tau_{ii'}^{-\sigma}\frac{I_{i'}}{P^g}, \qquad (9)
$$

where the third additive term reflects region i's market potential, which is defined as the sum of local incomes I of all potential trading partners i', lowered by the transport costs $\tau_{ii'}$ between region i and its trading partner i'.

2.6 Decomposing labor demand and employment effects

In order to derive the implications of technological change for labor demand and employment, we define total regional employment N_{it} as the sum of regional employment in the tradable N_{it}^g and non-tradable N_{it}^s sectors, which themselves are composed of occupational employment N_{ijt}^g and N_{ijt}^s within these sectors, $N_{it} = N_{it}^g + N_{it}^s = \sum_{j=1}^{J} N_{ijt}^g + \sum_{j=1}^{J} N_{ijt}^s$. Taking the derivative of this equation with respect to log occupation-specific capital costs $r_{j't}$, and substituting in Equations

(7), (8) and (6), we obtain two alternative decompositions – a *labor demand* and an *employment decomposition*. In the former, we measure the shift of the labor demand curve holding wages constant: this is analogous to assuming labor supply to be perfectly elastic ($\epsilon \to \infty$). Equation 10, below, first presents this labor demand decomposition.

$$\Delta LD = \underbrace{(1-\eta)(1-\kappa)\gamma_R}_{A} \sum_{i=1}^{I} \left[\underbrace{\sum_{j=1}^{J} R_j N_{ijt}^g + \frac{\eta}{1-\eta} R_{it}^I N_{it}^g}_{B_i} - \underbrace{\frac{\sigma}{1-\eta}}_{C_i} R_{it}^I N_{it}^g - \underbrace{\frac{\sigma}{1-\eta}}_{D_i} R_{it}^I N_{it}^s \right], \quad (10)$$

where ΔLD denotes the labor demand change, R_j is the RTI of occupation j and R_{it}^I is the average regional RTI, weighted by occupational employment shares in the tradable sector in region i.

Equation (10) consists of a scaling factor A, which we refer to as the routinization coefficient, as well as three additive elements in the square brackets. Multiplied by the routinization coefficient, the elements correspond to the three channels through which RRTC affects regional labor demand: substitution effects ($A \times \sum_i B_i$), the product demand effect ($A \times \sum_i C_i$), and the product demand spillover effect ($A \times \sum_i D_i$).

Analyzing employment effects requires taking into account labor supply responses, and these create interdependencies between labor market segments in our model. In particular, if labor supply is not perfectly elastic, a labor demand shock from RRTC will induce wage adjustments in the region and occupation where the shock occurs. This alters the local occupational wage structure and thus indirectly affects all other occupations in the region via changing relative occupational labor demand. Moreover, it induces changes in the local price index, inducing output and labor demand changes for all occupations. In Appendix A.1, we show that this employment decomposition relies on this same labor demand shock, but scales all effects to correct for labor supply responses. The employment change, ΔN, predicted from our model can be represented as

$$\Delta N = A \times \sum_{i=1}^{I} \left[LS_i^g \times (B_i - C_i) - LS_i^s \times D_i \right], \quad (11)$$

where A, B_i, C_i, and D_i are defined as in equation 10, and $0 \leq LS_i^g, LS_i^s \leq 1$ are the regional labor supply scaling factors for the tradable and non-tradable sectors, respectively. These scaling factors are derived in Appendix A.1 (equation 25), and are strictly smaller than one if labor supply is not perfectly elastic, and strictly larger than zero if labor supply is not perfectly inelastic.

Our theoretical framework requires $\eta > 0$, $0 < \kappa < 1$, $\sigma > 0$ and $\epsilon > 0$. Further, we expect $\gamma_R < 0$, reflecting that capital costs decline for routine tasks relative to non-routine tasks. This implies that we expect a negative routinization coefficient, which then leads to negative substitution effects and positive product demand effects. The effect of RRTC on economy-wide labor demand is the sum of these three channels and may be either positive or negative, depending on the relative sizes of the elasticity of substitution between tasks (η) and the elasticity of substitution between the regional bundles of tradables (σ), as well as on differences in regional task structures. If the net effect is positive, labor is racing *with* the machine, whereas labor is racing *against* the machine if this effect is negative.

2.7 Empirical implementation

We aim to estimate the net effect of RRTC on labor demand and employment, as well as the contribution of the three channels outlined above. For this, we estimate the labor demand equation for the tradable sector (Equation 7) and the product demand equation (Equation 9) in order to get estimates for the key labor demand parameters of our framework (γ_R, η, κ, and σ). We obtain the labor supply parameter (ϵ) from the literature. We then use these parameters jointly with the data to predict the labor demand and employment effects of RRTC, using Equations 10 and 11. Note that we do not need to estimate labor demand in the non-tradable sector (Equation 8) since it is only indirectly affected by RRTC and its parameter estimates do not enter in our decomposition.[20]

(A) Estimating labor demand. First, we estimate the labor demand equation for the tradable sector (Equation 7),

$$\log N^g_{ijt} = \beta_0 + \beta_1 \log Y^g_{it} + \beta_2 \log c^I_{it} + \beta_3 R_j \times t + \theta t + \beta_4 w_{it} + \upsilon_{ij} + \epsilon_{ijt} \tag{12}$$

where the number of employed workers for each region i, occupation j, and year t in the tradable sector (N^g_{ijt}) depends on the real regional production of tradables (Y^g_{it}) and on real regional

[20]Estimating non-tradable sector labor demand would be required only if we assume non-constant returns to scale in the production of non-tradables, or non-homothetic preferences. Since constant returns to scale is the standard assumption in this literature, and the effect of non-homothetic preferences on the task structure of employment has been found to be relatively small (Autor and Dorn 2013; Goos et al. 2014), we do not pursue these extensions here.

marginal costs of tradables production (c_{it}^I). Technological change is modeled by the occupational RTI measure interacted with a linear time trend $R_j \times t$ to reflect changes in the cost of capital for routine relative to non-routine tasks. To ensure that our measure of technological change does not capture trends that are unrelated to technological improvements, we further incorporate a linear time trend (t). Moreover, in order to control for differences in regional production technologies and resulting differences in the efficiencies of regions to utilize certain tasks (β_{ij}^g in the theoretical framework), we include region-occupation fixed effects (υ_{ij}). These fixed effects also capture unobserved factors related to the occupation-region cells. ϵ_{ijt} corresponds to the remaining error term.

In some specifications, wage variation is assumed to be absorbed by the time trend and region-occupation fixed effects, following Goos et al. (2014). As an alternative, we additionally report models where we include (instrumented) regional wages in the tradable sector (w_{it}) as a regressor.

We follow an IV strategy to capture the long-run components of real regional production and regional marginal costs and to reduce potential measurement errors. In particular, we instrument regional production with regional net capital stock (as in Goos et al. 2014) and regional marginal costs with a Bartik (1991) IV: this implies we only rely on national variation in marginal costs over time (see Appendix A.3.3 for a more detailed explanation of the instruments).

Based on the estimates of Equation (12), we obtain our estimated elasticity of substitution between job tasks, $\eta = \beta_2$. The effect of RTI on labor demand β_3 is an estimate of $(1-\eta)(1-\kappa)\gamma_R$. Lastly, we use the coefficient on wages, $\beta_4 = 1 - \kappa + \kappa\eta$,[21] jointly with the RTI coefficient, $\beta_3 = (1-\eta)(1-\kappa)\gamma_R$, and the elasticity of substitution between tasks, $\eta = \beta_2$, to back out both κ and γ_R from our estimated parameters. Note that besides providing all our labor demand parameters, this procedure provides a check on these estimates: a reasonable value for the labor share κ would be close to two-thirds, and our empirical model is in no way constrained to produce this.

(B) Estimating product demand. Next, we estimate the aggregate product demand equation (Equation 9):

$$\log Y_{it}^g = \delta_0 + \delta_1 \log c_{it}^I + \delta_2 \log MP_{it} + \nu_i + \varepsilon_{it} \tag{13}$$

[21] This represents the wage elasticity of labor demand.

where the real regional production of tradables (Y_{it}^g) depends on real regional marginal costs of producing tradable output (c_{it}^I)[22] as well as on a region's market potential (MP_t). Market potential for any one region is the sum of income in all regions, discounted by the transport costs towards these regions, which we construct from data on trade flows between German regions (see Appendix A.4.2 for details). It represents the size of the market which can be potentially accessed by region i. In order to control for further regional factors, we include a set of regional fixed effects (ν_i). Finally, ε_{it} captures the remaining error term. We follow an IV-strategy to capture the long-run components of market potential and regional marginal costs and to deal with potential measurement error in these variables. In particular, we instrument market potential with the spatially weighted capital stock[23] and regional marginal costs using a Bartik (1991) IV as before (see Appendix A.3.3 for a more detailed explanation).

Based on the estimates in Equation 13 we can then obtain $\sigma = -\delta_1$, our parameter of interest, the elasticity of substitution between regional bundles of tradables.

(C) Labor demand decomposition. Using our estimated parameters $\hat{\eta}$, $\hat{\kappa}$, $\hat{\gamma_R}$ and $\hat{\sigma}$ jointly with an estimate of ϵ from the literature, we calculate the components of equation (10), i.e. the effects of the three channels on labor demand. All other variables in Equation (10), i.e. R_{it}^I, R_j, N_{ijt}^g, N_{it}^g and N_{it}^s, are calculated from the data. The sum over all three effects reflects the net effect of RRTC on labor demand.

(D) Employment decomposition. Lastly, we scale the labor demand effects by their labor supply terms (see equation 11). These terms are obtained by backing out labor supply (resp. wage) responses and the related interdependencies between the labor market segments. The terms depend mainly on the elasticity of labor supply, ϵ, as well as on the employment- and wage-cost-shares of occupations within regions. This then gives us the three components of the employment decomposition, and their sum reflects the net effect of RRTC on employment.

[22]Product demand depends on relative prices p_{it}^g/p_i^g, which we replace with regional marginal costs since prices are a constant mark-up over marginal costs in our model, i.e. $p_{it}^g = \frac{\sigma_i^v}{\sigma_i^v - 1} c_{it}^I$.

[23]The weights correspond to the trade costs, such that the instrument is constructed analogously to market potential.

Table 1: Classification of European industries

NACE	Industry	Classification
C	Mining and quarrying	Tradable
D	Manufacturing	Tradable
E	Electricity, gas and water supply	Tradable
F	Construction	Non-Tradable
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	Non-Tradable
H	Hotels and restaurants	Non-Tradable
I	Transport, storage and communications	Tradable
J	Financial intermediation	Tradable
K	Real estate, renting and business activities	Tradable
L	Public administration and defense; compulsory social security	Non-Tradable
M	Education	Non-Tradable
N	Health and social work	Non-Tradable
O	Other community, social and personal services activities	Non-Tradable
P	Activities of private households as employers	Non-Tradable

Notes: Industries classified with NACE revision 1.1. Agriculture, Hunting and Forestry (NACE A); Fishing (NACE B); and Extraterritorial Organisations and Bodies (NACE Q) have been excluded from the dataset.

3 Data and parameter estimates

3.1 Data

Employment data for European regions is obtained from the European Union Labour Force Survey (EU LFS) provided by Eurostat. The EU LFS is a large household survey on labor force participation of people aged 15 and over, harmonized across countries. Following the literature, we exclude all military and agricultural employment. Although occupation and industry information is available as of 1993, consistent regional information is only available from 1999 onwards, and there are classification breaks in 2011: we therefore analyze the period 1999-2010.

The dataset includes data for 27 European countries including Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Latvia, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. For most countries, regional information is available at the level of two-digit or one-digit Nomenclature des Unités Territoriales Statistiques (NUTS-2006) codes. For five small countries (Estonia, Iceland, Latvia, Luxembourg, and Malta) we only observe employment at the national level. For some countries (Austria, the Netherlands, and the United Kingdom), the EU LFS micro-data has been supplemented with aggregated data from Eurostat online.

We divide industries classified by one-digit Nomenclature statistique des Activités économiques dans la Communauté Européenne (NACE revision 1.1) codes into either the tradable or non-tradable sector defined in our framework. This division is made based on the tradability of industries' output, inferred from the spatial concentration of these industries following Jensen and Kletzer (2006, 2010) (see Appendix A.4.1 for details on the procedure). The resulting division is outlined in Table 1. Note that the tradable sector includes both goods industries such as manufacturing, and service industries such as financial intermediation and transport, storage and communications. In contrast, the non-tradable sector includes services such as hotels and restaurants, education, and health and social work. We sum employment within region-occupation-sector-year cells to obtain our dependent variable for labor demand estimates.

Occupations are coded by one-digit International Standard Classification of Occupations (ISCO-1988) codes: for each of these, we obtain a Routine Task Intensity (RTI) index from the Dictionary of Occupational Titles 1977, constructed as in Autor and Dorn (2013), converted to European occupations as in Goos et al. (2014). The measure rises with the importance of routine tasks in each occupation and declines with the importance of manual and abstract tasks. Note that the index is standardized to have a zero mean and unit standard deviation across occupations. The routine intensity of occupations is reported in Table 2: office clerks and production jobs are the most routine occupations, whereas tasks performed by high-skilled professionals, managers, as well as lower-skilled service workers are less routine-intense.

As wage data, we use employee compensation data from the Cambridge Econometrics European Regional Database (ERD)[24], defined as the annual compensation of employees in 2005 Euros. We divide them by ERD employment figures to obtain annual wages per employee at the regional level. Unfortunately, ERD aggregates do not distinguish occupations, but they do vary by industry. However, industry codes are aggregated at a higher level than NACE major groups: this is problematic when trying to construct wage data for the tradable and non-tradable sector separately. In particular, the ERD industry aggregate "wholesale, retail, transport & distribution, communications, hotels & catering" contains both tradable and non-tradable sectors (see Table 1 in the main text or Table 9 in Appendix A.3.1). We deal with this by assigning this industry to tradables and checking for robustness when alternatively assigning it to non-tradables. Furthermore, we have to exclude Switzerland and Iceland from the analyses whenever control-

[24]ERD is based primarily on Eurostat's REGIO database, but is also supplemented with data from AMECO, a dataset provided by the European Commission's Directorate for General Economic and Financial Affairs.

