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Racing With or Against the Machine?

Evidence from Europe

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Racing With or Against the Machine? Evidence from Europe

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Abstract

A fast-growing literature shows that technological change is replacing labor in routine tasks, raising concerns that labor is racing against the machine. This paper is the first to estimate the labor demand effects of routine-replacing technological change (RRTC) for Europe as a whole and at the level of 238 European regions. We develop and estimate a task framework of regional labor demand in tradable and non-tradable industries, building on Autor & Dorn (2013a) and Goos, Manning and Salomons (2014), and distinguish the main channels through which technological change affects labor demand. These channels include the direct substitution of capital for labor in task production, but also the compensating effects operating through product demand and local demand spillovers. Our results show that RRTC has on net led to positive labor demand effects across 27 European countries over 1999-2010, indicating that labor is racing with the machine. This is not due to limited scope for human-machine substitution, but rather because sizable substitution effects have been overcompensated by product demand and its associated spillovers. However, the size of the product demand spillover -- and therefore also RRTC's total labor demand effect-- depends critically on where the gains from the increased productivity of technological capital accrue.

Keywords: Labor Demand, Routine-Replacing Technological Change, Tasks, Local Demand Spillovers

JEL classification: E24, J23, J24, R23

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1 Introduction

The labor market impacts of technological change are at the center of a long-standing debate. In recent years, there has been a revival of public concerns about technological change destroying jobs (Autor 2015; Mokyr et al. 2015; Nordhaus 2015), in part fueled by reports claiming that large shares of U.S. and European jobs are at risk of automation in coming decades as digital technologies increasingly replace humans at work (Bowles 2014; Frey and Osborne 2013). This suggests that labor demand will dwindle in the face of technological improvements. In the words of Brynjolfsson and McAfee (2011), labor is thought to be racing against the machine.

In contrast to this, the economic literature has long considered technological change to be labor-augmenting. In particular, the canonical skill-biased technological change (or SBTC) hypothesis argues that technology complements skilled workers (see Acemoglu and Autor 2011 for an overview): in SBTC frameworks, there is no replacement of human labor by technological capital. More recently, however, the academic consensus has shifted to a labor-replacing view of technological change. Specifically, information and communication technologies (ICT) are thought to replace human labor in so-called routine tasks (Autor et al. 2003).[1] This routine-replacing technological change (RRTC)[2] hypothesis predicts an increased demand for labor in non-routine relative to routine tasks and is supported by empirical evidence from a range of developed countries (surveyed in Acemoglu and Autor 2011 and Autor 2013). Overall, this literature provides important insights into the effects of technological change on relative labor demand across skill groups and occupations. However, the economy-wide labor demand effect of technological change – which lies at the heart of public concerns about labor racing against the machine – is only beginning to be explored, and its economic transmission channels are not yet well understood.

This paper therefore studies how routine-replacing technological change impacts aggregate labor demand, both theoretically and empirically. Our 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,

[1]As first outlined by Autor et al. (2003), routine tasks follow a set protocol which makes them codifiable in software, whereas non-routine tasks are as yet non-scriptable because they require either mental or physical adaptability. Examples of routine tasks include calculation, record-keeping, and repetitive customer service; examples of non-routine tasks include problem-solving and creative thinking as well as social interaction. Jobs intense in routine tasks include office clerks and machine operators; jobs intense in non-routine tasks include high-skilled occupations such as managers and professionals but also the low-skilled work done by hairdressers, janitors and truck drivers.

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

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 task inputs. However, RRTC also induces additional labor demand through a product demand effect, as declining capital costs reduce the prices of tradables and thus raise product demand. And thirdly, product demand spillovers create additional labor demand: the increase in product demand raises income, which is partially spent on low-tech non-tradables, leading to higher local labor demand. Given these opposing effects, the net labor demand effect of RRTC is ex ante ambiguous: labor may either be racing with or against the machine. We estimate key parameters from this framework using data over 1999-2010 for 238 regions across 27 European countries. This allows us to construct an empirical estimate of the economy-wide effect of RRTC on labor demand for Europe as a whole. Going beyond the net impact, we also decompose this economy-wide effect into the three channels, outlined above, through which RRTC affects labor demand.

This paper contributes to the literature in a number of ways. Firstly, we extend the theoretical framework in Goos et al. (2014) by distinguishing tradable and non-tradable goods, and modeling the spatial reallocation of labor demand resulting from RRTC.[3] This extension serves a dual purpose. 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. According to this literature, technological change creates high-tech jobs which in turn generate additional employment through local demand spillovers.[4] Secondly, this spatial framework also captures the technology-induced component of interregional trade.

Furthermore, and in contrast to both Autor and Dorn (2013) and Goos et al. (2014), we focus on the effects of RRTC on absolute labor demand rather than on relative changes across different occupations, since the former is more pertinent to the question of whether labor is racing with or against the machine.[5] Similar to ours, existing theoretical frameworks which focus on RRTC's

[3]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.

[4]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).

[5]Several other studies have related relative employment changes to RRTC by modeling and/or estimating relative task-demand (Antonczyk et al. 2010; Autor et al. 2006, 2008; Black and Spitz-Oener 2010; Dustmann et al. 2009; Goos and Manning 2007; Michaels et al. 2010; Spitz-Oener 2006; Senftleben and Wielandt 2014). These studies show that changes in employment structures are similar across a large set of developed economies, and are consistent with the RRTC hypothesis which predicts a relative decline in labor demand for jobs intense in routine tasks. While these studies provide important contributions to our understanding of how technological change affects relative employment changes across skill levels and job types, they do not address the effects on absolute employment which lie at the core of public concerns for the future of work.

absolute employment effects conclude that the labor demand effect of labor-saving technologies is theoretically ambiguous. In particular, Benzell et al. (2015) and Sachs et al. (2015) show that a rise in robotic productivity which substitutes for labor can result in declining product demand if the output produced by robots is sufficiently substitutable for the output produced by humans. This partially mirrors the theoretical results in Autor and Dorn (2013) and Goos et al. (2014), who show that the effect of RRTC on relative employment in routine jobs depends on the relative sizes of, on the one hand, the production elasticity of substitution between computer capital and routine labor[6] and, on the other hand, the consumption elasticity of substitution between different goods and services.[7] Lastly, Nordhaus (2015) more broadly studies the theoretical conditions for an "economic singularity", i.e. a situation in which technological change makes human labor obsolete, showing that this arises either if product demand is elastic, such that demand restructures to only ICT-produced goods, or if production is elastic, shifting production to ICT-inputs only.

Our empirical contribution is to provide the first estimate of the economy-wide effect of RRTC on labor demand. Existing work has so far considered more disaggregated levels – such as sectors, regions, and firms – and not found any evidence of negative employment effects of RRTC. At the sectoral level, Graetz and Michaels (2015) estimate the impact of industrial robots on 17 developed countries' utilities and manufacturing industries over 1993-2007 and find no adverse aggregate employment effects within these sectors. At the regional level, Autor et al. (2015) conclude that U.S. local labor markets initially specialized in routine tasks do not experience employment declines: rather, within these routine-intense regions, the employment effect of RRTC in the non-manufacturing sector is found to be weakly positive. Lastly, at the firm level, Cortés and Salvatori (2015) do not find evidence of absolute employment losses at establishments specialized in routine tasks. Besides providing an economy-wide estimate, we build on this existing reduced-form evidence by disentangling the relative sizes of the channels through which RRTC is affecting labor demand.[8] This is important because the relative sizes of these channels inform about the conditions under which labor demand is likely to rise or decline as a result of RRTC. Lastly, we also exploit the variation of these labor demand effects across

[6]Or, alternatively, the production elasticity of substitution between tasks varying in their routine intensity.

[7]This is a departure from canonical SBTC models which consider a single final consumption good, precluding such adjustments in the composition of product demand (e.g. see Katz and Murphy 1992; Card and Lemieux 2001).

[8]This is achieved by estimating the structural parameters of our labor demand framework, an approach based on Goos et al. (2014).

European regions to test the predictive power of our framework. These labor demand effects have not yet been studied for European regions, despite the significant regional heterogeneity in occupation and industry structures documented in the next section. For the U.S., Autor and Dorn (2013) and Autor et al. (2015) have already extensively studied the local labor market effects of RRTC, but previous related work on Europe has examined national labor market outcomes only (Goos et al. 2009, 2014). Indeed, the few existing studies on the effects of RRTC on regional labor market outcomes have so far focused on a single European country, Germany. Here, Senftleben and Wielandt (2014) confirm the relative decline in routine, middle-skilled occupations within German regions, while Dauth (2014) shows that this employment polarization pattern is not uniform across space.

Our results indicate that the total labor demand effect of routine-replacing technological change over the past decade has been positive, suggesting that labor is racing with rather than against the machine. Indeed, the decomposition of total labor demand changes into the three separate channels shows that the product demand effect and its spillovers to the non-tradable sector were large enough to overcompensate the substantial labor demand decrease resulting from the substitution of capital for labor. Specifically, RRTC is estimated to have raised labor demand by up to 11.6 million jobs across Europe, corresponding to almost half of the total observed employment increase over the 1999-2010 period: however, this estimate hinges critically on increasing non-wage income feeding back into local product demand. If only wage income is taken into account, the total labor demand effect is found to be only 1.9 million jobs. This substantial difference 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 labor demand 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 2.6. 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. We do this by modeling how firms' production processes shift towards capital inputs in the face of routine-replacing technological change, leading to subsequent output price changes as well as a spatial reallocation of labor demand.

We follow a regional modeling approach, which allows us to take into account local spillovers. Specifically, 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. RRTC is modeled as exogenously declining costs of capital in routine tasks relative to non-routine tasks, which can be 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.3.1).