Table 2: Occupational Routine Task Intensity (RTI) index

ISCO	Occupation	RTI
1	Legislators, senior officials and managers	-0.94
2	Professionals	-1.01
3	Technicians and associate professionals	-0.28
4	Clerks	2.01
5	Service workers and shop and market sales workers	-0.75
7	Craft and related trades workers	0.38
8	Plant and machine operators and assemblers	0.48
9	Elementary occupations	0.10

Notes: RTI standardized to have a zero mean and unit standard deviation across occupations. Armed forces (ISCO 6) and farming professionals (ISCO 0) have been excluded from the dataset.

ling for wages as these two countries are not included in ERD: this leaves 230 (rather than 238) regions to be considered.

Finally, data on output and regional marginal costs are obtained from the OECD Database for Structural Analysis (STAN). Following Goos et al. (2014), we define marginal costs as the logarithm of [(nominal production - nominal net operating surplus) / real production]. For real production we divide the sector-specific production values by the sector specific deflator provided in STAN. We regionalize this data by averaging across industries within regions using the employment shares of industries within regions as weights (see Appendix A.3.3).

A region's market potential is calculated as the sum of GDP across all other regions, lowered by the trading costs towards these trading partners. It thus represents the potential market which a region can serve, depending on the trading costs with these partners and the partners' market sizes (see Appendix A.4.2 for more details).

For a more detailed description of the data preparation and data availability for specific countries, see Appendix A.3.

3.2 Parameter estimates

Table 3 shows the estimates of labor demand in the tradable sector from Equation 12. The first column is an OLS estimate containing all observations and replacing tradable sector output, marginal costs, and wages with a set of region-year fixed effects. The second column shows the same estimates but restricted to the set of country-years for which we have output, marginal cost, and wage data: it can be seen that the coefficient on occupational RTI interacted with a linear time trend, which we refer to as the routinization coefficient, is very similar across these

Table 3: Labor demand in the tradable sector

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	FE Full sample (1)	FE Restricted sample (2)	FE-IV (3)	FE-IV with wages (4)	FE-IV with IV wages (5)
Standardized occupational RTI × timetrend	-1.678***	-1.743***	-1.743***	-1.743***	-1.743***
	(0.075)	(0.092)	(0.081)	(0.081)	(0.081)
Log regional gross production in tradables			0.748***	0.744***	0.745***
			(0.075)	(0.081)	(0.082)
Log regional marginal cost index			0.416**	0.285**	0.324*
			(0.129)	(0.103)	(0.164)
Log regional wage in tradables				-0.507***	-0.357
				(0.052)	(0.590)
Number of observations	21,632	11,744	11,744	11,744	11,744
R-squared	0.980	0.982	0.176	0.195	0.193

Notes: European regions, 1999-2010. Models (1) and (2) include region-occupation and region-year fixed effects. Models (3), (4) and (5) are estimated with region-occupation fixed effects and control for a linear timetrend. Standard errors clustered by region reported in parentheses. Coefficients on RTI multiplied by 100.

two samples. The third column then adds the instrument regional output and marginal costs to the model: output and marginal costs have positive and statistically significant coefficients.[25] A concern with these estimates, however, is that wage variation may not be absorbed by the time trend and region-occupation fixed effects. Column 4 therefore augments the specification by controlling for time-varying regional wages in the tradable sector: the wage elasticity of labor demand has the expected negative sign. In the fifth and final column, we instrument wages with a Bartik (1991) instrument based on the increase in female labor supply.[26] The instrumented wage coefficient is still negative and similar in size to the uninstrumented one, but imprecisely estimated. The coefficients of interest are largely robust to controlling for wages, however: the routinization coefficients are very similar, and although the coefficient on marginal costs (representing η, the elasticity of substitution between routine and non-routine tasks) declines somewhat as compared to the model without wages, it remains within the 95% confidence interval of the original estimate. We use the parameter estimates from model 4 as our baseline in Section 4, but Appendix A.5.1 present decomposition results for all parameter estimates reported in Table 3.

Table 4 reports estimates of product demand in the tradable sector from Equation 13. The first column shows results including region-occupation fixed effects, whereas column 2 shows our preferred model which additionally instruments for market potential and marginal costs:

[25]The first stage estimates, shown in Appendix Table 10 show that the instruments have the expected impact on the endogenous variables.

[26]In particular, we construct a counterfactual regional employment series in tradables by multiplying the national increase in female employment with regions' initial female employment share in each country. The first stage for wages, reported in Appendix Table 10, shows that this instrument is indeed negatively correlated with wages.

Table 4: Product demand in the tradable sector

Dependent variable: log regional production of tradables (in region-year cells)		
	FE	FE-IV
	(1)	(2)
Log market potential	1.275***	1.416***
	(0.097)	(0.116)
Log regional marginal cost index	-0.653***	-0.862***
	(0.130)	(0.166)
Number of observations	1,904	1,904
R-squared	0.607	0.604

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Standard errors clustered by region reported in parentheses.

the first stages are reported in Table 11 in the Appendix, and the instruments are statistically significant and have the expected sign. The coefficient on marginal costs reflects our parameter estimate for the elasticity of substitution in consumption between regional bundles of tradables, σ, which is required for the decomposition.

Table 5 summarizes the baseline parameter estimates we will use to construct predictions. In particular, we list the direct estimates of three key parameters: (1) the routinization coefficient, $\beta_3 = (1-\eta)(1-\kappa)\gamma_R$; (2) the elasticity of substitution between tasks, η; and (3) the elasticity of substitution in consumption between regional bundles of tradables, σ. We also report the wage elasticity of labor demand and the implied estimates for both the labor share (κ), and for the annual log capital price change for routine-intense tasks (γ_R) which are also used in constructing our predictions.

Overall, the framework yields plausible parameter values. Firstly, as expected, the routinization coefficient is significantly negative, suggesting that an increase in the RTI index by 1 standard deviation decreases employment by 1.74%, on average.

The estimate of $\hat{\eta} = 0.29$ for the elasticity of substitution between tasks in tradables production within regions is statistically significant and lies between 0 (perfect complements) and 1 (unit-elasticity).[27] Note that the elasticity may theoretically also approach infinity (perfect substitutes). To our knowledge, there are no estimates of our η coefficient in the literature, but the size is similar to the the elasticity of substitution between tasks within industries of 0.9

[27] This estimate is from model 2 in Table 3, where we control for wages. If we instrument wages, the estimate is 0.32 (see model 3 in Table 3) and without controlling for wages, the estimate is 0.66 as reported in Table 3. In Section A.5.1, we present robustness checks using these alternative parameter values.

Table 5: Parameter estimates

Parameter	Description	Estimate
$(1-\eta)(1-\kappa)\gamma_R$	routinization coefficient ($\times100$)	-1.743***
		(0.081)
η	substitution elasticity between tasks	0.285**
		(0.103)
$-[(1-\kappa)+\kappa\eta]$	wage elasticity of labor demand	-0.509**
		(0.052)
κ	labor share	0.689***
		(0.136)
γ_R	annual log routine-replacing capital price change ($\times100$)	-7.833*
		(4.441)
σ	substitution elasticity between bundles of tradables	0.862***
		(0.166)

Notes: All estimates are obtained from column 4 in Table 3, except for the σ estimate which is obtained from column 2 in Table 4. Standard errors reported in parentheses.

estimated by Goos et al. (2014).[28] Intuitively, the estimate suggests that firms have only limited scope for substituting between tasks as a reaction to a relative price change, although it is not impossible. As such, the estimate may reflect that firms' production steps require very different and/or specialized tasks which can not be easily substituted: indeed, Cortés and Salvatori (2015) find that firms are highly specialized in their task content along routine versus non-routine lines.

Our estimate of the wage elasticity of labor demand (-0.51) is close to the estimate of Beaudry et al. (2018) for the USA.[29] Note that the wage elasticity in our model is represented by $-[(1-\kappa)+\kappa\eta]$, so that we can use its estimate and our estimated elasticity of task-substitution η to obtain estimates for κ and γ_R. In particular, we find $\kappa = 0.69$, a value very close to the aggregate labor share as usually measured: this increases confidence in the validity of our parameter estimates. Lastly, the implied γ_R is negative, reflecting that a decrease in the price of capital indeed leads to a stronger substitution of routine compared to non-routine labor by capital. Hence, as shown in the literature on job polarization (e.g. see Autor and Dorn 2013; Goos and Manning 2007; Goos et al. 2014), there is a shift in employment away from occupations that are more routine towards those that are less routine. The size of this estimate suggests routine-replacing capital prices are declining by some 7.8% per year, on average. For comparison, Byrne and Corrado (2017) report annual ICT investment price declines of 9.9% over 2004-2014.

[28] However, note that the estimate in Goos et al. (2014) cannot be directly compared to ours, not only because we estimate the substitution of tasks across tradables production within regions instead of tasks between industries, but also since we include a larger set of EU countries and consider a different time period.

[29] Beaudry et al. (2018) report an estimate of -0.3 at the city-level and -1.0 at the industry-city-level, whereas we estimate a wage elasticity of -0.51 at the regional level.

The estimate of the substitution elasticity between regional bundles of tradables is $\hat{\sigma} = 0.86$, indicating that the demand for regional goods bundles is somewhat more elastic, although it is still smaller than one. Our results thus lie within the range of estimates for the elasticity of international trade by Imbs and Mejean (2010), ranging from 0.5 to 2.7 at the country level for 30 countries worldwide. Furthermore, they typically find lower estimates for small countries, suggesting that it is reasonable that we find an estimate at the regional level that lies towards the lower end of their range.[30]

Lastly, for the labor supply elasticity (denoted by ϵ in our model) we use the Hicksian macro elasticity estimate of 0.5 from Chetty et al. (2011) as a baseline. This is best suited to our purpose since we use macro data and are interested in a long-term steady-state effect. In Appendix A.5.1, we explore the sensitivity of our results to this parameter choice.

4 Results

4.1 European labor demand and employment effects

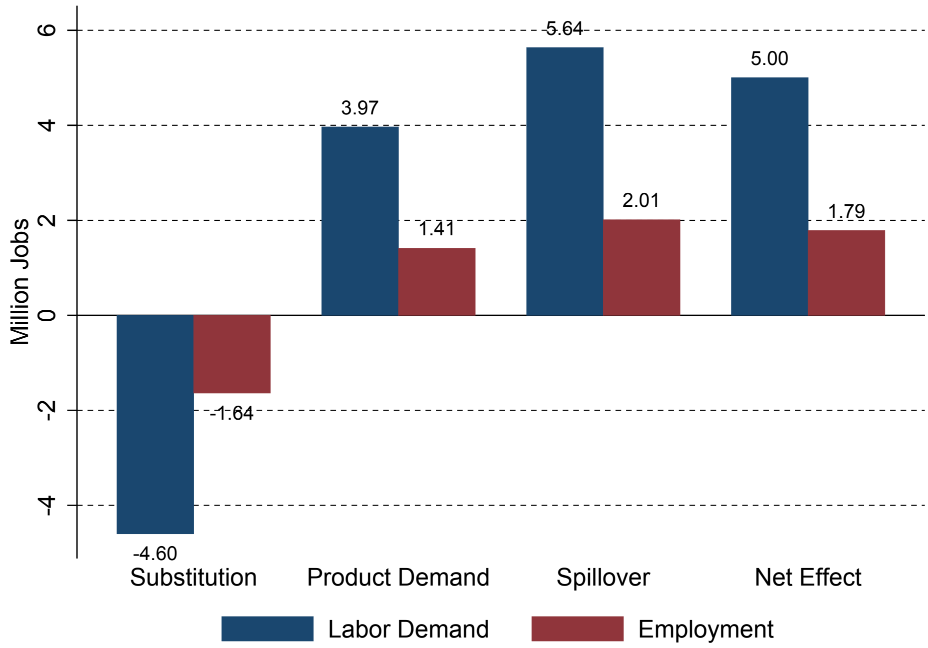
Using the decomposition outlined in Section 2.7, we construct an estimate of the labor demand and employment impact of RRTC. Specifically, we obtain predicted labor demand and employment effects for each of the three distinct channels from our framework over 1999-2010.

Figure 3 shows the results at the European level. It can be seen that all three channels are empirically relevant and have the expected signs. The substitution effects are negative, suggesting that labor demand has decreased by 4.6 million jobs as technology substitutes for labor in routine tasks, and as production has restructured towards routine tasks. These are the direct substitution effects that have played a central role in the public debate. However, the product demand and local demand spillover effects on labor demand are positive and larger in absolute value, respectively implying an increase in labor demand of 4.0 and 5.6 million jobs across Europe. These arise because lower goods prices lead to higher demand for tradables, increasing labor demand; and because the rise in product demand spills over to the non-tradable sector so that additional labor demand is created. As a result, labor demand *increases* by 5.0 million jobs, on net.

These labor demand effects only correspond to employment effects if labor supply is as-

[30] Our estimates for σ are similar when additionally controlling for a linear timetrend in the product demand models, namely 0.67 in the OLS specification and 1.09 in the IV specification (and both are statistically significant at the 1 percent level).

Figure 3: Predicted European labor demand and employment change, 1999-2010



sumed to be perfectly elastic, which is inconsistent with a large literature finding finite supply elasticities. Implementing a supply elasticity of 0.5 in our employment decomposition model produces employment effects which are identically signed but more muted than their labor demand counterparts, as illustrated by the second set of bars in Figure 3. In particular, after accounting for labor supply rigidities, substitution effects within the tradable sector produce an employment loss of 1.6 million jobs, which is not fully outweighted by employment gains from product demand effects of 1.4 million jobs. This implies our model predicts a decline in employment for those sectors directly affected by routinization, similar to findings for overall productivity growth in Autor and Salomons (2018). However, on net, employment *increases* by 1.8 million jobs because of positive spillover effects (amounting to 2.0 million jobs) occurring in the non-tradable sector.