Our model also predicts regional variation in the labor demand effects of RRTC, since different regions are differently routine-intense in terms of their production due to different occupation and industry structures: Figure 1 illustrates this by showing the intensity of routine task usage across European regions in 1999.[10] The European map reveals significant regional heterogeneity in susceptibility to RRTC.[11] Furthermore, although our framework does not account for any labor demand effects of exogenously decreasing trade barriers[12], the regional modeling approach

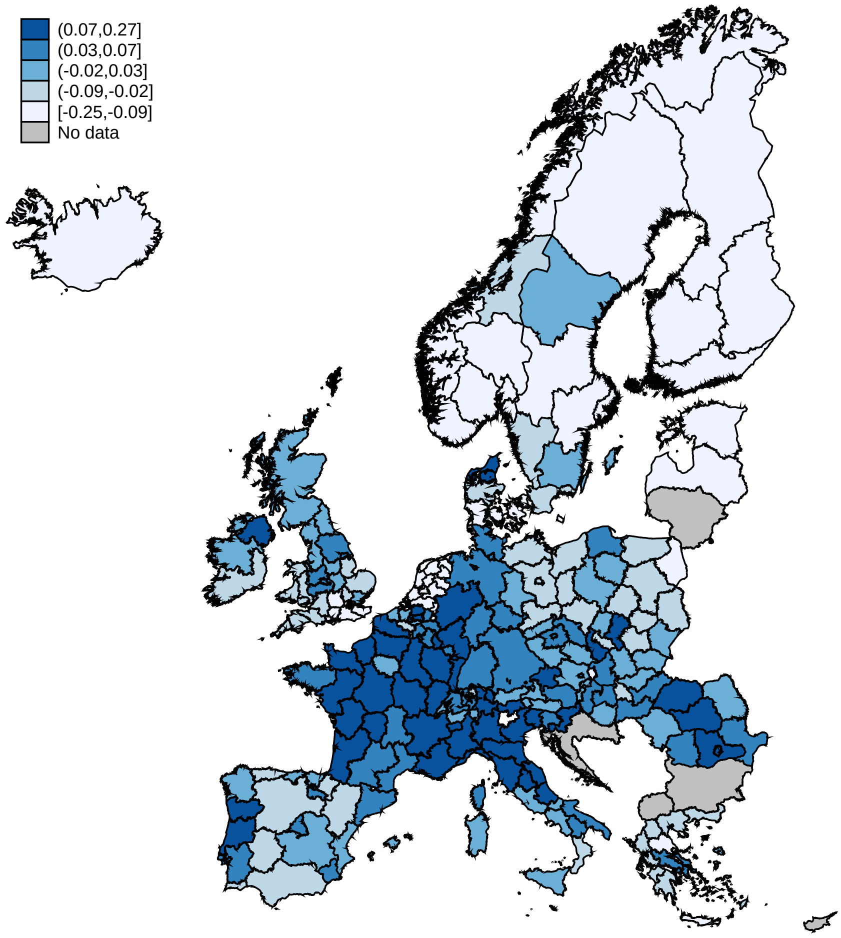
[9]The empirical classification we implement to distinguish tradables from non-tradables is reported in Table 1 from Section 3.

[10]Routine intensity indicates to what extent employment in a region is likely to be substituted by computer capital. A higher value indicates that a higher fraction of jobs in the region can be automated. The Routine Task Intensity (RTI) measure is outlined in Section 3.

[11]Specifically, the most routine intense and least 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.

[12]Previous work has shown that one such exogenous change, the accession of China to the WTO, has had an economically sizable impact on labor demand in U.S. regions (Autor et al. 2013; Caliendo et al. 2015) and on German regions (Dauth et al. 2014) but that these effects are not strongly correlated with the labor demand effects of RRTC at the regional or occupational level, or across time (Autor et al. 2015).

Figure 1: 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.).

accounts for the component of trade that is induced by technological change. Since we will estimate this framework using regional data 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).

In this stylized labor demand framework, we abstract from any wage responses to RRTC, and thus implicitly assume perfectly elastic labor supply. Although this is a strong assumption, we do not consider this approach to be ill-suited to the European case where wages are relatively rigid (Arpaia et al. 2015).[13] Indeed, Goos et al. (2014) make a similar assumption in studying changes in relative occupational labor demand in Europe.[14]

[13]Arpaia et al. (2015) find that wages in Europe react little to labor demand shocks and that these shocks are instead mostly absorbed by the activity rate and by unemployment. However, the responsiveness of wages to labor demand shocks seems to have increased since 2008.

[14]In Appendix A.4.1, we use Cambridge Econometrics' European Regional Database (ERD) to test this assumption: there, we find that wage changes across European regions indeed do not strongly co-move with employment changes, lending some empirical support to this assumption.

2.1 Production of tradables

The production structure in the tradable sector g is depicted in Figure 2. 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.[15] 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 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, $T_{ij} = (N_{ij}^g)^\kappa (K_{ij})^{1-\kappa}$, where the production of tasks depends on labor from occupation j N_j^g, task-specific capital inputs K_j, and the share of labor in the costs of producing a task, $0 < \kappa < 1$.[16]

Firms minimize the costs of producing Y_i^g, which leads to the regional task demand,

$$T_{ij} = Y_i^g \beta_{ij}^{1-\eta} \left(\frac{c_i^I}{w_{ij}^\kappa r_j^{1-\kappa}} \right)^\eta, \tag{1}$$

which rises in tradable production Y_i^g, in the efficiency of that task β_{ij}, and in the ratio of marginal costs c_i^I relative to the task-specific costs $w_{ij}^\kappa r_j^{1-\kappa}$, 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 labor demand,

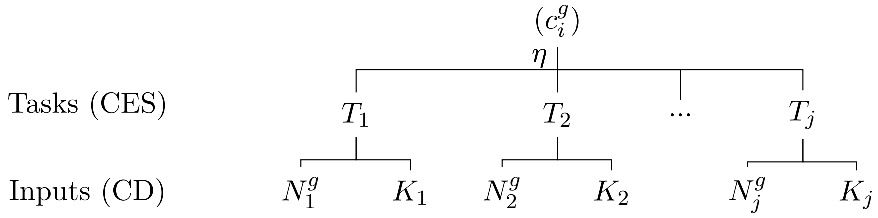
$$N_{ij}^g = T_{ij} \left(\frac{r_j}{w_j} \frac{\kappa}{1-\kappa} \right)^{1-\kappa}, \tag{2}$$

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 falling capital costs

[15] 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: the firm-level only serves to allow σ to be smaller than one.

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

Figure 2: Regional production



for routine tasks induce firms to 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 labor demand through substitution effects, where workers are replaced by machines in the production of routine tasks. This effect is further reinforced as firms shift their production technology towards routine task inputs. Overall, these two substitution effects lead to a decline in labor demand. The size of the negative labor demand 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.

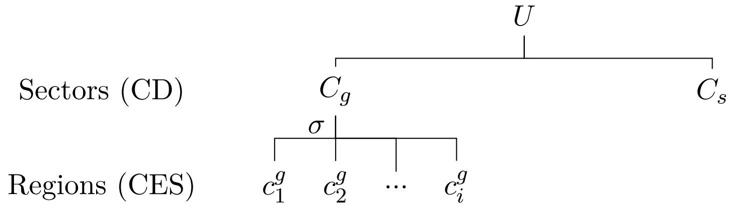
2.2 Consumption

The product demand structure is depicted in Figure 3. 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.[17] 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.

Individuals maximize utility by optimizing the composition of regional bundles, which leads

[17]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 11. However, empirically, non-homothetic preferences have been found to have only small effects on relative task demand (Goos et al., 2014; Autor and Dorn, 2013) so we do not pursue this extension further.

Figure 3: Product demand



to the demand for regional tradables,

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

where P^g is an aggregated 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).

Product demand effect. This consumption structure provides us with the second channel through which RRTC affects labor demand. 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, leading to higher production and income, inducing additional labor demand in the tradable sector. This product demand effect of RRTC thus raises labor demand. 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 aggregate L_i^s to be performed by occupations $j = 1, .., J$, $L_i^s = \left[\sum_{j=1}^{J} (\beta_{ij}^s N_{ij})^{\frac{\eta^s - 1}{\eta^s}}\right]^{\frac{\eta^s}{\eta^s - 1}}$ with $\eta^s > 0$.

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

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

Labor demand generally decreases with wages in the non-trabable sector w_i^s and increases with total local income I_i. Occupational labor demand 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^s).

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, $I_i = w_i^s Li^s + p_i^g Y_i^g - \sum_{j=1}^J r_j K_j$.[18] We define $\phi_{1-K} = p_i^g - \sum_{j=1}^J r_j K_{ij}/Y_i^g$ as the disposable income resulting from tradable sales per unit of real output. Local income is then

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

RRTC thus affects labor demand indirectly through its effect on disposable income arising from tradable sales. In particular, RRTC leads to rising output Y_i^g and thus rising disposable income in the tradable sector in routine-intense regions. In addition, RRTC may affect the disposable income per unit of output, 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 multiplier effect. This framework leads to the third channel through which RRTC impacts labor demand. In particular, RRTC leads to higher production (see product demand effect), which results in additional income among local households. This induces a product demand multiplier effect as the additional local income is partly spent on local non-tradables, creating additional product and labor demand in the local economy. These spillovers are larger in regions with a higher initial share of routine tasks.

[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.

However, note that the product demand multiplier 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 (see Section 4.2), we therefore assume two different 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 effects under the second assumption can be found in Appendix A.5.1.

2.4 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]

$$\begin{aligned}\log N_{ij}^{g} =& \log Y_i^g + (1-\eta)\log \beta_{ij} + \eta \log c_i^I + (1-\kappa)\log \frac{\kappa}{1-\kappa} \\ &+(1-\eta)(1-\kappa)\log r_j - [(1-\kappa)+\kappa\eta]\log w_j \qquad (6)\\ \log N_{ij}^{s} =& \log Y_i^g + (1-\eta^s)\log \beta_{ij}^s + (\eta^s - 1)\log w_i^s + \log\frac{1-\mu}{\mu} \\ &-\eta^s \log w_j + \log \phi_{1-K} \qquad (7)\end{aligned}$$

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 therefore 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 of occupation j interacted with a linear time trend t. The occupational Routine Task Intensity 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 more 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

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

to non-routine tasks.

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

$$\log Y_i^g = \log \mu - \sigma \log \frac{p_i^g}{P^g} + \log \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \frac{I_{i'}}{P^g}, \tag{8}$$

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'.

2.5 Decomposing total labor demand effects

In order to derive the implications of technological change for labor demand, 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 sector, 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 (6) and (7), we receive the following expression for the RRTC-driven total labor demand change in region i:

$$\Delta N_{it} = \underbrace{(1-\eta)(1-\kappa)\gamma_R}_{A} \left[\underbrace{\sum_{j=1}^{J} R_j N_{ijt}^g + \frac{\eta}{1-\eta} R_{it}^I N_{it}^g}_{B} - \underbrace{\frac{\sigma}{1-\eta} R_{it}^I N_{it}^g}_{C} - \underbrace{\frac{\sigma}{1-\eta} R_{it}^I N_{it}^s}_{D} \right], \tag{9}$$

where R_j is the Routine Task Intensity of occupation j and R_{it}^I is the average regional Routine Task Intensity, weighted by occupational employment shares in the tradable sector in region i.

Equation (9) consists of a scaling factor A, which we refer to as the routinization factor, as well as three additive elements in the square brackets. Multiplied by the routinization factor, the elements correspond to the three channels through which RRTC affects regional labor demand: substitution effects (A×B), the product demand effect (A×C), and the product demand multiplier effect (A×D).

Our theoretical framework requires $\eta > 0$, $0 < \kappa < 1$ and $\sigma > 0$. 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 factor, 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.

2.6 Empirical implementation

We aim to estimate the net effect of RRTC on labor demand, as well as the contribution of the three channels outlined above. For this, we estimate the labor demand equation for the tradable sector (Equation 6) and the product demand equation (Equation 8) in order to get estimates for the parameters of our framework. We then use the estimated parameters jointly with the data to predict the labor demand change for each of the three channels from our framework, using Equation 9, and calculate the predicted net effect of RRTC on labor demand. Note that we do not need to estimate labor demand in the non-tradable sector (Equation 7) 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 6),

$$\log N_{ijt}^{g} = \beta_0 + \beta_1 \log Y_{it}^{g} + \beta_2 \log c_{it}^{I} + \beta_3 R_j \times t + \theta t + \upsilon_{ij} + \epsilon_{ijt} \tag{10}$$

where the number of employed workers for each region i, occupation j, and year t in the tradable sector (N_{ijt}^{g}) depends on the real regional production of tradables (Y_{it}^{g}) and on real regional 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 the change of relative cost of capital in 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

[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 labor demand has been found to be relatively small (Autor and Dorn 2013; Goos et al. 2014), we do not pursue these extensions here.

time trend (t). Moreover, in order to control for differences in the regional production technologies and the resulting differences in the efficiencies of regions to utilize certain tasks (β_{ij}^g in the theoretical framework), we control for region-occupation dummies (υ_{ij}). These dummies further capture unobserved factors related to the occupation-region cells. Wage variation is assumed to be absorbed by the time trend and region-occupation dummies, following Goos et al. (2014).[21] Finally, ϵ_{ijt} corresponds to the remaining error term. 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.2.3 for a more detailed explanation of the instruments). Based on the estimates of Equation (10), we obtain our estimated elasticity of substitution between job tasks $\hat{\eta} = \hat{\beta}_2$, and the effect of RTI on labor demand $\hat{\beta}_3$. Note that $\hat{\beta}_3$ is an estimate of $(1-\eta)(1-\kappa)\gamma_R$ in Equation (9), hence we do not need to separately estimate γ_R or κ.

(B) Estimating product demand. Second, we estimate the aggregate product demand equation (Equation 8):

$$\log Y_{it}^g = \delta_0 + \delta_1 \log c_{it}^I + \delta_2 \log MP_{it} + \nu_i + \varepsilon_{it} \tag{11}$$

where the real regional production of tradables (Y_{it}^g) depends on real regional marginal costs of producing tradables (c_{it}^I)[22] as well as on the market potential (MP_t). Market potential 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.3.2 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 dummies (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

[21] In Appendix A.4.1, we additionally present estimation results where we include regional wages in the tradable sector (i.e. w_{it}, based on ERD data) as a regressor. Wage coefficients have the expected negative sign and our results are robust to this inclusion. However, because ERD data is not available for all countries and we cannot perfectly reproduce the empirical distinction between tradables and non-tradables due to more aggregated industry codes in ERD, our baseline results do not control for wages.

[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, i.e. $p_{it}^g = \frac{\sigma_i^v}{\sigma_i^v - 1} c_{it}^I$.

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.2.3 for a more detailed explanation).

Based on the estimates in Equation 11 we can then obtain $\hat{\sigma} = \hat{\delta_1}$, our parameter of interest, the elasticity of substitution between regional bundles of tradables.

(C) Decomposition. Using our estimated parameters $\hat{\eta}$, $\hat{\beta}_3$ and $\hat{\sigma}$, we then calculate the components of Equation (9), i.e. the effects of the three channels on labor demand. All other variables in Equation (9), i.e. R^I_{it}, R_j, N^g_{ijt}, N^g_{it} and N^s_{it}, are calculated from the data. The sum over all three effects reflects the net effect of RRTC on labor demand.

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 labour force participation of people aged 15 and over, including data on employment status and weekly hours worked. 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: 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.

Occupations are coded by one-digit International Standard Classification of Occupations (ISCO-1988) codes. Lastly, we divide industries classified by one-digit Nomenclature statistique

[23]The weights correspond to the trade costs, such that the IV 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.

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.3.1 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.

The Routine Task Intensity (RTI) index is obtained from the Dictionary of Occupational Titles 1977, and 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.

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.

Finally, data on output and industry marginal costs are obtained from the OECD Database for Structural Analysis (STAN). Following Goos et al. (2014), we define industry 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 by the STAN. We regionalize this data by averaging across industries within regions using the employment shares of industries within regions as weights (see Appendix A.2.3).

Our region-specific market potential is calculated as the sum of GDP across all potential trading partners of the region, 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.3.2 for more details).

For a more detailed description of the data preparation and data availability for specific countries, see Appendix A.2.

3.2 Parameter estimates

Table 3 shows the estimates of the labor demand in the tradable sector from Equation 10. The first column is a pooled OLS estimate containing all observations and replacing tradable sector output and marginal costs with a set of region-year dummies. The second column shows the same estimates but restricted to the set of country-years for which we have output and marginal cost data: it can be seen that the coefficient on occupational RTI interacted with a linear time trend, which we refer to as routinization, is very similar across these two samples. Finally, the third column reports our preferred IV specification from which we obtain the parameter estimates used in our decomposition, including the coefficient on routinization, β_3, as well as the coefficient on

Table 3: Labor demand in the tradable sector

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	POLS Full sample	POLS Restricted sample	FE-IV	First stage Regional gross production	First stage Regional marginal cost index
	(1)	(2)	(3)	(4)	(5)
Standardized occupational RTI × timetrend	-1.678***	-1.700***	-1.700***	0.000**	-0.000***
	(0.075)	(0.093)	(0.083)	(0.000)	(0.000)
Log regional gross production in tradable sector			0.766***		
			(0.075)		
Log industry marginal cost index			0.664***		
			(0.175)		
Log spatially weighted net capital stock				0.544***	-0.014**
				(0.040)	(0.004)
Log counterfactual industry marginal cost index				-0.444**	0.901***
				(0.151)	(0.022)
Number of observations	21,632	12,416	12,416	12,416	12,416
R-squared	0.980	0.981	0.145	0.634	0.982
F-statistic	.	.	163.9	152.3	4633.3

Notes: European regions, 1999-2010. Models (1) and (2) include region-occupation and region-year dummies. Models (3), (4) and (5) are estimated with region-occupation fixed effects and controls for a linear timetrend. Standard errors clustered by region reported in parentheses. Coefficients on RTI × timetrend multiplied by 100. ***p<0.01, **p<0.05, *p<0.1

marginal costs, which reflects our elasticity of substitution between tasks, η. Columns 4 and 5 report the first stages for regional output and marginal costs, respectively. The first stage estimates suggest that the instruments have the expected impact on the endogenous variables. One remaining concern regarding the estimates in Table 3 is that wage variation might not be absorbed by the time trend and region-occupation dummies as assumed. We therefore conduct several robustness check controlling for regional wages (see Appendix A.4.1). Wage coefficients have the expected negative sign and our results are robust to this inclusion. However, because our wage data are not available for all countries and because we cannot perfectly reproduce the empirical distinction between tradables and non-tradables due to more aggregated industry codes in the available wage data, we prefer the estimates reported in Table 3.

Table 4 reports the estimates of product demand in the tradable sector from Equation 11. The first column shows estimates including region-occupation fixed effects, whereas column 2 shows our preferred model which additionally instruments for market potential and marginal costs: the instruments 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 estimates of the three key parameters: (1) the routinization coefficient, β_3, (2) the elasticity of substitution between tasks, η, and (3) the elasticity of substitution in consumption between regional bundles of tradables, σ. Overall, the framework yields plau-

Table 4: Product demand in the tradable sector

Dependent variable: log regional production of tradables (in region-year cells)	FE	FE-IV	First stage Market potential	First stage Regional marginal cost index
	(1)	(2)	(3)	(4)
Log market potential	1.282***	1.375***		
	(0.096)	(0.128)		
Log industry marginal cost index	-0.765***	-0.913***		
	(0.130)	(0.185)		
Log regional net capital stock in tradable sector			1.307***	0.068**
			(0.038)	(0.021)
Log counterfactual industry marginal cost index			0.321***	0.907***
			(0.033)	(0.025)
Number of observations	1597	1597	1597	1597
R-squared	0.578	0.577	0.918	0.971
F-statistic	193.9	168.4	6937.7	5564.8

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1

sible estimates.[24] As expected, the routinization coefficient is significantly negative, suggesting that an increase in the RTI index by 1 standard deviation decreases employment by 1.7%, on average. Since we find that $(1-\eta) > 0$ (see below) and since $(1-\kappa) > 0$ by definition, the estimate for routinization in Table 5 implies that γ_R is negative suggesting that a decrease in the price for capital 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 Goos and Manning 2007; Autor and Dorn 2013; Goos et al. 2014), there is a shift in employment away from occupations that are more routine towards those that are less routine.