Table 6 additionally reports the confidence intervals for these labor demand and employment results, reflecting sensitivity to our parameter estimates. In particular, we create 10,000 bootstrapped predictions from our model, as such varying our key parameter estimates (σ, η, and γ_R; reported in Table 5). Table 6 reports the mean, standard deviation, and the 5th and 95th percentiles of the resulting distribution of predictions, for each of the three channels of our model as well as for the net labor demand and employment effects.[31] It can be seen that

[31] The means of the simulated effects slightly diverge from our point estimates. This divergence is due to outliers:

Table 6: Confidence intervals for predicted labor demand and employment changes

	Mean	Std dev	5th pctile	95th pctile
Labor demand change (in millions of jobs)				
Substitution	-4.71	0.83	-6.23	-3.61
Product Demand	4.08	1.07	2.57	6.00
Spillover	5.80	1.51	3.65	8.53
Net Effect	5.17	2.12	2.02	8.92
Employment change (in millions of jobs)				
Substitution	-1.68	0.33	-2.30	-1.24
Product Demand	1.44	0.30	1.01	1.98
Spillover	1.89	0.54	1.13	2.88
Net Effect	1.64	0.79	0.43	3.00

Notes: Distribution of predicted effects obtained by bootstrapping predictions with 10,000 draws. Bootstrap clustered by region-occupation for labor demand parameter estimates; and by region for the product demand parameter estimate.

there is some variation around our baseline labor demand prediction of 5.1 million jobs, with the 5th percentile of the prediction corresponding to 2.1 million jobs and the 95th percentile to 8.8 million jobs – but predictions are positive over the entire interval. Furthermore, our predicted net employment effects lie within a relatively tight range of 0.8 to 3.0 million jobs (reflecting a 90 percent confidence interval). Lastly, also for all three channels operating on both labor demand and employment, the predicted effects have the expected sign within the 5th to 95th percentile interval, increasing confidence in our overall conclusion of net positive labor demand and employment effects.[32]

In addition, appendix A.5.1 provides extensive robustness checks on our findings. In particular, we rely on estimates from other specifications reported in Tables 3 and 4 for all parameters. Using these to construct our predictions, we find very similar results.

Finally, Table 7 compares our predictions to regions' actual employment evolutions. In particular, it shows regressions of actual employment-to-population changes onto the employment-to-population change predicted from our model. Each region is one observation, and observations are weighted by the initial regional employment size to ensure that the results aggregate up to the total change. We find that our model of routine-replacing technological change is predictive of actual regional employment rate changes: across specifications, the coefficients are positive and statistically significant. Further, our model can help explain regions' employment rate evo-

in some draws η is close to 1, resulting in large estimates of γ_R, leading to an upward bias of our estimates. When excluding these outliers, the differences between the means of the simulated effects and the point estimates vanish.

[32]If we additionally allow the estimated labor share, κ, to vary, the confidence intervals predictably widen somewhat, but all results are still identically signed and statistically significantly different from zero.

Table 7: Actual versus predicted employment-to-population change

Dependent variable: actual regional employment-to-population change	(1)	(2)	(3)	(4)
Predicted regional employment-to-population change	0.714*** (0.125)	0.426*** (0.083)	0.480*** (0.061)	0.411*** (0.072)
Number of observations	238	238	216	216
Sample	All regions		5th-95th percentile	
Fixed effects	None	Country	None	Country
R-squared	0.122	0.853	0.226	0.599

Notes: European regions, 1999-2010 long difference. All models are weighted by the region's initial employment size in 1999. Models in columns 3 and 4 exclude regions with an actual employment-to-population change below the 5th and above the 95th percentile.

lutions both within and across countries, as can be seen by comparing the models with and without country fixed effects. Further, results are robust to excluding outlier regions in terms of the actual employment change.[33]

The results reported in this section highlight four main findings. Firstly, we provide the first estimate in the literature of the overall effect of RRTC on the number of jobs, finding that the net labor demand and employment effects of routine-replacing technologies are positive. This implies there is no support for the scenario of overall routinization leading to a net displacement of humans from the labor market. Of course, this does not rule out that there could be individual (automation) technologies which produce net disemployment effects, such as those found for industrial robots in the U.S. (Acemoglu and Restrepo 2017). Further, it does not imply that technological progress is the main driver behind job growth: indeed, the estimated labor demand and employment increases of, respectively, 5.0 and 1.8 million jobs over 1999-2010 across Europe are non-negligible but modest compared to the total employment growth of 23 million jobs, observed across these countries over the period considered (see Appendix Figure 5).[34]

The second important finding is that all three channels are quantitatively relevant: there are substantial substitution effects at the task level, leading to decreases in labor demand and employment, but these are countervailed by product demand effects and local spillovers. As such, the positive overall employment effect of RRTC is *not* the result of a negligible amount

[33]These outliers are in part the result of imputing actual employment evolutions for countries which have limited data coverage over 1999-2010, such as Denmark – see Table 8 in the Appendix. Regression results are similar when weighting by initial population size, or when giving all regions equal weight; and from an alternative model specification regressing actual employment changes to predicted employment changes while controlling for regions' initial employment size.

[34]This is consistent with findings by Autor and Salomons (2017), who point out that population growth is the most important driver of overall employment growth.

of substitution of capital for labor: rather, product market effects dominate these substitution effects. This highlights the importance of considering the interactions between labor and product markets when thinking about the employment effects of technological change, as also pointed out by Autor (2015) and Acemoglu and Restrepo (2018a,c).[35] These interactions cannot be studied in canonical SBTC models, which typically only consider a single final consumption good; or in reduced-form empirical approaches which do not uncover the channels through which aggregate effects come about.

Thirdly, the product demand effect alone nearly offsets the employment decline resulting from the substitution of capital for labor and the reorganization of task production: even within the tradable sector, there is no mass decline in employment as a result of routine-replacing technological change, consistent with Autor et al. (2015)'s findings for the U.S.[36] However, all job growth is in non-tradables, industries which are not directly affected by technological progress: this reallocation of employment to technologically lagging sectors is consistent with Baumol (1967). These predictions from our model match the overall patterns seen in the European labor market: employment is strongly reallocating towards non-tradables (see also Figure 5 in the Appendix).

The fourth result is that localized spillover effects to industries which are not directly affected by technological progress play a quantitatively important role for understanding the total labor demand and employment effects of RRTC. Although we are the first to model and estimate product demand spillovers in the RRTC context, we can compare our estimates with related studies on local multipliers. In particular, the findings shown in Figure 3 imply that each job generated in the local tradable industry as a result of increased product demand results in an additional employment effect of 2.0 million/1.4 million=1.4 jobs in the local non-tradable industry. This employment multiplier is similar to the one found by Moretti (2010), who concludes that for each additional job in the tradable industry in a given U.S. city, 1.6 jobs are created in the local non-tradable sector. And more generally, our finding that routinization has significant spillover effects to the non-tradable sector is in line with Autor and Dorn (2013), who show that U.S. regions that were initially relatively intense in routine jobs experienced both greater adoption

[35]Our macro-economic findings are also consistent with studies at the micro level such as Harrison et al. (2014), who find that productivity improvements and process innovations reduce employment in firms only when output is held constant, since accounting for output increases results in net employment gains.

[36]Although suggestive, one caveat is that their and our results cannot be compared directly since Autor et al. (2015) consider manufacturing employment, whereas our tradable sector comprises several additional industries, as outlined in Table 1.

of information technology and a greater reallocation of workers from routine task intense jobs to non-routine service jobs.

However, it is important to note that our estimate of the product demand spillover effect may be considered as an upper bound, since it hinges on the assumption that non-wage income earners reside in the region where their income is generated. The next section relaxes this assumption and assesses its importance for our findings.

4.2 The role of non-wage income

To consider the role of non-wage income in the spillover effect, we relax the assumption that non-wage income earners spend their income locally by assuming the other extreme: namely, that non-wage income does not feed back into consumption at all.[37] Conceptually, this represents the case where non-wage earners do not reside in Europe.[38] As such, we calculate product demand spillovers resulting from changes in wage income only, providing a lower-bound estimate of the spillover effect.

Figure 4 shows the empirical results from this alternative decomposition for both labor demand and employment. Note that the first two channels are unaltered: only the product demand spillover effect has changed. In particular, the predicted spillover effect is smaller, reflecting an employment increase of 1.7 million instead of 2.0 million jobs. This smaller prediction for the demand spillover effect is the result of less tradable income being spent on non-tradables, since we now exclude any non-wage income. As such, our original estimate represents an upper bound for the spillover effect, whereas the estimate shown here is a lower bound. Note that the local employment spillover implied by this lower bound is 1.2 (=1.7/1.4). Given that completely abstracting from non-wage income is rather extreme, and that our upper bound is closer to the value of the spillover found in the literature, we interpret the larger spillover as our baseline result. Most importantly, we find a positive employment effect even in this lower-bound scenario.[39]

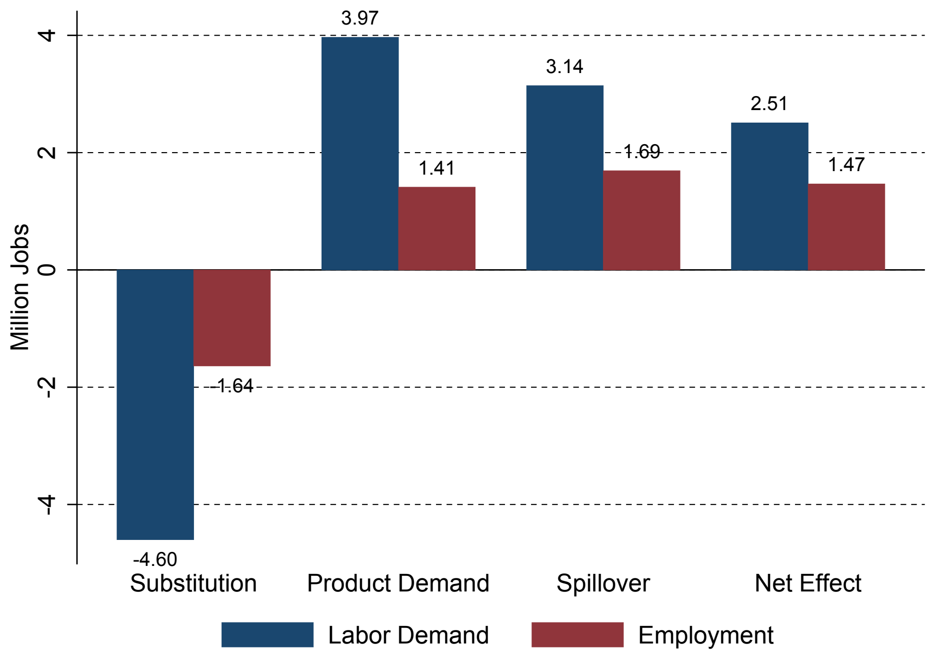
However, this sensitivity exercise does make the more substantive point that the labor de-

[37]See Appendix A.2 for a derivation of this alternative model, where we also show that this assumption does not affect the first two channels in our framework.

[38]We make this assumption both to obtain a lower bound on our estimate and because we do not have an alternative prior about to which region to allocate the additional consumption from any increases in non-wage income.

[39]Analogously to the robustness checks for our baseline estimates in Appendix A.5.1, we check the sensitivity of our alternative decomposition with respect to alternative parameter estimates and again find our results to be very robust.

Figure 4: Predicted European labor demand and employment change, lower bound, 1999-2010



mand effects of routine-replacing technological change depend crucially on where the benefits of RRTC accrue. Indeed, if we take our lower bound estimate at face value, RRTC is still predicted to increase labor demand, but only by half as much – 2.5 million instead of 5.0 million jobs. This empirical prediction is in line with recent theoretical models which stress that the labor market effects of technological change depend on the allocation of the gains from these innovations (Benzell et al., 2016; Sachs et al., 2015).

5 Conclusion

There are long-standing public concerns about technological change destroying jobs, invoking images of labor racing against the machine. These concerns are echoed in a recent crop of theoretical models which allow technology to be labor-replacing, showing the conditions under which labor-displacement occurs in the aggregate as a result of technological change. However, empirical evidence on such aggregate effects is scarce, as most existing studies have focused on the relative effects of technological progress across worker skill levels and job types; or on very specific technologies such as industrial robots. Furthermore, the body of empirical evidence considering absolute labor demand and employment effects uses reduced-form specifications, thus remaining largely silent on the countervailing transmission channels highlighted in theoretical models. This paper contributes by developing and estimating an empirically tractable framework modeling the key job-creating and job-destroying channels of technological change and quantifying their empirical relevance for the overall effect. Our approach complements work focusing solely on industrial robots by studying routine-replacing technologies (RRTC) as a whole: unlike robotics, these technologies have already permeated many jobs and sectors.

We find that routine-replacing technologies increased employment by 1.5 million jobs in Europe over the period 1999-2010. Breaking down these employment effects into the underlying transmission channels, we show that this is *not* due to an absence of displacement effects. To the contrary, our results suggest that employment falls by 1.6 million jobs as a result of machines replacing workers in performing routine tasks. These are the substitution effects ignored in canonical frameworks where technology is thought of as strictly factor-augmenting. However, our study also shows that these job losses were more than outweighed by the job-creating effects of RRTC. These countervailing effects result both from lower product prices and from growing local incomes, both of which raise local product demand and thereby employment.

Our results thus suggest that recent technological change has created more jobs than it destroyed. In fact, the net labor demand effect exceeds the employment effect by 1 million jobs, suggesting that even more jobs would have been created had labor supply adjusted more elastically. While we cannot rule out that certain technologies are more labor-displacing in nature than others, or assert that these positive net effects will continue to arise in the future, our results highlight that focusing on substitution potentials alone is misleading. Indeed, countervailing effects leading to new job creation are quantitatively important and have to be taken into consideration.

A final key finding is that the aggregate labor market effects depend on who receives the gains from technological progress. Although we lack precise data on income flows, an analysis of two extreme scenarios – all (wage and non-wage) income flows into the local economy vs. all non-wage income remains outside the European Union – highlights that the distribution of gains from technological progress is critical for the size of the overall labor demand and employment effects. Indeed, in the scenario where only labor's share of the gains flows back into the economy, the positive aggregate labor demand effect is only half as large. This stresses the importance of the debates about who owns the capital (Freeman, 2015) and the apparently negative impact of recent technological change on labor's share in national income (Autor et al. 2017; Autor and Salomons 2018; Karabarbounis and Neiman 2014).

References

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

Acemoglu, D. and Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. Working Paper 23285, National Bureau of Economic Research.

Acemoglu, D. and Restrepo, P. (2018a). Artificial Intelligence, Automation and Work. In Agrawal, A. K., Gans, J., and Goldfarb, A., editors, *The Economics of Artificial Intelligence*. University of Chicago Press.

Acemoglu, D. and Restrepo, P. (2018b). Modeling Automation. *American Economic Review: Papers and Proceedings*, forthcoming.

Acemoglu, D. and Restrepo, P. (2018c). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6):1488–1542.

Arntz, M., Gregory, T., and Zierahn, U. (2017). Revisiting the Risk of Automation. *Economics Letters*, 159:157–160.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2017). Concentrating on the Fall of the Labor Share. Working Paper 23108, National Bureau of Economic Research.

Autor, D. and Salomons, A. (2017). Robocalypse Now: Does Productivity Growth Threaten Employment? In *Proceedings of the ECB Forum on Central Banking: Investment and Growth in Advanced Economie*, pages 45–118. European Central Bank.

Autor, D. and Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share. *Brookings Papers on Economic Activity*, Forthcoming.

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

Autor, D. H. and Dorn, D. (2013). The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market. *American Economic Review*, 103(5):1553–1597.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–68.

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling Trade and Technology: Evidence from Local Labour Markets. *The Economic Journal*, 125(584):621–646.

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

Bartik, T. J. (1991). Boon or Boondoggle? The Debate Over State and Local Economic Development Policies. In *Who Benefits from State and Local Economic Development Policies*, pages 1–16. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Baumol, W. J. (1967). Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis. *The American Economic Review*, 57(3):415–426.

Beaudry, P., Green, D. A., and Sand, B. M. (2018). In Search of Labor Demand. *American Economic Review*, 108(9):2714–57.

Benzell, S. G., Kotlikoff, L. J., LaGarda, G., and Sachs, J. D. (2016). Robots Are Us: Some Economics of Human Replacement. NBER Working Paper 20941, National Bureau of Economic Research, Inc.

Bowles, J. (2014). The Computerization of European Jobs. Technical report, The Bruegel Institute.

Byrne, D. and Corrado, C. (2017). ICT Services and Their Prices: What Do They Tell Us About Productivity and Technology? *International Productivity Monitor*, 33:150–181.

Caliendo, L., Dvorkin, M., and Parro, F. (2015). The Impact of Trade on Labor Market Dynamics. NBER Working Paper 21149, National Bureau of Economic Research, Inc.

Card, D. and Lemieux, T. (2001). Can Falling Supply Explain The Rising Return To College For Younger Men? A Cohort-Based Analysis. *The Quarterly Journal of Economics*, 116(2):705–746.

Caselli, F. and Manning, A. (2018). Robot Arithmetic: New Technology and Wages. *American Economic Review: Insights*, forthcoming.

Chetty, R., Guren, A., Day, M., and Weber, A. (2011). Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins. *American Economic Review*, 101(3):471–475.

Chiacchio, F., Petropoulos, G., and Pichler, D. (2018). The Impact of Industrial Robots on EU Employment and Wages: A Local Labour Market Approach. Working Paper. 2, Bruegel.

Cortés, G. and Salvatori, A. (2015). Task Specialization within Establishments and the Decline of Routine Employment. mimeo University of Manchester.

Dauth, W., Findeisen, S., Südekum, J., Wößner, N., et al. (2017). German Robots – The Impact of Industrial Robots on Workers. Technical report, Institute for Employment Research, Nuremberg, Germany.

Dauth, W., Findeisen, S., and Suedekum, J. (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association*, 12(6):1643–1675.

Freeman, R. (2015). Who Owns the Robots Rules the World. *IZA World of Labor*, 5:1–10.

Frey, C. B. and Osborne, M. (2016). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Goos, M., Konings, J., and Vandeweyer, M. (2015). Employment Growth in Europe: The Roles of Innovation, Local Job Multipliers and Institutions. TKI Discussion Paper 15-10, Utrecht University School of Economics.

Goos, M. and Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *The Review of Economics and Statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–2526.

Graetz, G. and Michaels, G. (2018). Robots at Work. *Review of Economics and Statistics*, forthcoming.

Harrison, R., Jaumandreu, J., Mairesse, J., and Peters, B. (2014). Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-data from Four European Countries. *International Journal of Industrial Organization*, 35:29–43.

Imbs, J. and Mejean, I. (2010). Trade Elasticities: A Final Report for the European Commission. Technical report, Directorate General Economic and Monetary Affairs (DG ECFIN), European Commission.

Jensen, J. B. and Kletzer, L. G. (2006). Tradable Services: Understanding the Scope and Impact of Services Offshoring. In Brainard, L. and Collins, S. M., editors, *Offshoring White-Collar Work, Issues and Implications*. Brookings Institution Press.

Jensen, J. B. and Kletzer, L. G. (2010). Measuring Tradable Services and the Task Content of Offshorable Services Jobs. In *Labor in the New Economy*, NBER Chapters, pages 309–335. National Bureau of Economic Research, Inc.

Karabarbounis, L. and Neiman, B. (2014). The Global Decline of the Labor Share. *The Quarterly Journal of Economics*, 129(1):61–103.

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

Krugman, P. (1991). *Geography and Trade*. MIT Press.

Moretti, E. (2010). Local Multipliers. *American Economic Review*, 100(2):373–77.

Moretti, E. (2011). Local Labor Markets. *Handbook of Labor Economics*, 4:1237–1313.

Moretti, E. and Thulin, P. (2013). Local Multipliers and Human Capital in the United States and Sweden. *Industrial and Corporate Change*, 22(1):339–362.

Nordhaus, W. D. (2015). Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth. NBER Working Paper 21547, National Bureau of Economic Research, Inc.

Sachs, J. D., Benzell, S. G., and LaGarda, G. (2015). Robots: Curse or Blessing? A Basic Framework. NBER Working Paper 21091, National Bureau of Economic Research, Inc.

Susskind, D. (2017). A Model of Technological Unemployment. Economics Series Working Papers 819, University of Oxford, Department of Economics.

WTO (2012). International Trade Statistics 2012. Technical report, World Trade Organization.

A For Online Publication: Appendix

This supplemental appendix contains 1) a more detailed description of our theoretical model, including 2), an extension where the role of non-wage income is considered; 3) a data overview; 4) more detailed information on our empirical implementation; and 5) further robustness checks on our baseline results.

A.1 Theoretical model

This Appendix provides a more formal description of the model outlined in Section 2. In our model, households have CD preferences for homogeneous non-tradables C_s and heterogeneous tradables C_g, $U = C_g^{\mu} C_s^{1-\mu}$. They spend their entire income on consumption, so that μ resp. $1-\mu$ reflect the expenditure shares of tradables resp. non-tradable consumption in income. We use P^g for the price index in the tradable sector and P^s for the price index in the non-tradable sector. C_g is a CES-bundle of regional bundles of tradables c_i^g, $C_g = \left[\sum_{i=1}^{I} (c_i^g)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, where σ is the elasticity of substitution between the regional bundles of tradables. Individuals optimize the composition of their bundle of tradables such that the demand for each regional bundle is

$$c_i^g = \left(\frac{p_i^g}{P^g}\right)^{-\sigma} \mu \frac{I}{P^g}, \tag{14}$$

where $P^g = \left[\sum_{i=1}^{I} (p_i^g)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is the price index.[40]

Each regional bundle $c_i^g = \left[\sum_{f_i=1}^{F_i} (c_{if}^g)^{\frac{\sigma_i^v-1}{\sigma_i^v}}\right]^{\frac{\sigma_i^v}{\sigma_i^v-1}}$ contains the varieties produced by local firms $f = 1, \ldots, F$, such that the demand for each variety is

$$c_{if}^g = \left(\frac{p_{if}^g}{p_i^g}\right)^{-\sigma_i^v} c_i^g, \tag{15}$$

where $p_i^g = \left[\sum_{f_i=1}^{F_i} (p_{if}^g)^{1-\sigma_i^v}\right]^{\frac{1}{1-\sigma_i^v}}$ is the regional price index and σ_i^v the region-specific elasticity of substitution between varieties.

Firms combine tasks $T_1, T_2, ..., T_J$ to produce tradables Y_i^g, where the task-intensities and

[40] Note that there are transport costs $\tau_{ii'}$ between the regions, such that the price index is actually region-specific, $P_i^g = \left[\sum_{i'=1}^{I} (\tau_{ii'} p_{i'}^g)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$. We drop the regional index for illustrative purposes.

-compositions vary across regions i. The underlying production function is CES[41]:

$$Y_i^g(T_{i1}, T_{i2}, ..., T_{iJ}) = \left[\sum_{j=1}^{J} (\beta_{ij} T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \quad \text{with } \eta > 0 \tag{16}$$

Firms minimize the cost of producing Y_i^g, such that their task demand is:

$$T_{ij} = Y_i^g \beta_{ij}^{1-\eta} \left(\frac{c_i^I}{c_{ij}^T}\right)^{\eta}, \tag{17}$$

where c_i^I are the region's marginal costs $c_i^I = \left[\sum_{j=1}^{J} \left(\frac{c_{ij}^T}{\beta_{ij}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}$ and c_{ij}^T are the region's task-specific marginal costs. Firms produce tasks by combining labor N_{ij}^g, which differs by occupations j, and task-specific capital K_{ij} through a CD technology, $T_{ij}(N_{ij}^g, K_{ij}) = (N_{ij}^g)^{\kappa}(K_{ij})^{1-\kappa}$, with $0 < \kappa < 1$. They minimize the cost of producing tasks, such that occupational labor demand is

$$N_{ij}^g(w_j, r_j | T_{ij}) = T_{ij} \frac{c_{ij}^T}{w_j} \left(\frac{\kappa}{1-\kappa}\right)^{1-\kappa} \tag{18}$$

where $c_{ij}^T = w_j^{\kappa} r_j^{1-\kappa}$ are the costs of producing one unit of task j, w_j are occupational wages, and r_j are task-specific capital costs.

Firms in region i face the same marginal costs. Due to monopolistic competition they charge a mark-up over marginal costs. As firms in a specific region face the same elasticity of substitution, the price mark-up is the same for all firms of the same region, so that each firm f in region i charges the price $p_{if}^g = \frac{\sigma_i^v}{\sigma_i^v - 1} c_i^I$. The regional price index p_i^g hence is equal to the price charged by the firms p_{if}^g.

Assume that there are iceberg transport costs $\tau_{ii'}$ between regions i and i'. Then the demand for tradables produced in region i is $Y_i^g = \sum_{i'=1}^{I} \left(\frac{p_i^g \tau_{ii'}}{P^g}\right)^{-\sigma} \mu \frac{I_{i'}}{P^g}$. After factoring out and taking logs, this becomes

$$\log Y_i^g = \log \mu - \sigma \log \frac{p_i^g}{P^g} + \log \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \frac{I_{i'}}{P^g} \tag{19}$$

Demand for tradables produced in region i depends on their relative price, their expenditure share in income, and market-potential $\sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \frac{I_{i'}}{P^g}$, where $I_{i'}$ is the nominal income in region i'. Note that demand for tradables produced in a region therefore depends on income in other

[41] Note that since firms within a region are identical, and since our framework has constant returns to scale, we can directly derive the equations at the regional level. Therefore, we apply the index i instead of f.

regions, as well as on income in the region itself, such that market potential is endogenous, as it is itself a function of regional production.

The production function in the non-tradable sector is $C_i^s = \alpha_s L_i^s$, where C_i^s is the supply of non-tradables in region i, and α_s is the productivity of labor L_i^s in production. There is full competition in the non-tradable sector, and non-tradables are produced and consumed locally. Firms maximize profits, such that the marginal product equals real marginal costs. In the non-tradable sector equilibrium, labor demand is $L_i^s = (1-\mu)\frac{I_i}{w_i^s}$, where I_i is local income and w_i^s are wages in the non-tradable sector. Local income I_i is composed of income from the non-tradable and the tradable sectors. In the non-tradable sector, as firms make no profits and no capital is used, income consists of labor income $w_i^s L_i^s$ only. In the tradable sector, we did not include any restriction on the number of firms (or regions). Therefore profits in the tradable sector can be larger than zero (or even negative if $\sigma_i^v < 1$). Hence, income in the tradable sector is composed of labor income $\sum_{j=1}^J w_j N_{ij}^g$ and profits. We assume that there is a competitive capital sector producing task-specific capital K_j at marginal costs r_j, which represent a real resource cost so that they do not feed back into income. As the sector is competitive, r_j also reflects capital prices. This implies that tradable sector income equals its production, lowered by capital costs. We define $\phi_{1-K} = p_i^g - \sum_{j=1}^J r_j K_{ij}/Y_i^g$ as the disposable income per unit of real output in the tradable sector. We furthermore assume that firm owners are located in the region of production.[42] Then local income is $I_i = w_i^s L_i^s + \phi_{1-K} Y_i^g$, and we can rewrite conditional labor demand in the non-tradable sector as $L_i^s = \frac{1-\mu}{\mu} Y_i^g w_i^{s-1} \phi_{1-K}$.

The labor input L_i^s is a bundle of occupations $L_i^s = \left[\sum_{j=1}^J (\beta_{ij}^s N_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ with $\eta > 0$, where we assume that tasks T_{ij} in the non-tradable sector are produced using labor N_{ij}^s only, and that one unit of labor input produces exactly one unit of task input. Firms in the non-tradable sector minimize the cost of attaining the labor input.[43] Occupational labor demand in the non-tradable sector then is:

$$N_{ij}^s = L_i^s \beta_{ij}^{s\,1-\eta^s} \left(\frac{w_j}{w_i^s}\right)^{-\eta}, \tag{20}$$

where $w_i^s = \left[\sum_{j=1}^J \left(\frac{w_j}{\beta_{ij}^s}\right)^{1-\eta^s}\right]^{\frac{1}{1-\eta^s}}$ is the factor price index of the non-tradable sector, which

[42]See Appendix A.2 for an alternative specification.

[43]Note that $w_i^s L_i^s = \sum_{j=1}^J w_j N_{ij}^s$ implies that $w_i^s L_i^s$ remains the costs of labor (i.e. labor income in the non-tradable sector), such that we can still define $I_i = w_i^s L_i^s + Y_i^g$ and do not have to make any further changes to the previously derived labor demand equation in the non-tradable sector.

consists of occupational wages.

Using these arguments, we can explicitly derive the labor demand equations (7) and (8) for the two sectors, reported in the main text.