The estimate of $\hat{\eta} = 0.66$ 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). 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 estimated by Goos et al. (2014).[25] 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)

[24] Appendix A.4.3 furthermore shows that these parameter estimates do not vary substantially across the economic cycle.

[25] 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.

Table 5: Parameter estimates

Parameter	Estimate
$(1-\eta)(1-\kappa)\gamma_R$ – routinization	-1.700***
	(0.083)
η – substitution elasticity between tasks	0.664***
	(0.175)
σ – substitution elasticity between bundles of tradables	0.913***
	(0.185)

Notes: $(1-\eta)(1-\kappa)\gamma_R$ and η estimates obtained from model (3) in Table 3. σ estimate obtained from model (2) in Table 4. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

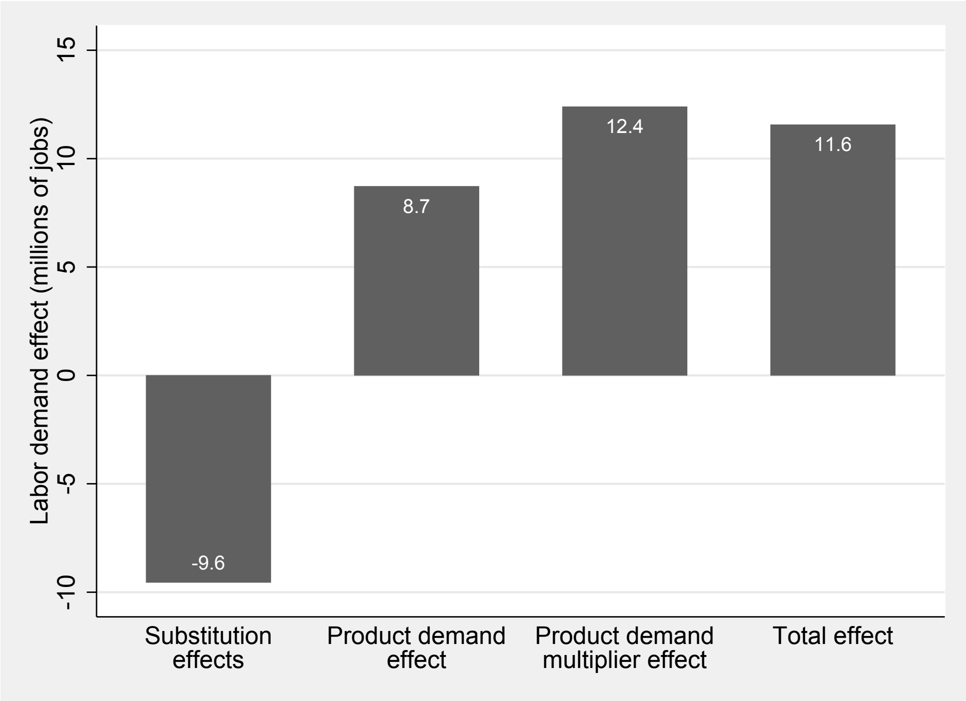
find that firms are highly specialized in their task content along routine versus non-routine lines.

The estimate of the substitution elasticity between regional bundles of tradables is $\hat{\sigma} = 0.91$, indicating that the demand for regional goods bundles is somewhat more elastic, although it is still smaller than one. This is in contrast to estimates from the trade or new economic geography literature where mostly elastic ($\sigma > 1$) demand is found.[26] However, these estimates refer to the substitution elasticity between goods, whereas our results refer to the substitution elasticity between regional goods bundles. Imbs and Mejean (2010) provide a closer reference to our results by estimating elasticities for international trade at the country level for 30 countries worldwide. Their results range from 0.5 to 2.7 and are thus in line with our results. Furthermore, they typically find lower estimates for small countries, suggesting that it is reasonable that we find an estimate towards the lower end of the range for economies at the regional level.

Table 5 further indicates that the elasticity of substitution between regional bundles of tradables is larger than the elasticity of substitution between tasks, making it more likely that the product demand effect is strong enough to overcompensate the substitution effects. The reason is that our σ reflects to what extent consumers switch to cheaper regional goods bundles as a result of falling capital costs, leading to higher product demand and, hence, higher production and employment in routine-intense regions. In contrast, our parameter η reflects how easily firms shift towards more routine tasks, where it is easier to substitute capital for human labor, resulting in lower employment. If $\sigma > \eta$, the sum of the two effects is more likely to be positive in routine-intense regions. Moreover, the larger σ, the stronger the product demand spillover effect. Further, both σ and η are smaller than one, indicating that neither demand nor production are sufficiently elastic to make human labor obsolete in the long run, in line with the indicators

[26] See, for example, Mion (2004); Hanson (2005); Simonovska and Waugh (2014).

Figure 4: Predicted European labor demand change (upper bound), 1999-2010



provided by Nordhaus (2015).[27] Finally, the parameter estimates suggest that labor and capital are gross complements.[28]

4 Results

4.1 European labor demand effects

Using the decomposition outlined in Section 2.6, we construct an estimate of the labor demand change resulting from RRTC as predicted by our framework. Specifically, we obtain a predicted labor demand effect for each of the three distinct channels for each European region over 1999-2010.

Figure 4 shows the results aggregated to 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 9.6 million jobs as routine-replacing technologies substitute 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

[27]Note, however, that the elasticities η and σ in this framework cannot be directly compared to Nordhaus (2015), since η refers to the substitutability between tasks which are differently capital intense, whereas Nordhaus (2015) focuses on direct labor-capital substitution. Further, σ refers to the substitutability between regional goods bundles whereas Nordhaus (2015) analyzes substitution between ICT- vs. labor-produced goods.

[28]This can be shown by deriving the cross-elasticity of unconditional labor demand with respect to capital costs and substituting in the values of σ and η from Table 5.

Table 6: Predicted European labor demand change: robustness to parameter estimates

Effect (in millions of jobs)	Mean	Std dev	10th pctile	90th pctile
Substitution	-9.5	0.5	-10.1	-8.9
Product demand	8.7	1.9	6.4	11.1
Product demand multiplier	12.3	2.7	9.1	15.8
Total	11.4	4.4	6.0	17.3

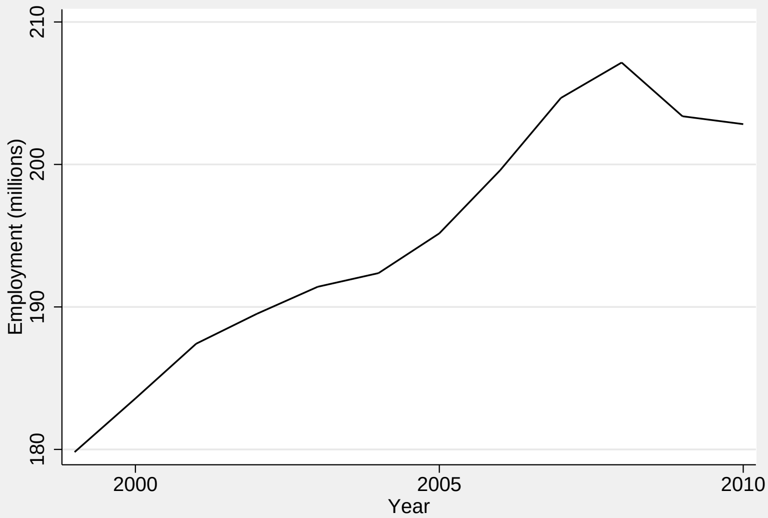
Notes: Distribution of predicted effects obtained by taking 1,000 random draws from the distributions of our 3 parameter estimates reported in Table 5. Draws for parameter σ are independent from draws for parameters $(1-\eta)(1-\kappa)\gamma_R$ and η, which are interdependent.

public debate. The product demand and local demand spillover effects, however, are positive and larger in absolute value, respectively implying an increase in labor demand of 8.7 and 12.4 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.

Table 6 additionally reports the sensitivity of these results to our parameter estimates. In particular, we create 1,000 predictions from our model by randomly drawing from the respective distributions of our three parameter estimates (reported in Table 5). Table 6 reports the mean, standard deviation, and the 10th and 90th percentiles of the resulting distribution of predictions, for each of the three channels of our model as well as for the total labor demand effect. It can be seen that there is some variation around our baseline labor demand prediction of 11.6 million jobs, with the 10th percentile of the prediction corresponding to 6.0 million jobs and the 90th percentile to 17.3 million jobs. However, for all channels, the predicted effects have the expected sign within the 10th to 90th percentile interval, increasing confidence in our overall conclusion of a net positive effect.

The results reported in this section highlight four main findings. Firstly, the net labor demand effect of new technologies is strongly positive. Indeed, the estimated labor demand increase of 11.6 million jobs over 1999-2010 across Europe is sizable when compared to the total employment growth of 23 million jobs, shown in Figure 5, observed across these countries over the period considered. This is the first estimate of the overall labor demand effect of RRTC in the literature. Since we abstract from labor supply rigidities, this should be interpreted as a long run estimate: in the face of short- or medium-run frictions, labor demand changes should not be expected to correspond one-to-one to employment creation. Nevertheless, this large impact of technological change on long-run employment outcomes is consistent with a

Figure 5: Total employment in Europe, 1999-2010



Note: Non-military, non-agricultural employment across 27 European countries.

macro-economic literature which considers technological change to be a major driver of long-run economic growth.[29]

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, but these are countervailed by product demand effects and local spillovers. As such, the positive overall effect of RRTC on labor demand is *not* the result of a negligible amount 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).[30] These interactions have been largely ignored in canonical SBTC models, which typically only consider a single final consumption good.

Thirdly, the product demand effect alone nearly offsets the labor demand decline resulting from the substitution of capital for labor and the reorganization of task production: this means that even within the tradable sector, there is no mass decline in labor demand as a result of routine-replacing technological change, consistent with Autor et al. (2015)'s findings for the U.S.[31]

[29] This view is deeply rooted in both the neoclassical growth theory and endogenous growth models, although more recently authors additionally highlight the role of institutions (Mokyr 2005).

[30] 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.

[31] 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.

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 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 4 imply that each job generated in the local tradable industry as a result of increased product demand results in an additional labor demand effect of 12.4 million/8.7 million=1.4 jobs in the local non-tradable industry. This multiplier is very 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 of information technology and a greater reallocation of low-skilled workers from routine task intense jobs to non-routine service jobs. However, it is important to note that our estimate of the product demand multiplier 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 therefore investigates this in more detail.

4.2 The role of non-wage income

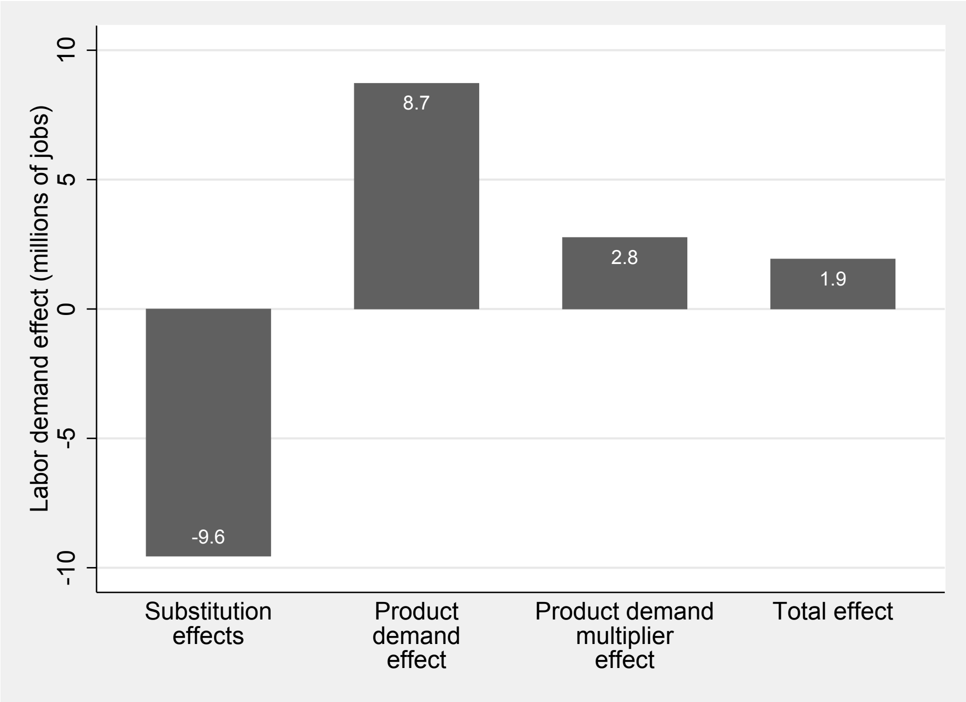
To consider the role of non-wage income in the multiplier effect, we relax the assumption that non-wage income earners spend their income locally by assuming the other extreme: namely, that non-wage income does not feed back into consumption at all (see Appendix A.5.1 for a derivation of this alternative model[32]). Conceptually, this represents the case where non-wage earners do not reside in Europe.[33] As such, we calculate product demand spillovers resulting from changes in wage income only, providing a lower-bound estimate of the multiplier effect.

Figure 6 shows the empirical results from this alternative decomposition. Note that the first two channels are unaltered: only the product demand multiplier effect has changed. In particular, the predicted spillover effect is significantly smaller, reflecting a labor demand increase of 2.8 million jobs instead of 12.4 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

[32]Appendix A.5.1 also shows that this assumption does not affect the first two channels in our framework.

[33]We make this assumption since we do not have an alternative prior about to which region to allocate the additional consumption from any increases in non-wage income.

Figure 6: Predicted European labor demand change (lower bound), 1999-2010



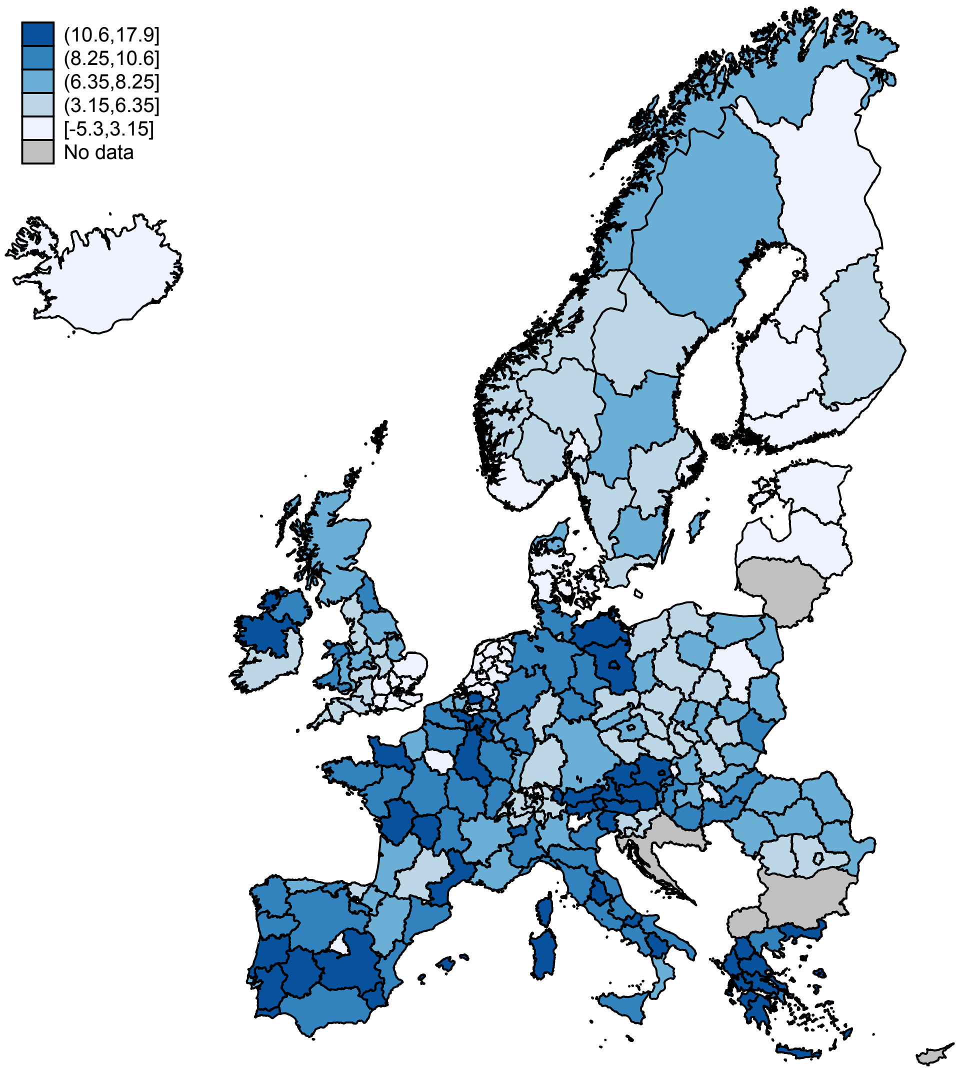
any non-wage income. As such, our original estimate represents an upper bound for the spillover effect, whereas the estimate shown here is a lower bound.

The local multiplier implied by this lower bound is 0.32 (=2.8/8.7). Given that completely abstracting from non-wage income is rather extreme, and that our upper bound is closer to the value of the multiplier found in the literature, we interpret the larger spillover as our baseline result. However, this sensitivity exercise does make the more substantive point that the labor demand 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 1.9 million instead of 12.6 million jobs – a very sizable difference. This is in line with a recent theoretical models which stress that the labor market effects of RRTC depend on the allocation of the gains from these routine-replacing innovations (Benzell et al., 2015; Sachs et al., 2015).

4.3 Regional labor demand effects

So far, we have documented how routine-replacing technological change impacts labor demand across Europe as a whole. However, our decomposition actually provides estimates for the three channels and their net labor demand effect at the regional level: Figure 7 illustrates these predictions, revealing substantial regional variation in predicted labor demand changes

Figure 7: Predicted regional labor demand effects, 1999-2010



Notes: Regions grouped into quintiles based on the predicted labor demand effect relative to 1999 regional employment. Numbers are percentages.

(expressed as a percentage relative to initial regional employment).

Although this regional variation is not the focus of this paper, it allows us to better assess the predictive power of our framework. For this, Table 7 regresses actual regional employment changes over 1999-2010[34] onto the regional labor demand changes predicted from our model, while controlling for the initial employment size of the region. Column (1) of Table 7 reports results for all European regions without further controls, showing that predicted labor demand changes are indeed positively correlated with regional employment trajectories: an increase in labor demand of 1,000 jobs that our model predicts to have been generated by routine-replacing technological progress is associated with 598 jobs actually being created in the local economy.

[34]Represented graphically on the European map in Figure 9 in Appendix A.2.1.

Table 7: RRTC-induced labor demand changes and actual employment changes for European regions

Dependent variable: actual regional employment change				
	OLS All regions (1)	FE All regions (2)	OLS 5th-95th pctile (3)	FE 5th-95th pctile (4)
Predicted regional labor demand change	0.598*** (0.149)	0.327*** (0.125)	0.615*** (0.101)	0.501*** (0.098)
Number of observations	238	238	216	216
R-squared	0.543	0.775	0.734	0.824
F-statistic	139.7	183.8	293.4	269.3

Notes: European regions, long difference 1999-2010. All models control for the region's initial employment size in 1999. Models in columns (2) and (4) include country fixed effects. Models in columns (3) and (4) exclude regions with employment growth below the 5th and above the 95th percentile. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Although the correspondence is not one-to-one, this does suggest that employment changes at the regional level appear to respond to RRTC-induced changes in labor demand. In Appendix A.4.2, we alternatively relate our predicted labor demand changes to regional employment-to-population ratios, and confirm a positive correlation there, as well.

Since some 40 percent of the actual variation in regional employment growth occurs within countries, column (2) further tests whether our framework can predict within-country regional employment growth heterogeneity by adding country dummies to the specification of column (1). This is the case: also within countries, predicted regional labor demand changes are positively correlated with actual regional employment changes, although the coefficient is somewhat lower.