We follow Acemoglu and Restrepo (2017) and model labor supply for the two sectors as follows,

$$N_{ij}^g = \bar{N}_{ij}^g {w_{ij}^g}^{\epsilon} \quad \text{and} \quad N_{ij}^s = \bar{N}_{ij}^s {w_{ij}^s}^{\epsilon}, \tag{21}$$

where ϵ is the wage elasticity of labor supply.

Next, we decompose aggregate employment changes. Total regional employment N_i is the sum of regional employment in the tradable N_i^g and non-tradable N_i^s sector, which themselves are composed of occupational employment within these sectors:

$$N_i = N_i^g + N_i^s = \sum_{j=1}^{J} N_{ij}^g + \sum_{j=1}^{J} N_{ij}^s \tag{22}$$

Employment responds to changes in log capital prices:

$$\frac{\partial N_i}{\partial \log r_{j'}} = \sum_{j=1}^{J} \frac{\log N_{ij}^g}{\partial \log r_{j'}} N_{ij}^g + \frac{\log N_{ij}^s}{\partial \log r_{j'}} N_{ij}^s \tag{23}$$

Aggregate changes in employment can then be rewritten as

$$\Delta N = \sum_{j'=1}^{J'} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(\frac{\log N_{ij}^g}{\partial \log r_{j'}} N_{ij}^g + \sum_{j=1}^{J} \frac{\log N_{ij}^s}{\partial \log r_{j'}} N_{ij}^s \right) \underbrace{\Delta \log r_{j'}}_{=\gamma_R R_{j'}} \tag{24}$$

We rewrite the last line in matrix notation:

$$\Delta N = \sum_{j'=1}^{J'} \left(\mathbf{n^g N^{g,j'}} + \mathbf{n^s N^{s,j'}} \right) \gamma_R R_{j'} \tag{25}$$

where $\mathbf{n^g}$ is an $1 \times ij$ vector of initial employment in the tradable sector, $\mathbf{N^{g,j'}}$ is an $ij \times 1$ vector with elements $\frac{\partial \log N_{ij}^g}{\partial \log r_{j'}}$. $\mathbf{n^s}$ and $\mathbf{N^{s,j'}}$ are defined analogously for the service sector. Equation (25) represents our decomposition, where we have to derive the two matrices $\mathbf{N^{g,j'}}$ and $\mathbf{N^{s,j'}}$.

Using equation (7), we derive

$$\frac{\partial \log N^g_{ij}}{\partial \log r_{j'}} = (1-\eta)(1-\kappa) + (\eta-\sigma)\frac{\partial \log c^I_i}{\partial r_{j'}} - (1-\kappa+\kappa\eta)\frac{\partial \log w_{ij}}{\partial \log r_{j'}} \text{ for } j = j' \tag{26}$$

$$\frac{\partial \log N^g_{ijt}}{\partial \log r_{j'}} = (\eta-\sigma)\frac{\partial \log c^I_i}{\partial \log r_{j'}} - (1-\kappa+\kappa\eta)\frac{\partial \log w_{ij}}{\partial \log r_{j'}} \text{ for } j \neq j' \tag{27}$$

For this, we have used $\partial \log Y^G_i / \partial \log r_{j'} = -\sigma \partial \log p_i / \partial \log r_{j'}$ and $\partial \log p_i / \partial \log r_{j'} = \partial \log c^I_i / \partial \log r_{j'}$.

Further, we approximate regional marginal costs based on a CD technology

$$c^I_i \approx \prod_{j=1}^{J} \left(\frac{c^T_{ij}}{\beta_{ij}}\right)^{\kappa_{j|i}} = \prod_{j=1}^{J} \left(\frac{r_j^{1-\kappa} w_j^{\kappa}}{\beta_{ij}}\right)^{\kappa_{j|i}} \tag{28}$$

where $\kappa_{j|i}$ is the share of task j in the cost of production in region i and we assume that this share is equal to the share of employment in occupation j within region i, $s_{j|i}$. Accordingly marginal costs react to changes in capital prices, $\frac{\partial \log c^I_i}{\partial \log r_{j'}} = s_{j'|i}(1-\kappa) + \kappa \sum_{j=1}^{J} s_{j|i} \frac{\partial \log w_{ij}}{\partial \log r_{j'}}$. Moreover, from labor supply we can derive wage responses $\frac{\partial \log w^g_{ij}}{\partial \log r_{j'}} = \frac{1}{\epsilon}\frac{\partial \log N^g_{ij}}{\partial \log r_{j'}}$ and $\frac{\partial \log w^s_{ij}}{\partial \log r_{j'}} = \frac{1}{\epsilon}\frac{\partial \log N^s_{ij}}{\partial \log r_{j'}}$.

Using the elements from above, we can thus rewrite employment responses to capital price changes in the tradable sector in matrix notation as

$$\begin{aligned}\mathbf{N^{g,j'}} = & \left[\mathbf{I} - \frac{\kappa(\eta-\sigma)}{\epsilon}\mathbf{S^g} + \frac{1-\kappa+\kappa\eta}{\epsilon}\mathbf{I}\right]^{-1} \Big[(\eta-\sigma)(1-\kappa)\mathbf{S^{j'}} \\ & +(1-\eta)(1-\kappa)\mathbf{T^{j'}}\Big]\end{aligned} \tag{29}$$

where $\mathbf{N^{g,j'}}$ is an $ij \times 1$ matrix consisting of the elements $\frac{\partial \log N^g_{ij}}{\partial \log r_{j'}}$, $\mathbf{S^{j'}}$ is an $ij \times 1$ matrix consisting of the elements $s_{j'|i}$, $\mathbf{S^g}$ is an $ij \times i'j'$ matrix consisting of the elements $s_{j'|i}$ $\forall\ i = i'$ and $0\ \forall\ i \neq i'$, and where $\mathbf{T^{j'}}$ is an $ij \times 1$ matrix consiting of the elements $1\ \forall\ j = j'$ and $0\ \forall\ j \neq j'$

Analogously, using equation (8), we derive responses of labor demand to capital prices in non-tradables:

$$\frac{\partial \log N^s_{ij}}{\partial \log r_{j'}} = -\sigma\frac{\partial \log c^I_i}{\partial \log r_{j'}} + (\eta-1)\frac{\partial \log w^s_i}{\partial \log r_{j'}} - \eta\frac{\partial \log w^s_{ij}}{\partial \log r_{j'}} \tag{30}$$

In our decomposition we thus assume that the disposable income per unit of real output in the tradable sector remains constant or, in other words, that the share of sales that is consumed by capital costs remains constant. As RRTC is expected to lead to declining capital costs, this assumption implies that we ignore potential increases in local income that are induced by the declining capital costs.

Using the elements from above, we can rewrite employment responses to capital price changes in the non-tradable sector in matrix notation as

$$\mathbf{N}^{\mathbf{s},\mathbf{j}'} = \left[\mathbf{I} + \frac{\eta}{\epsilon}\mathbf{I} - \frac{\eta - 1}{\epsilon}\mathbf{S}^{\mathbf{s}}\right]^{-1} \left[-\sigma(1-\kappa)\mathbf{S}^{\mathbf{j}'} - \frac{\kappa\sigma}{\epsilon}\mathbf{S}^{\mathbf{g}}\mathbf{N}^{\mathbf{g},\mathbf{j}'}\right] \tag{31}$$

The matrix $\mathbf{S}^{\mathbf{s}}$ is analogous to $\mathbf{S}^{\mathbf{g}}$, but instead relies on the shares of occupations within regions in the non-tradable sector.

Using equations (29) and (31) in equation (25), we arrive at our employment decomposition. It consists of the same labor demand shocks as our labor demand decomposition from equation (10), although the effects are scaled by the labor supply responses. To implement the labor demand decomposition, we assume $\epsilon \to \infty$, implying that wages do not respond. The decomposition then simplifies to equation (10).

A.2 Extension: The role of non-wage income

In our baseline model, we assume that non-wage earners reside in the region where their income is generated. However, it turns out this assumption is relevant for the formulation of the local spillover effect in the non-tradable sector, only. To the extent that non-wage income does not feed back into European product and labor markets (e.g. because capital and firms are owned by non-EU residents), we can relax this assumption. This means we alternatively rely on local wage income only for deriving the local spillover effect. Since this implies none of the additional non-wage income from RRTC feeds back into the European economy, this alternative assumption provides us with a lower bound for the product demand spillover effect.

In our alternative decomposition, we rely on wage income, only. That is, income is the sum of wage income in the two sectors, only:

$$I_i = w_i^s L_i^s + \sum_{j=1}^{J} w_{ij}^g N_{ij}^g \tag{32}$$

Labor demand in non-tradables then is

$$N_{ij}^S = \frac{1-\mu}{\mu} \beta_{ij}^{1-\eta} {w_{ij}^s}^{-\eta} {w_i^s}^{\eta-1} \sum_{j=1}^{J} w_{ij}^g N_{ij}^g \tag{33}$$

Hence, employment responses to changes in capital costs are

$$\frac{\partial \log N_{ij}^s}{\partial \log r_{j'}} = -\eta \frac{\partial \log w_{ij}^s}{\partial \log r_{j'}} + (\eta - 1)\frac{\partial \log w_i^s}{\partial \log r_{j'}} + \frac{\partial \log \sum_{j''=1}^{J''} w_{ij''}^g N_{ij''}^g}{\partial \log r_{j'}} \tag{34}$$

We rewrite this in matrix notation, use the definitions from above and rearrange to get:

$$\mathbf{N^{s,j'}} = \left[\frac{\epsilon+\eta}{\epsilon}\mathbf{I} + \frac{1-\eta}{\epsilon}\mathbf{S^s}\right]^{-1} \frac{1+\epsilon}{\epsilon}\mathbf{S^W}\mathbf{N^{g,j'}} \tag{35}$$

where $\mathbf{S^W}$ is an $ij \times i'j'$ matrix consisting of the elements $s_{j'|i}^w \; \forall \; i = i'$ and $0 \; \forall \; i \neq i'$, where $s_{j|i}^w$ is the wage-bill share of occupation j in region i.

Using these marginal responses of non-tradable employment as a replacement for equation (31) in equation (25), we can compute our decomposition as before.

A.3 Data

A.3.1 Employment

Our analyses use employment data in 1-digit occupations within the tradable and non-tradable sector for European regions over time. Table 8 outlines the data coverage for employment, outlining for each country the level of regional disaggregation and years for which we have data. This has been constructed from EU LFS micro-data for all 27 countries, partially supplemented with aggregated Eurostat data for Austria, the Netherlands, and the United Kingdom.

Industries are classified with 1-digit NACE revision 1 codes until 2005; 1-digit NACE revision 1.1 codes between 2005 and 2008; and 1-digit NACE revision 2 codes from 2008 onwards. Although the Eurostat crosswalk[44] between 1-digit NACE revision 1.1 and 2 codes is not one-to-one, this classification change does not matter given our level of aggregation. In particular, we classify industries as tradable or non-tradable based on NACE revision 1.1[45], and all 1-digit NACE revision 2 codes correspond to NACE revision 1.1 codes within either the tradable or the non-tradable group. We remove employment in industries Agriculture, Hunting and Forestry; Fishing; as well as Extraterritorial Organisations and Bodies from the dataset. Figure 5 shows the development of employment separately for the tradable and non-tradable sectors. It can be seen that employment has grown in both, but much more strongly so in the non-tradable sector.

Occupations are classified with ISCO 1988 codes throughout the sample period (1999-2010): we use the 1-digit codes to avoid unacceptably small sample sizes at the regional level, and exclude Farming Professionals (ISCO 6) and Armed Forces (ISCO 0).

Although occupation and industry data are typically available from 1993 onwards in the EU LFS, regional information only starts in 1999 for most countries. Furthermore, there are some countries (namely the Czech Republic, Germany, Denmark, Malta, Poland and Slovenia), where consistent regional data is only available in a later year: see Table 8. In Figures 3, 4, 5, 8, and 6, and Table 7, employment data for these countries is calculated by log-linearly extrapolating employment within region-occupation-industry cells. Breaks in the employment series constructed from micro-data (for Austria, Finland, France, Italy, Luxembourg, Portugal and the UK) have been adjusted as in Goos et al. (2014).

Finally, we supplement EU LFS micro-data for Austria, the Netherlands and the United

[44] Available at `http://ec.europa.eu/eurostat/web/nace-rev2/correspondence_tables`

[45] See Appendix A.4.1, below.

Kingdom with aggregate Eurostat data[46], to add more regional detail for these countries. In particular, in the EU LFS micro-data, regional information is only available at the 1-digit NUTS level for Austria and the UK, and at the national level for the Netherlands. For these countries, we therefore additionally use the aggregated datasets lfst_r_lfe2en1 and lfst_r_lfe2en2[47], which provide EU LFS employment data aggregated by Eurostat to the region-industry-year level.[48] This allows us to construct 2-digit NUTS employment by occupation-industry-year for Austria, the Netherlands, and seven out of twelve 1-digit NUTS regions in the UK.[49] Specifically, we use the following imputation method for regional employment in tradables over time (and analogously for regional employment in non-tradables over time):

$$N^g_{ijt} = N^g_{it} \times N^g_{j|\tilde{i}t}$$

where $\tilde{i}$ indicates the regional code available in the EU LFS micro-data and i its disaggregated (i.e. 2-digit NUTS) counterpart; and we have obtained N^g_{it} from aggregated Eurostat data and $N^g_{j|\tilde{i}t}$ from EU LFS micro-data. Note that this imputation assumes the same employment distribution across occupation-industry cells within more and less aggregated regions.

Figure 5 shows the development of employment over time for Europe as a whole, in total and separately by sector.

Figure 6 shows the actual changes in employment shares[50] for the 238 European regions between 1999 and 2010 divided into quintiles. The first quintile (light blue) depicts the 20 percent regions with the strongest decrease in their employment share whereas the fifth quintile (dark blue) contains the 20 percent regions with the strongest increase. The map shows that whereas employment shares have increased by up to 0.28 percentage points for some regions, reflecting employment growth above the European average; they have decreased in others by up to 0.21 percentage points. Furthermore, a regression of regional employment growth onto country dummies (not reported) reveals that this variation occurs both between and within countries: 60 percent of the variation in regional employment growth is due to differences between countries,

[46] Available from `http://ec.europa.eu/eurostat/data/database`.