Finally, columns (3) and (4) of Table 7 show that the results reported in columns (1) and (2) are robust to excluding regions with actual employment growth below the 5th or above the 95th percentile[35]: on average, each predicted labor demand increase of 1,000 jobs from RRTC is associated with some 500 to 600 actual additional jobs over 1999-2010, both between and within countries.[36]

Overall, the results in this section confirm that the regional labor demand impacts resulting from routine-replacing technological change predicted by our model are related to the different employment trajectories actually experienced by European regions.

[35] As an alternative, we have used median regression which provides results very similar to mean regression: the estimated coefficient is 0.574 with a standard error of 0.085.

[36] Any differences in the estimated coefficient in Table 7 between the full sample and the sample excluding outlier regions in terms of employment growth could be related to agglomeration externalities which are not included in our baseline model. For a further discussion of agglomeration externalities within the context of our framework, see Appendix A.5.2.

5 Conclusion

There exist long-standing public concerns about technological change destroying jobs, invoking images of labor racing against the machine. So far, scientific evidence on the aggregate labor demand effects of technological change as well as its underlying transmission channels is scarce, as most existing studies have focused on the relative effects of technological change across worker skill levels and job types. In this paper, we contribute to this debate by investigating the economy-wide effect of routine-replacing technological change (RRTC) on labor demand. To this end, we develop a framework that distinguishes the different channels through which RRTC affects the demand for labor. These channels include the direct substitution of capital for labor, but also product demand adjustments in response to technology-driven changes in relative output prices and spillovers to the non-tradable sector: as such, the net effect is theoretically ambiguous. We then empirically assess the economy-wide labor demand effect as well as the contributions of the separate transmission channels by estimating the model at the level of 238 regions across 27 EU countries over the years 1999-2010.

Overall, we find that the net effect of routine-replacing technological change on labor demand has been positive. In particular, our baseline estimates indicate that RRTC has increased labor demand by up to 11.6 million jobs across Europe – a non-negligible effect when compared to a total employment growth of 23 million jobs across these countries over the period considered. Importantly, this does not result from the absence of significant replacement of labor by capital. To the contrary, by performing a decomposition rooted in our theoretical model, we show that RRTC has in fact decreased labor demand by 9.6 million jobs as capital replaces labor in production. However, this has been overcompensated by product demand and spillover effects which have together increased labor demand by some 21 million jobs. As such, fears of technological change destroying jobs may be overstated: at least for European countries over the period considered, we can conclude that labor has been racing with rather than against the machine in spite of these substitution effects. These results also highlight the importance of considering product demand and particularly its spillovers when assessing the labor market effects of technological change: these channels are not only often overlooked in the public debate, but also in canonical skill-biased technological change frameworks which consider only a single final consumption good.

Furthermore, in a more detailed analysis of the quantitatively important product demand spillover effect, we find that RRTC's product demand spillovers accrue to a large extent from non-wage income feeding back into the local economy: when only considering wage income as a transmission mechanism for spillovers, we find a much smaller total labor demand effect of 1.9 million jobs (as opposed to 11.6 million jobs for the baseline results). Tentatively, this suggests that public concern about the employment effects of technological progress should focus more on who owns the capital, as highlighted by Freeman (2015), Benzell et al. (2015), and Sachs et al. (2015), rather than the direct substitution effects of automation.

Finally, since our analysis considers the impact of RRTC on labor demand, it informs about employment outcomes in the longer run only. Work complementary to these findings could consider to what extent labor market frictions (e.g. inelastic labor supply across regions or jobs) are resulting in different short- and medium-run adjustments to these labor demand changes, such as transitions into unemployment or inactivity. Indeed, an emerging literature is studying this by examining worker-level outcomes (Cortés et al. 2014; Cortés 2016).

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A Appendix for *Racing With or Against the Machine? Evidence from Europe*

This supplemental appendix contains 1) a more detailed description of our theoretical model; 2) a data overview; 3) more detailed information on our empirical implementation; 4) robustness checks on our baseline results; and, finally, 5) several theoretical and empirical extensions of these 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

$$c_i^g = \left(\frac{p_i^g}{P^g}\right)^{-\sigma} \mu \frac{I}{P^g}, \tag{12}$$

where $P^g = \left[\sum_{i=1}^{I} (p_i^g)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is the price index.[37]

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

$$c_{if}^g = \left(\frac{p_{if}^g}{p_i^g}\right)^{-\sigma_i^v} c_i^g, \tag{13}$$

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 -compositions vary across regions i. The underlying production function is CES[38]:

$$Y_i^g(T_{i1}, T_{i2}, ..., T_{iJ}) = \left[\sum_{j=1}^{J} (\beta_{ij} T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \quad \text{with } \eta > 0 \tag{14}$$

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

$$T_{ij} = Y_i^g \beta_{ij}^{1-\eta} \left(\frac{c_i^I}{c_{ij}^T}\right)^{\eta}, \tag{15}$$

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

[38]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.

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

$$N_{ij}^g(w_j, r_j | T_{ij}) = T_{ij}\frac{c_{ij}^T}{w_j}\left(\frac{\kappa}{1-\kappa}\right)^{1-\kappa} \tag{16}$$

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

$$\log Y_i^g = \log\mu - \sigma\log\frac{p_i^g}{P^g} + \log\sum_{i'=1}^{I}\tau_{ii'}^{-\sigma}\frac{I_{i'}}{P^g} \tag{17}$$

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 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.[39] 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 $L_i^s = \left[\sum_{j=1}^{J} (\beta_{ij}^s N_{ij})^{\frac{\eta^s-1}{\eta^s}}\right]^{\frac{\eta^s}{\eta^s-1}}$ with $\eta^s > 0$, 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.[40] Occupational labor demand in the non-tradable sector then is:

$$N_{ij}^s = L_i^s \beta_{ij}^{s\,1-\eta^s} \left(\frac{w_j}{w_i^s}\right)^{-\eta^s}, \tag{18}$$

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 consists of occupational wages.

Using these arguments, we can explicitly derive the labor demand equations (6) and (7) for the two sectors, reported in the main text.

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

$$N_{it} = N_{it}^g + N_{it}^s = \sum_{j=1}^{J} N_{ijt}^g + \sum_{j=1}^{J} N_{ijt}^s \tag{19}$$

[39] See Appendix A.5.1 for an alternative specification.

[40] 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.

Employment reacts to changes in log capital prices $\log r_{j't}$:

$$\frac{\partial N_{it}}{\partial \log r_{j't}} = \sum_{j=1}^{J} \frac{\log N^g_{ijt}}{\partial \log r_{j't}} N^g_{ijt} + \sum_{j=1}^{J} \frac{\log N^s_{ijt}}{\partial \log r_{j't}} N^s_{ijt} \tag{20}$$

Using equation (6), we derive

$$\frac{\partial \log N^g_{ijt}}{\partial \log r_{j't}} = (1-\eta)(1-\kappa) + (\eta-\sigma)\frac{\partial \log c^I_{it}}{\partial r_{j't}} \text{ for } j = j' \tag{21}$$

$$\frac{\partial \log N^g_{ijt}}{\partial \log r_{j't}} = (\eta-\sigma)\frac{\partial \log c^I_{it}}{\partial \log r_{j't}} \text{ for } j \neq j' \tag{22}$$

For this, we have used $\partial \log Y^G_{it}/\partial \log r_{j't} = -\sigma \partial \log p_{it}/\partial \log r_{j't}$ and $\partial \log p_{it}/\partial \log r_{j't} = \partial \log c^I_{it}/\partial \log r_{j't}$. Analogously, using equation (7), we derive

$$\frac{\partial \log N^s_{ijt}}{\partial \log r_{j't}} = -\sigma \frac{\partial \log c^I_{it}}{\partial \log r_{j't}} \tag{23}$$

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.

For our decomposition we are only interested in changes which are induced by changing relative task-specific capital prices r_j. We thus assume that any other changes are uncorrelated with changes in r_j.

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

$$c^I_{it} \approx \prod_{j=1}^{J} \left(\frac{c^T_{ijt}}{\beta_{ij}}\right)^{\kappa_{j|it}} = \prod_{j=1}^{J} \left(\frac{r^{1-\kappa}_{jt} w^{\kappa}_{jt}}{\beta_{ij}}\right)^{\kappa_{j|it}} \tag{24}$$

where $\kappa_{j|it}$ 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, $s_{j|it}$. Accordingly marginal costs react to changes in capital prices, $\frac{\partial \log c^I_{it}}{\partial \log r_{j't}} = s_{j'|it}(1-\kappa)$. Hence, we can rewrite

(20) as

$$\frac{\partial N_{it}}{\partial \log r_{j't}} = (1-\eta)(1-\kappa)N^g_{ij't} + \sum_{j=1}^{J}\Big[(\eta-\sigma)(1-\kappa)s_{j'|it}N^g_{ijt} - \sigma(1-\kappa)s_{j'|it}N^s_{ijt}\Big] \tag{25}$$

We are interested in the effect of changes in all capital prices on total regional employment

$$\begin{aligned}
\Delta N_{it} =& \sum_{j'=1}^{J'} \frac{\partial N_{it}}{\partial \log r_{j't}} \Delta \log r_{j't} \text{ where } \Delta \log r_{j't} = \gamma_R R_{j'} && (26)\\
=& \sum_{j'=1}^{J'} \Bigg[(1-\eta)(1-\kappa)\gamma_R R_{j'} N^g_{ij't} + (\eta-\sigma)(1-\kappa)s_{j'|it}\gamma_R R_{j'} \sum_{j=1}^{J} N^g_{ijt} \\
& -\sigma(1-\kappa)s_{j'|it}\gamma_R R_{j'} \sum_{j=1}^{J} N^s_{ijt} \Bigg] && (27)\\
=&(1-\eta)(1-\kappa)\gamma_R \sum_{j=1}^{J}\left[R_j N^g_{ijt} + \frac{\eta-\sigma}{1-\eta} R^I_{it} N^g_{ijt} - \frac{\sigma}{1-\eta} R^I_{it} N^s_{ijt} \right] && (28)\\
& \text{where } R^I_{it} = \sum_{j=1}^{J} s_{j|it} R_j
\end{aligned}$$

This can be rearranged to our decomposition in Equation 9.