[47] There are two separate datasets because of the change in industry classification from NACE rev. 1.1 to NACE rev. 2: lfst_r_lfe2en1 uses rev. 1.1 and covers 1999-2008 and lfst_r_lfe2en2 uses rev. 2 and covers 2008-2010.

[48] As such, this is the same data source as our micro-data: however, Eurostat aggregates from the non-anonymized micro-data. The anonymized regional identifier released to researchers is less detailed because Austria, the Netherlands and the UK have not authorized Eurostat to release micro-data at the 2-digit NUTS level.

[49] In particular, we can disaggregate data for 1-digit NUTS codes UKF, UKH, UKI, UKJ, UKK and UKL; but not for 1-digit NUTS codes UKC, UKD, UKE, UKG, UKM and UKN, due to data availability in the aggregated Eurostat data.

[50] Share of regional employment in total European employment.

Table 8: Employment data coverage by country

Country	Years	NUTS level(s)	Number of regions
AT	1999-2010	2	9
BE	1999-2010	2	11
CH	2001-2010	2	7
CZ	1999-2010	2	8
DE	2002-2010	1	16
DK	2007-2010	2	5
EE	1999-2010	.	1
ES	1999-2010	2	18
FI	1999-2010	2	5
FR	1999-2010	2	22
GR	1999-2010	2	13
HU	1999-2010	2	7
IE	1999-2010	2	2
IS	1999-2010	.	1
IT	1999-2010	2	20
LU	1999-2010	.	1
LV	1999-2010	.	1
MT	2009-2010	.	1
NL	1999-2010	2	12
NO	1999-2010	2	7
PL	2001-2010	2	16
PT	1999-2010	2	7
RO	1999-2010	2	8
SE	1999-2010	2	8
SI	2001-2010	2	2
SK	1999-2010	2	4
UK	1999-2010	1 & 2	26

Notes: European Union Labour Force Survey micro-data. A missing (.) NUTS level means there is no regional information available: for these countries, we only observe country-level data (i.e. a single region).

and the remaining 40 percent is due to differences within countries.

A.3.2 Routine Task Intensity

The definition and data for the Routine Task Intensity (RTI) measure is described in Section 3.1 in the main text. Table 2 in the main text shows the Routine Task Intensity of occupations: note that agricultural professionals (ISCO 6) and armed forces (ISCO 0) have been excluded from the dataset.

Further, Figure 7 shows that the decrease in the routine intensity of European employment documented in the paper is observed both in the sub-sample of 15 countries covered in Goos et al. (2014) and the 12 countries not included in the analysis in Goos et al. (2014).[51]

[51] Namely, the Czech Republic, Estonia, Hungary, Iceland, Latvia, Malta, Poland, Romania, Slovakia, Slovenia

Figure 5: Employment in Europe, total and by sector, 1999-2010

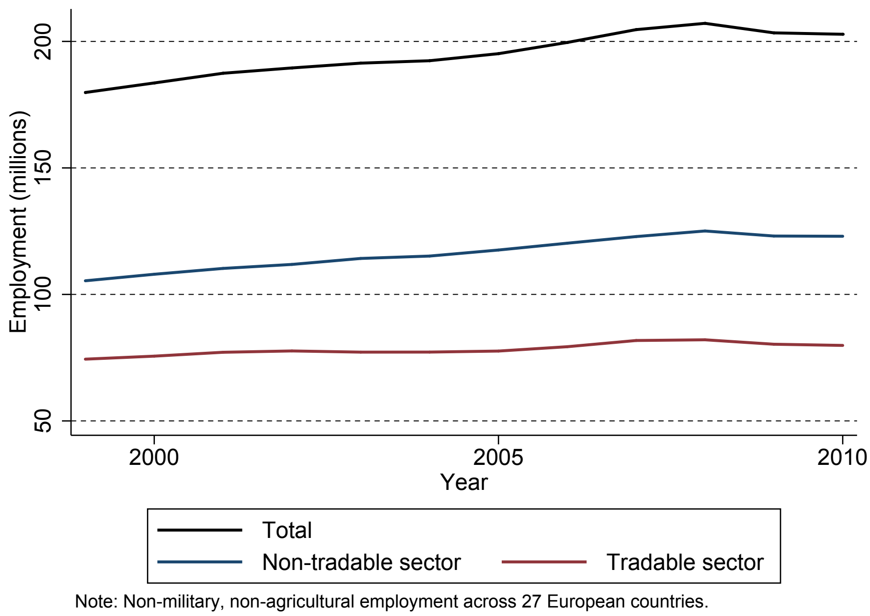
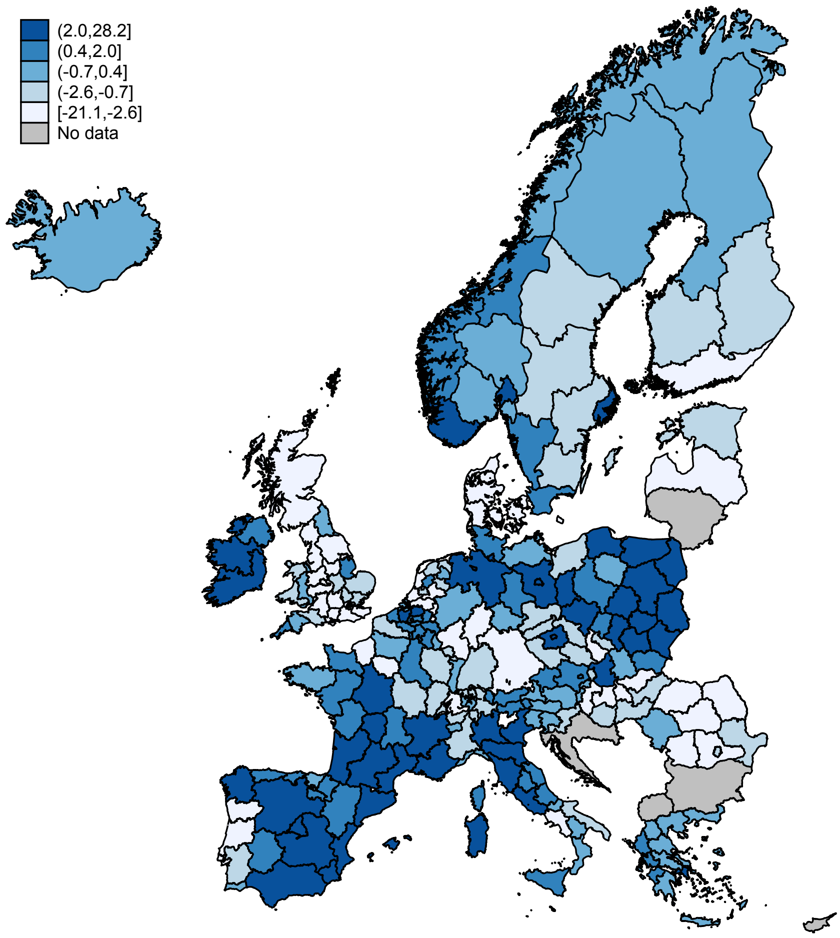


Figure 6: European regional employment growth, 1999-2010

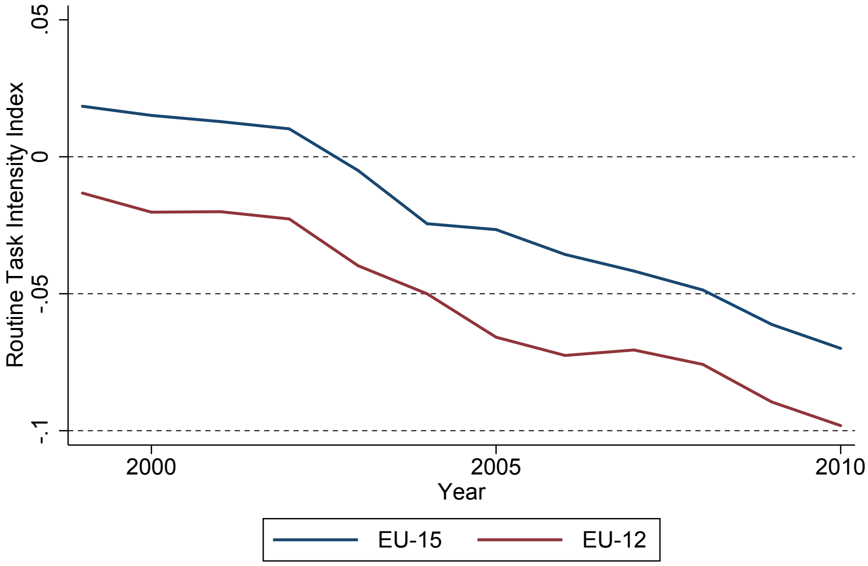


Notes: Regions grouped into quintiles based on regional employment growth. Numbers are in percentages.

and Switzerland.

Figure 8 highlights the regional variation in the routine intensity of employment in 1999: this variation arises because regions have different occupational employment shares. A higher RTI indicates that a higher fraction of jobs in the region can be automated. This map reveals significant regional heterogeneity in susceptibility to RRTC: Specifically, the most and least routine intense regions differ by an amount of 0.50 on the index, which corresponds to half a standard deviation of the index across one-digit occupations. For comparison, Figure 9 shows the 2010 spatial distribution of RTI.

Figure 7: Routine Task Intensity (RTI) of employment, 1999-2010



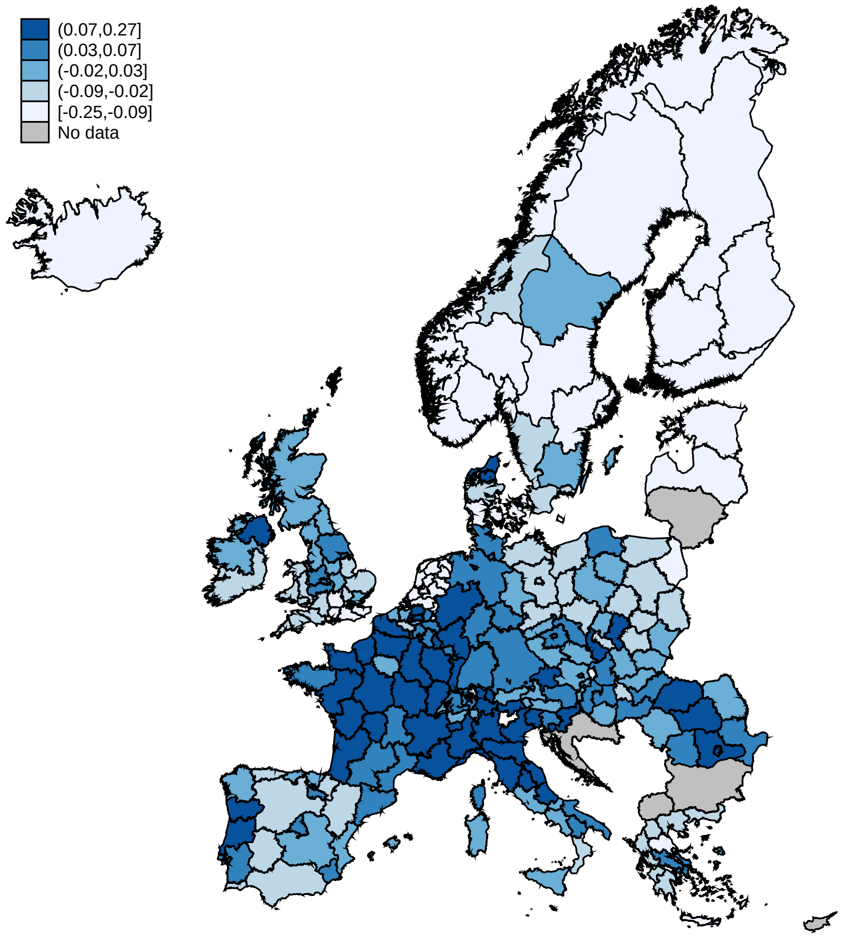
Note: EU-15 = 15 Western-European countries not included in Goos et al (2014);
EU-12 = 12 European countries not included in Goos et al (2014)

A.3.3 Output, marginal costs and capital stock

We construct measures of regional output in tradables, total regional income, regional marginal costs in tradables, and regional capital stock from the OECD's structural analysis database (OECD STAN).[52] We use the ISIC revision 3 version of STAN as a baseline, since this covers most countries and most years, supplemented with the ISIC revision 4 version whenever revision 3 data is not available.[53] This requires resetting the baseyear from 2005 to 2000 in the revision 4 database, as well as crosswalking the ISIC revision 4 code (which is equal to NACE revision 2 at the 1-digit level) to ISIC revision 3 codes (which is equal to NACE revision 1.1 at the 1-digit level). Data is available for all countries except Latvia, Malta, Romania and Slovenia, due to

[52] Available at `http://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm`.
[53] This is typically for years 2009 and 2010.

Figure 8: Spatial distribution of Routine Task Intensity (RTI) across European regions, 1999



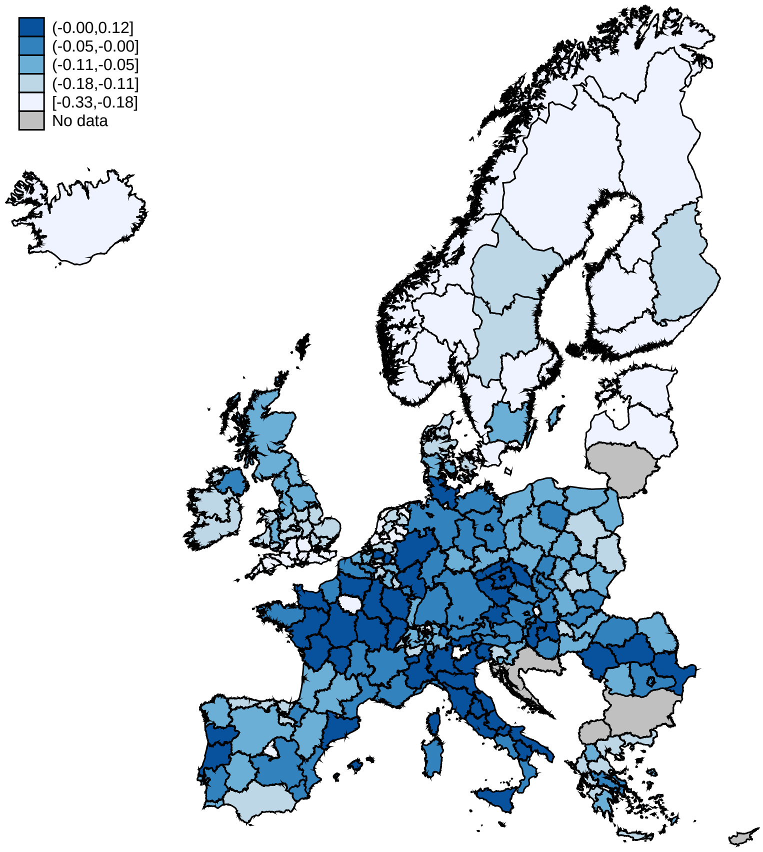
Notes: Regions grouped into quintiles based on their RTI-index (see Section 3.1 for more details on the construction of the RTI index.).

these countries not being covered in STAN; and Ireland, due to the absence of industry-varying deflators.

Industry output is measured as real production by 1-digit industry, obtained from deflating nominal production by industry-country-year varying deflators. Total income is the sum of real production across all industries: this is used to construct market potential, as described in Appendix A.4.2. Industry marginal costs for tradables are defined as the industry-level difference between nominal production and net operating surplus, divided by real production, following Goos et al. (2014). Capital stock is defined as real net capital stock summed across all industries, deflated by country-year varying deflators.

Since these measures are only available at the national level in OECD STAN, we perform an imputation procedure to obtain regional variation for each of these. In particular, our imputation method exploits regional variation in output, marginal costs and capital stock arising from

Figure 9: Spatial distribution of Routine Task Intensity (RTI) across European regions, 2010



Notes: Regions grouped into quintiles based on their RTI-index (see Section 3.1 for more details on the construction of the RTI index.).

industry composition differences at the regional level within tradables and non-tradables. For each year, we assign national production and net capital stock at the level of 1-digit industries to regions based on the share of regional to national employment by industry, and then sum production across tradable 1-digit industries and net capital stock across all 1-digit industries. That is, for production:

$$Y_{it}^{g} = \sum_{\tilde{g}=1}^{\tilde{G}} Y_{\bar{i}t}^{\tilde{g}} \frac{N_{it}^{\tilde{g}}}{N_{\bar{i}t}^{\tilde{g}}}$$

where Y indicates production; $\bar{i}$ subscripts countries; and $\tilde{g}$ subscripts 1-digit NACE industries within tradables.

To obtain regional variation in marginal costs for tradables, we weight national marginal costs at the level of 1-digit industries with the regional employment shares of 1-digit industries to total tradable employment and sum across all tradable 1-digit industries. This is done separately for each year, such that:

$$c_{it}^{I} = \sum_{\tilde{g}=1}^{\tilde{G}} c_{\bar{i}t}^{\tilde{g}} \frac{N_{it}^{\tilde{g}}}{N_{it}^{g}}$$

where c indicates marginal costs; $\bar{i}$ subscripts countries; and $\tilde{g}$ subscripts 1-digit NACE industries within tradables.

The instrument for regional industry marginal costs is national industry marginal costs reweighted by industry shares within regions, for each year. In particular, we use the weights of the starting year for each country (i.e. holding constant the industry shares and using changes in industry marginal costs at the national level only). Following Goos et al. (2014), who instrument income with net capital stock, we construct our instrument for market potential by replacing income with net capital stock (see Appendix A.4.2 for details).

A.4 Empirical implementation

This appendix provides further details on the empirical implementation.

A.4.1 Classification of industries: tradability and ICT-intensity

To classify 1-digit NACE industries as tradable or non-tradable, we follow Jensen and Kletzer (2006, 2010) by calculating a Gini coefficient of spatial concentration: the most spatially concentrated industries are considered tradable. For this, we rely on data from Eurostat. More precisely, we combine aggregated data from the EU Labor Force Survey (LFS) on region-industry employment at the NUTS2 and NACE 1-digit level with information on region-industry employment at the NUTS2 and NACE 2-digit level from the EU Structural Business Statistics (SBS). Whereas the EU SBS provides more detailed sectoral data, these do not cover the primary sector and public sectors, which we obtain from the EU LFS. We then use iterative proportional fitting to fit the data to total regional employment and total industry employment (at the national level), which we obtain from Eurostat. These data are available for the EU-15 excluding Denmark for the time period 1995-2008.[54] We calculate spatial Gini coefficients as a measure for industry localization, as described by Krugman (1991), for all years individually. We calculate the spatial Gini coefficients at the level of the NACE 2-digit industries and then calculate the average spatial Gini coefficient for each NACE 1-digit industry across all years.[55] These are reported in column 1 of Table 9. We distinguish between tradable and non-tradable industries at the cut-off value of 0.25: industries with a Gini coefficient above 0.25 are classified as tradable. Note that industries L, M, N, O and P are all grouped together in this dataset, hence they have the same Gini coefficient.

Furthermore, the tradable industries have been more affected by technological change than non-tradable industries, as is assumed in our theoretical set-up and the resulting empirical implementation. This is shown in columns 2 and 3 of Table 9, which provide the level and change in ICT intensity for 15 Western European countries based on EUKLEMS data. These results are stable across countries.

[54] Due to the territorial reform in Denmark, these data are unavailable at the NUTS2-level in Denmark.

[55] The spatial Gini coefficients are based on the employment shares of the region-industries within EU-wide industry employment. For robustness, we further calculate the spatial Gini coefficients for each country individually. However, the average of country-specific spatial Gini coefficients differs little from the EU-wide spatial Gini coefficients.

Table 9: Spatial Gini coefficients for industries

NACE	Industry	Classification	Gini	ICT-intensity Level	Δ
			(1)	(2)	(3)
C	Mining and quarrying	Tradable	0.54	2.70	11.03
D	Manufacturing	Tradable	0.37	2.39	1.93
E	Electricity, gas and water supply	Tradable	0.27	5.65	4.09
F	Construction	Non-Tradable	0.16	0.45	0.26
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	Non-Tradable	0.15	1.96	2.39
H	Hotels and restaurants	Non-Tradable	0.21	0.42	0.28
I	Transport, storage and communications	Tradable	0.34	7.32	5.09
J	Financial intermediation	Tradable	0.30	9.51	11.56
K	Real estate, renting and business activities	Tradable	0.37	4.07	5.16
L	Public administration and defense; compulsory social security	Non-Tradable	0.10	0.95	1.49
M	Education	Non-Tradable	0.10	0.72	1.13
N	Health and social work	Non-Tradable	0.10	0.67	1.79
O	Other community, social and personal services activities	Non-Tradable	0.10	1.58	1.99
P	Activities of private households as employers	Non-Tradable	0.10	0.00	0.00

Notes: Industries classified with NACE revision 1.1.

A.4.2 Construction of market potential

Production in a region depends on the size of the potential market for the products of this region. The potential market is defined as the sum of income in all other regions, lowered by the transport costs towards these regions. While we have data on income in all other regions from OECD STAN, we do not know the trade costs to these regions. However, we have information on trade flows between all regions in Germany,[56] from which we estimate an index of trade costs for all region-pairs in Germany. We then estimate the relationship between this index and the distance between regions, in order to extrapolate the trade costs for all region-pairs in Europe. Finally, we use these trade costs to calculate market potential in Europe. The procedure is outlined below.

Our product demand equation is:

$$Y_i^g = \left(\frac{p_i^g}{P^g}\right)^{-\sigma} \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \mu \frac{I_{i'}}{P^g}, \tag{36}$$

[56] Eurostat provides information on transport flows, which we use to construct a transport flow matrix for Germany by types of goods. We apply goods prices from international trade statistics provided by Eurostat and information on industry production at the regional level provided by the Statistical Offices of the Länder and the Federal Statistical Office of Germany to convert transport volumes into transport values.

where demand for tradables produced by region i depends on the prices of these products and a weighted aggregate of income in all regions, with the weights depending on transport costs. Therefore, this weighted aggregate is a measure of market potential, since it represents the size of the market that region i can potentially serve with its products given the transport costs to this market. That is, market potential is the last term in the product demand equation (now in logs)

$$\log Y_{it}^{g} = -\sigma \log \left(\frac{p_{it}^{g}}{P_{t}^{g}} \right) + \log \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \mu \frac{I_{i't}}{P_{t}^{g}} \tag{37}$$

Market potential depends on unknown variables and parameters and thus cannot be directly empirically measured. In the trade flow specification of product demand, however, one can estimate the trade costs from fixed effects. This trade flow specification is:

$$\log c_{ii't}^{g} = -\sigma \log \left(\frac{p_{it}^{g}}{P_{t}^{g}} \right) - \sigma \log \tau_{ii'} + \log \mu + \log \frac{I_{i't}}{P_{t}^{g}} \tag{38}$$

We translate this into a fixed-effects model:

$$\log c_{ii't}^{g} = \beta_0 + \beta_{ii'} + \beta_1 timetrend + \beta_2 \log \frac{I_{i't}}{P_{t}^{g}} + \beta_3 \log c_{i}^{I} + \epsilon_{ii't} \tag{39}$$

We use the total real income of private households as a measure for $\frac{I_{i't}}{P_{t}^{g}}$[57] and we replace the regional price level $\frac{p_{it}^{g}}{P_{t}^{g}}$ with regional marginal costs c_{i}^{I}.[58] The trade-pair fixed effects $\beta_{ii'}$ in this equation contain estimates of $-\sigma \log \tau_{ii'}$, that is, the weights for constructing the market potential. We therefore extract the fixed effects from the trade flow equation to get our index of trade costs $\tilde{\tau_{ii'}}$. There is a close relationship between trade costs and distance, which we exploit to extrapolate the trade costs for Europe. More precisely, we regress estimated trade costs (i.e. the fixed effects $\hat{\beta}_{ii'}$ resp. $\tilde{\tau_{ii'}}$) on distance:[59]

$$\log \tilde{\tau_{ii'}} = \beta_0 + \beta_1 \log \text{distance}_{ii'} + \varepsilon_{ii'} \tag{40}$$

From this, we calculate extrapolated trade costs $\hat{\tau_{ii'}^{*}} = \hat{\beta}_0 + \hat{\beta}_1 \text{distance}_{ii'}$. We use the average of $\tilde{\tau_{ii'}}$ for those region-pairs where the distance is zero (i.e. sales of a tradables within the region

[57]Source: Statistical Offices of the Länder and the Federal Statistical Office of Germany.
[58]See Appendix A.3.3 for the measurement of regional marginal costs.
[59]Distance is measured as the great-circle distance between the centroids of the regions in our sample.

of production). We scale the trade costs as follows:

$$\hat{\tau_{ii'}} = \frac{\hat{\tau^*_{ii'}}}{\sum_{i'=1}^{I} \sum_{i=1}^{I} \hat{\tau^*_{ii'}}} \tag{41}$$

Due to this scaling, $\hat{\tau_{ii'}}$ represents the share of each transport flow in total sales across all flows. Market potential then is defined as

$$\mathrm{MP}_{it} = \sum_{i'=1}^{I} \hat{\tau_{ii'}} \frac{I_{i'}}{P^g} \tag{42}$$

As such, a region's market potential represents the sales of that region to all destination regions. Through the scaling, the sum of market potential across all regions equals total income (or total production). To construct the market potential for Europe, we use output in European regions (see Appendix A.3.3) as a measure for $I_{i'}$. To construct our IV for market potential, we replace $I_{i'}$ with regional net capital stock (see Appendix A.3.3).

A.4.3 First-stage estimates

Here, we present our first-stage estimates for both labor and product demand.

Table 10: Labor demand in the tradable sector: first stages

	FE-IV model 1		**FE-IV model 2**	
	First stage	First stage	First stage	First stage
	Output	Marginal costs	Output	Marginal costs
	(1)	(2)	(3)	(4)
Log regional net capital stock in tradables	0.536***	-0.013**	0.537***	-0.013**
	(0.040)	(0.004)	(0.043)	(0.004)
Log counterfactual regional marginal cost index	-0.069	0.896***	0.038	0.900***
	(0.109)	(0.027)	(0.132)	(0.027)
Number of observations	11,744	11,744	11,744	11,744
Sanderson-Windmeijer first-stage F-statistic	183.1	1,606.3	156.1	2,028.2

	FE-IV model 3		
	First stage	First stage	First stage
	Output	Marginal costs	Wages
	(5)	(6)	(7)
Log regional net capital stock in tradables	0.519***	-0.013**	0.003
	(0.040)	(0.004)	(0.025)
Log counterfactual regional marginal cost index	-0.107	0.896***	-0.222
	(0.102)	(0.027)	(0.174)
Female labor supply shock	0.717***	-0.007	-0.175*
	(0.096)	(0.011)	(0.087)
Number of observations	11,744	11,744	11,744
Sanderson-Windmeijer first-stage F-statistic	26.6	3.1	4.4

Notes: European regions, 1999-2010. All models include region-occupation fixed effects and control for a linear timetrend. Standard errors clustered by region reported in parentheses. Coefficients on RTI multiplied by 100.

Table 11: Product demand in the tradable sector: first stages

Dependent variable: log regional production of tradables (in region-year cells)		
	First stage	First stage
	Market potential	Marginal costs
	(1)	(2)
Log regional net capital stock in tradable sector	1.284***	0.050**
	(0.038)	(0.018)
Log counterfactual regional marginal cost index	0.235***	0.914***
	(0.033)	(0.022)
Number of observations	1,904	1,904
Sanderson-Windmeijer first-stage F-statistic	751.5	769.1

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Standard errors clustered by region reported in parentheses.

A.5 Empirical robustness checks

This appendix provides further empirical robustness checks.