A.2 Data

A.2.1 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[41] 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[42], 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 8 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 1, 4, 5, 6, 7, and Table 7 in the main text, as well as Figures 9 through 13 and Table 12 in the Appendix, 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

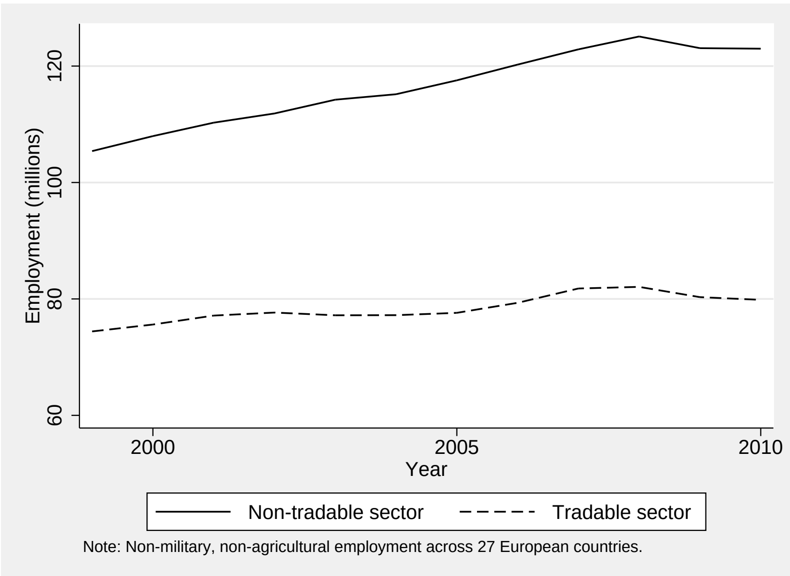
[41] Available at `http://ec.europa.eu/eurostat/web/nace-rev2/correspondence_tables`
[42] See Appendix A.3.1, below.

Kingdom with aggregate Eurostat data[43], 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[44], which provide EU LFS employment data aggregated by Eurostat to the region-industry-year level.[45] 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.[46] 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 8: Employment by sector in Europe, 1999-2010



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

[44] 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.

[45] 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.

[46] 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.

Table 8: Employment data coverage by country

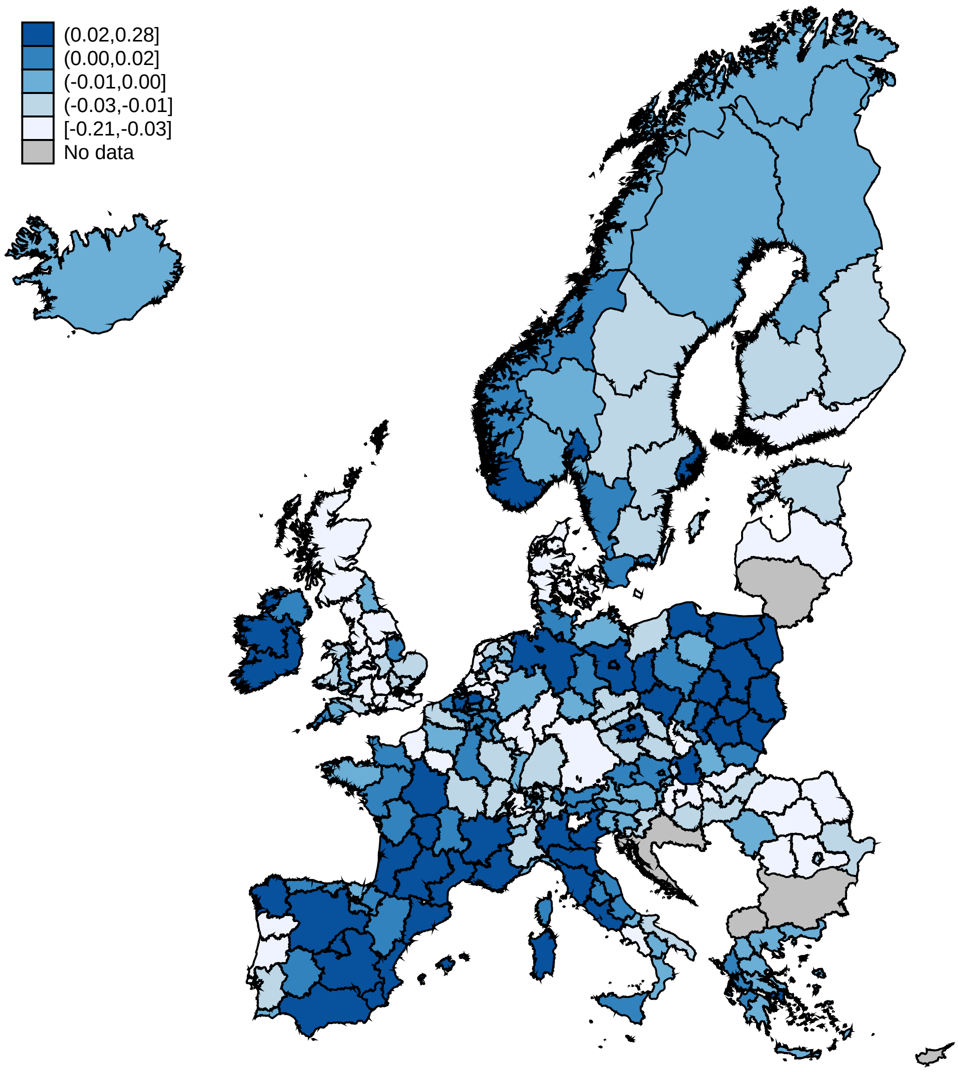
Country	Years	NUTS level(s)	Number of regions
AT	1999-2010	2	9
BE	1999-2010	2	11
CH	2001-2010	2	7
CZ	1999-2010	2	8
DE	2002-2010	1	16
DK	2007-2010	2	5
EE	1999-2010	.	1
ES	1999-2010	2	18
FI	1999-2010	2	5
FR	1999-2010	2	22
GR	1999-2010	2	13
HU	1999-2010	2	7
IE	1999-2010	2	2
IS	1999-2010	.	1
IT	1999-2010	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).

Figure 9 shows the actual changes in employment shares[47] 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, and the remaining 40 percent is due to differences within countries.

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

Figure 9: European regional employment growth, 1999-2010



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

A.2.2 Routine Task Intensity

The definition and data for the Routine Task Intensity 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, Figures 10 and 11 show 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).[48]

Finally, Figure 12 shows the 2010 spatial distribution of RTI, to complement the 1999 dis-

[48]Namely, the Czech Republic, Estonia, Hungary, Iceland, Latvia, Malta, Poland, Romania, Slovakia, Slovenia and Switzerland.

tribution reported in the paper.

Figure 10: Routine Task Intensity (RTI) of employment, 15 European countries, 1999-2010

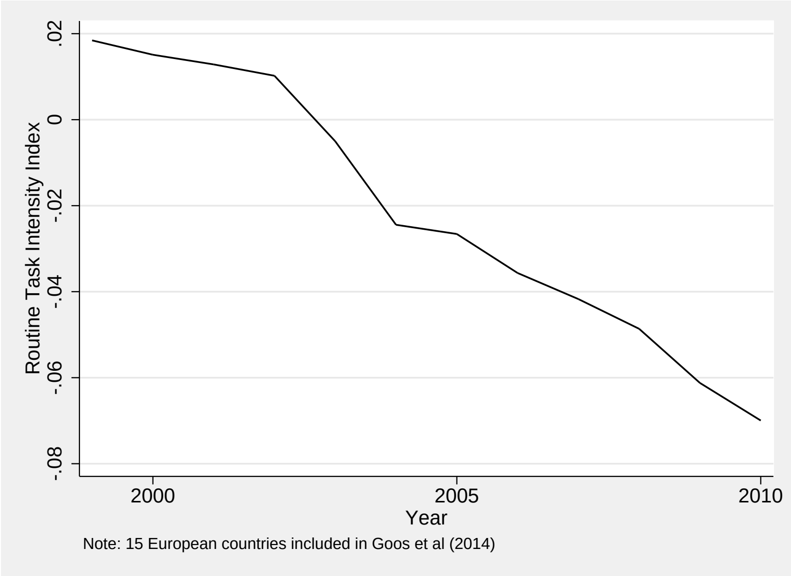


Figure 11: Routine Task Intensity (RTI) of employment, 12 European countries, 1999-2010