A.5.1 Alternative parameter estimates

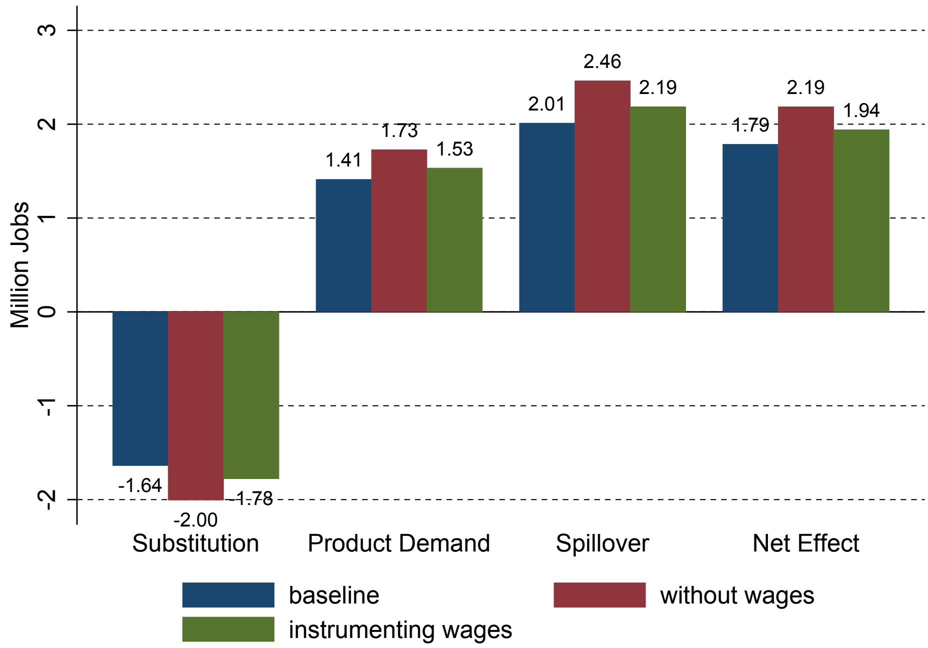
This section presents robustness checks using alternative parameter estimates. We first consider the parameters obtained from the labor demand equation, i.e. $(1-\eta)(1-\kappa)\gamma_R$ and η. These parameter estimates (and the assumed or implied values for κ and γ_R) are reported in Table 12, along with the baseline. In particular, in panel A we show the baseline estimates used in Sections 4.1 and 4.2. Panel B shows estimates from the labor demand model without controlling for wages (model 3 in Table 3), and panel C the labor demand model where wages are instrumented by labor supply shocks (model 5 in Table 3).

Firstly, note that the routinization coefficient $(1-\eta)(1-\kappa)\gamma_R$ is identical across all model specifications. The estimated substitution elasticity between tasks, η, does differ somewhat across models: in both alternative specifications reported here, it is higher than the baseline of 0.29. Further, note that without controlling for wages, we have no way to back out both κ and γ_R: we therefore assume κ to be 0.69, the plausible value obtained from our baseline estimates. This suggests an implied annual log capital price decline of 9.6 percent (versus 7.8 percent in our baseline estimates). In panel C, we again use the estimated wage elasticity of labor demand to obtain estimates of κ and γ_R. However, because this coefficient is very imprecisely estimated (-0.36 with standard error of 0.59, as reported in Table 3's model 5), these implied parameters have a lot of variance. Their averages are also less plausible than in the baseline and first alternative models, suggesting a labor share of 0.95 rather than 0.69, and a stark decline in the price of capital of 52 percent annually.[60]

Figure 10 reports point estimates for these two alternative parameter constellations along with the baseline, showing the predicted employment effects from each of the three channels as well as the net effect. Note that all predictions shown in this figure still use our baseline product demand elasticity (σ) of 0.86 for now. The predicted net employment effect is both qualitatively identical and quantitatively similar for all three parameter sets: 1.8 million jobs in the baseline, versus 2.2 million and 1.9 million in the two alternative scenarios. This is because a higher elasticity of substitution across tasks (η) leads to both stronger (negative) substitution

[60] In Byrne and Corrado (2017), values in this range are only found for computer storage and computing technologies (25 to 50% annually).

Figure 10: Robustness check: alternative labor demand estimates



effects and stronger (positive) product demand effects, creating two countervailing forces on the net effect. Moreover, variations in the capital price decline γ_R across specifications are mostly compensated by inverse changes in the capital share (via the labour share κ), since both are backed out from the estimate of routinization $\beta_3 = (1-\eta)(1-\kappa)\gamma_R$ which is empirically very robust across specifications.

We additionally take an alternative value for σ, the product demand elasticity parameter estimated in Table 4. Our baseline uses the specification where market potential and marginal costs are instrumented (model 2), but as a robustness check we consider the OLS specification shown in model 1: this reduces the estimated elasticity from 0.86 to 0.65. Figure 11 implements this for both the baseline parameter set reported in Table 12's panel A, and the two alternatives shown in panels B and C. As before, employment predictions are quite similar across baseline and alternative specifications, showing that our results do not hinge on any particular labor or product demand specification.[61]

Further, note that increasing the labor supply elasticity ϵ simply moves the predictions for employment closer to the ones for labor demand predictions: these two converge as the supply elasticity approaches infinity. Figure 12 illustrates this by showing how the predicted net

[61] Although not reported here for succinctness, results for the role of non-wage income are also robust to these alternative parameter configurations – results are available from the authors.

Figure 11: Robustness check: alternative product demand estimate

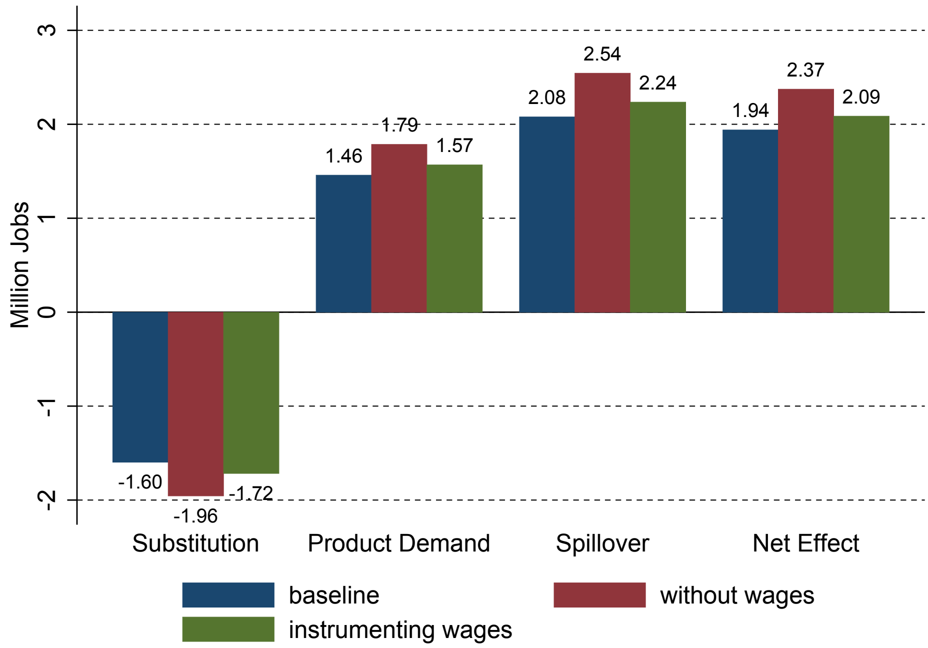


Table 12: Alternative parameter estimates

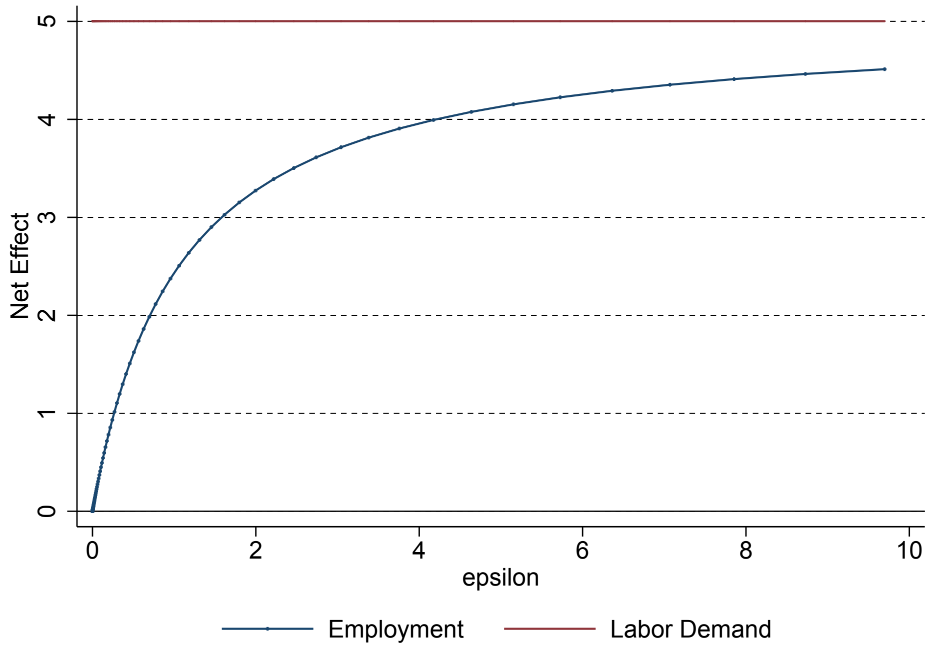
Parameter	Description	Estimate		
		A. Baseline	*B. Without wages*	C. *Instrumenting wages*
$(1-\eta)(1-\kappa)\gamma_R$	routinization coefficient ($\times$100)	-1.743***	-1.743***	-1.743***
		(0.081)	(0.081)	(0.081)
η	substitution elasticity between tasks	0.285**	0.416**	0.324*
		(0.103)	(0.129)	(0.164)
$-[(1-\kappa)+\kappa\eta]$	wage elasticity of labor demand	-0.507**	–	0.357
		0.052)		(0.590)
κ	labor share	0.689***	0.689***	0.951
		(0.136)	(0.136)	(1.066)
γ_R	annual log routine-replacing capital price change ($\times$100)	-7.833*	-9.597***	-52.467
		(4.441)	(2.167)	(1150.072)

Notes: Estimates in Panels A, B, and C are obtained from model 4, 3, and 5, respectively, in Table 3. In panel B, κ is assumed to be equal to the estimate obtained from the baseline model (panel A). Standard errors reported in parentheses.

employment effect asymptotically approaches the predicted net labor demand effect over a range of ϵ from 0 to 10. Lastly, Appendix A.5.2 shows that our labor and product demand parameter estimates do not vary substantially across the economic cycle.

All in all, the results presented here show that our baseline effects (reported in Section 4) are robust to alternative parameter configurations.

Figure 12: Robustness check: labor supply elasticity



A.5.2 Business cycles

Our theoretical model examines how RRTC impacts long-run labor demand, and does not consider business cycles. Indeed, we model technological progress as a task measure interacted with a linear timetrend to capture a steady secular process, implying we should pool information across the economic cycle. Indeed, there have been both booms and recessions over our observation window 1999-2010, and as a robustness check we examine whether our parameter estimates are significantly different across different parts of the economic cycle. This appendix therefore presents estimates of our labor and product demand equations where our respective independent variables have been interacted with a dummy for recession and/or boom years. In particular, we obtain country-specific business cycle indicators from the OECD, which classifies years as peaks, troughs, or neither, for each country in our sample: around 20 percent of years are peak years, 20 percent are troughs, and the remainder is neither.[62]

Table 13 shows estimates of the labor demand equation, allowing parameters $(1-\eta)(1-\kappa)\gamma_R$ and η to differ during peaks and troughs. It can be seen that the deviations from the parameter estimate for $(1-\eta)(1-\kappa)\gamma_R$, given by the coefficient on RTI $\times$ timetrend, are economically

[62]The OECD does not have indicators for Iceland, Latvia, and Romania– for these countries, we use indicators for the UK, Estonia, and Hungary, respectively. Results are robust to alternatively constructing a business cycle indicator common across countries, where a year is classified as a peak or trough if it is classified as such for at least half of all countries in our sample.

Table 13: Labor demand in the tradable sector: business cycle interactions

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	FE Full sample (1)	FE Restricted sample (2)	FE-IV (3)	FE-IV with wages (4)	FE-IV with IV wages (5)
Standardized occupational RTI × timetrend	-1.675***	-1.741***	-1.741***	-1.741***	-1.741***
	(0.074)	(0.092)	(0.082)	(0.082)	(0.082)
Standardized occupational RTI × timetrend	0.000	0.000	0.000	0.000	0.000
× trough dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Standardized occupational RTI × timetrend	0.000*	0.000	0.000	0.000	0.000
× peak dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log regional gross production in tradables			0.738***	0.737***	0.737***
			(0.071)	(0.077)	(0.075)
Log regional marginal cost index			0.435**	0.281*	0.321
			(0.133)	(0.110)	(0.165)
Log regional marginal cost index			0.046	0.053	0.051
× trough dummy			(0.052)	(0.045)	(0.042)
Log regional marginal cost index			0.114**	0.158***	0.146*
× peak dummy			(0.042)	(0.041)	(0.058)
Log regional wage in tradables				-0.506***	-0.376
				(0.051)	(0.505)
Number of observations	21632	11744	11744	11744	11744
R-squared	0.980	0.982	0.179	0.197	0.196

Notes: European regions, 1999-2010. Models (1) and (2) include region-occupation and region-year fixed effects. Model (3), is estimated with region-occupation fixed effects and controls for a linear timetrend. Standard errors clustered by region reported in parentheses. Coefficients on RTI multiplied by 100.

negligble. Furthermore, the estimated η parameter is not significantly different in recession years. Although only borderline statistically significant, η is slightly higher during peak years– however, the deviation easily falls within the confidence interval we consider in Table 6.

Table 14 contains the corresponding product demand demand estimates: also here, we do not find a statistically significant deviation for our estimated σ parameter during peaks or troughs.

In conclusion, we do not find evidence to suggest our parameter estimates are affected by pooling both recession and boom years.

Table 14: Product demand in the tradable sector: business cycle interactions

Dependent variable: log regional production of tradables (in region-year cells)		
	FE	FE-IV
	(1)	(2)
Log market potential	1.182***	1.289***
	(0.091)	(0.103)
Log industry marginal cost index	-0.508***	-0.663***
	(0.132)	(0.156)
Log industry marginal cost index × trough dummy	0.033	0.024
	(0.044)	(0.046)
Log industry marginal cost index × peak dummy	0.047	0.026
	(0.040)	(0.042)
Number of observations	2,048	2,048

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Standard errors clustered by region reported in parentheses.