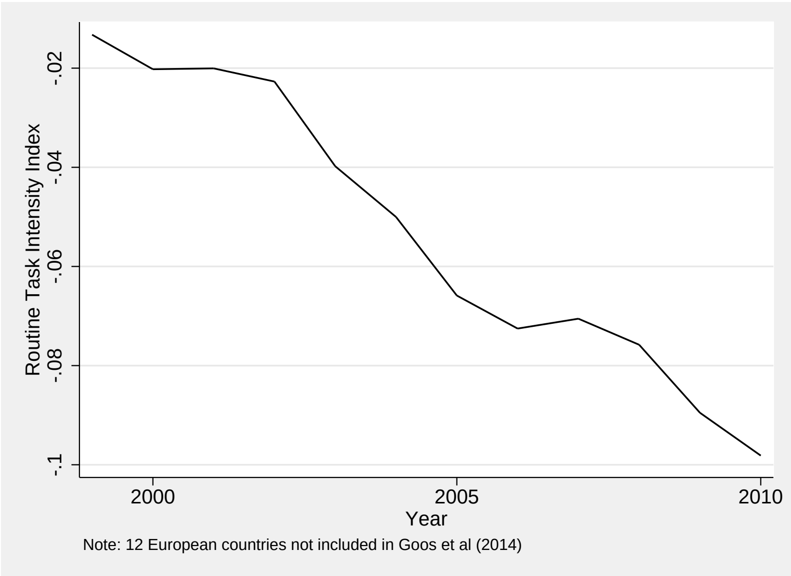
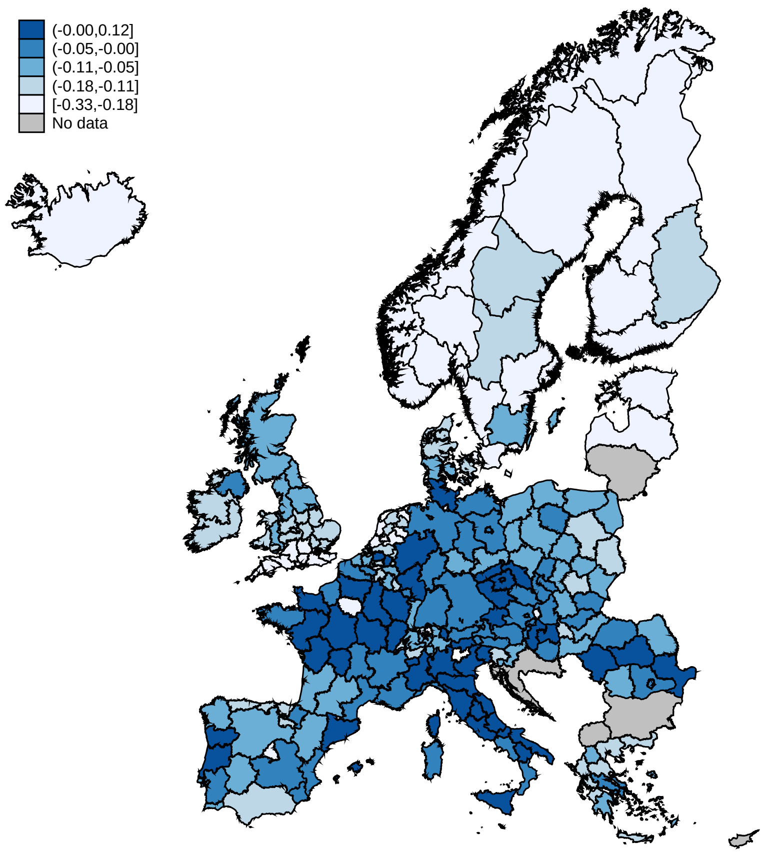


Figure 12: Spatial distribution of Routine Task Intensity (RTI) across European regions, 2010



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

A.2.3 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).[49] 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.[50] 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 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

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

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.3.2. 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 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.3.2 for details).

A.3 Empirical implementation

This appendix provides further details on the empirical implementation.

A.3.1 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.[51] 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.[52] 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.

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

[52] 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.3.2 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,[53] 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:

$$Y_i^g = \left(\frac{p_i^g}{P^g}\right)^{-\sigma} \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \mu \frac{I_{i'}}{P^g}, \tag{29}$$

[53] 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)

$$\ln Y_{it}^g = -\sigma \ln \left(\frac{p_{it}^g}{P_t^g} \right) + \ln \sum_{i'=1}^{I} \tau_{ii'}^{-\sigma} \mu \frac{I_{i't}}{P_t^g} \tag{30}$$

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:

$$\log c_{ii't}^g = -\sigma \log \left(\frac{p_{it}^g}{P_t^g} \right) - \sigma \log \tau_{ii'} + \log \mu + \log \frac{I_{i't}}{P_t^g} \tag{31}$$

We translate this into a fixed-effects model:

$$\log c_{ii't}^g = \beta_0 + \beta_{ii'} + \beta_1 timetrend + \beta_2 \log \frac{I_{i't}}{P_t^g} + \beta_3 \log c_i^I + \epsilon_{ii't} \tag{32}$$

We use the total real income of private households as a measure for $\frac{I_{i't}}{P_t^g}$[54] and we replace the regional price level $\frac{p_{it}^g}{P_t^g}$ with regional marginal costs c_i^I.[55] 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:[56]

$$\ln \tilde{\tau_{ii'}} = \beta_0 + \beta_1 \ln \text{distance}_{ii'} + \varepsilon_{ii'} \tag{33}$$

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

[54]Source: Statistical Offices of the Länder and the Federal Statistical Office of Germany.
[55]See Appendix A.2.3 for the measurement of regional marginal costs.
[56]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:

$$\hat{\tau_{ii'}} = \frac{\hat{\tau^*_{ii'}}}{\sum_{i'=1}^{I}\sum_{i=1}^{I}\hat{\tau^*_{ii'}}} \tag{34}$$

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

$$\text{MP}_{it} = \sum_{i'=1}^{I}\hat{\tau_{ii'}}\frac{I_{i'}}{P^g} \tag{35}$$

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.2.3) 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.2.3).

A.4 Empirical estimates and robustness checks

A.4.1 Robustness: wage adjustments

This appendix contains descriptive evidence on the extent to which regional wages adjust along with actual employment changes across European regions, as well as with the labor demand changes predicted from our model. For this, we use employee compensation data from the Cambridge Econometrics European Regional Database (ERD)[57], 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.

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.2.1). We deal with this by constructing two alternative definitions: one where this aggregate is included among tradables (labeled Tradables-I & Non-tradables-I in Table 10), and one where it is included among non-tradables instead (labeled Tradables-II & Non-tradables-II). It should be noted, though, that neither classification corresponds one-to-one with our model estimates, and results by sector are therefore inherently less insightful than results for the economy as a whole. Furthermore, we have to exclude Switzerland and Iceland from the analyses in this appendix as these two countries are not included in ERD: this leaves 230 (rather than 238) regions to be considered.

Firstly, Panel A of Table 10 reports correlations between changes over 1999-2010 in log wages per employee and in log employment, at the regional level. We do not find that wages and employment positively covary: instead, within tradables, the correlation is even slightly negative. Although the absence of evidence of a positive correlation does not necessarily mean European regional wages are unresponsive to demand shocks, it does suggest there is no strong evidence that wage and employment adjustments are co-determined by the same labor demand forces.

On the other hand, panel B shows that the predicted labor demand changes from our model are in fact positively correlated with regional wage changes in the tradable sector, even if no

[57]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.

such positive correlation is found for the regional economy as a whole or within non-tradables. However, since there are no comprehensive European regional wage data available that also vary by occupation, we cannot test to what extent such correlations, or the absence thereof, arise from occupational composition changes within regions (which is not at odds with our model) or from differently changing occupational wages (which would violate our assumptions to the extent that such wage changes are caused by RRTC).

Table 10: Correlations with log change in regional wage per employee

	All sectors (1)	Tradables-I (2)	Tradables-II (3)	Non-tradables-I (4)	Non-tradables-II (5)
A. Log change in actual regional employment	-0.146 [0.027]	-0.154** [0.019]	-0.148** [0.025]	-0.025 [0.703]	-0.074 [0.264]
B. Log change in predicted regional labor demand	-0.192*** [0.004]	0.2052*** [0.002]	0.2282*** [0.001]	-0.099 [0.135]	-0.106 [0.110]
Number of observations	230	230	230	230	230

Notes: European regions, excluding Switzerland and Iceland, 1999-2010 long difference. Correlation coefficients reported, p-values in square brackets. ***p<0.01, **p<0.05, *p<0.1

Finally, we can re-estimate our labor demand equation for the tradable sector while controlling for regional wages in tradables: results are reported in Table 11. Note that these estimates are not exactly the same as the ones reported in Table 3, since wage data is missing for Switzerland and Iceland: column 1 therefore first re-estimates the model without including wages as a regressor (columns 2 and 3 report the corresponding first stages for regional production and marginal cost). Columns 4 and 7 then add log regional wages in tradables, where tradables are respectively defined in the two different ways as explained above. From this, it can be seen that the wage coefficient has the expected negative sign. The coefficients of interest are largely robust to this inclusion, however: the routinization parameters in columns 4 and 7 are remarkably similar to the one estimated in column 1, and although the coefficient on marginal costs (representing 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.

A.4.2 Robustness: regional labor demand effects

Table 12 reports correlations between the predicted labor demand change from RRTC and actual employment-to-population changes[58] at the regional level. In constructing regions' employment-to-population change over 1999-2010, the dependent variable in Table 12, we consider four oper-

[58]Rather than the actual employment change, reported in the main text.

Table 11: Labor demand in the tradable sector, controlling for wages

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	FE-IV	First stage Regional gross production	First stage Regional marginal cost index
	(1)	(2)	(3)
Standardized occupational RTI × timetrend	-1.679***	0.000**	-0.000***
	(0.081)	(0.000)	(0.000)
Log regional gross production in tradables	0.775***		
	(0.076)		
Log industry marginal cost index	0.791***		
	(0.154)		
Log regional net capital stock in tradables		0.542***	-0.014**
		(0.040)	(0.004)
Log counterfactual industry marginal cost index		-0.510***	0.897***
		(0.151)	(0.024)
Number of observations	12320	12320	12320
R-squared	0.148	0.634	0.981
F-statistic	156.3	156.3	4451.7
	(4)	(5)	(6)
Standardized occupational RTI × timetrend	-1.679***	0.000***	-0.000***
	(0.081)	(0.000)	(0.000)
Log regional gross production in tradables	0.748***		
	(0.076)		
Log industry marginal cost index	0.511***		
	(0.103)		
Log regional wage in tradables I	-0.588***	0.522***	0.014*
	(0.058)	(0.073)	(0.007)
Log regional net capital stock in tradables		0.551***	-0.014**
		(0.042)	(0.004)
Log counterfactual industry marginal cost index		-0.299	0.903***
		(0.165)	(0.025)
Number of observations	12320	12320	12320
R-squared	0.182	0.681	0.982
F-statistic	132.8	132.3	3793.1
	(7)	(8)	(9)
Standardized occupational RTI × timetrend	-1.679***	0.000***	-0.000***
	(0.081)	(0.000)	(0.000)
Log regional gross production in tradables	0.770***		
	(0.083)		
Log industry marginal cost index	0.567***		
	(0.103)		
Log regional wage in tradables II	-0.512***	0.437***	0.014
	(0.065)	(0.060)	(0.008)
Log regional net capital stock in tradables		0.541***	-0.014***
		(0.043)	(0.004)
Log counterfactual industry marginal cost index		-0.341*	0.903***
		(0.154)	(0.025)
Number of observations	12320	12320	12320
R-squared	0.178	0.676	0.982
F-statistic	125.6	134.1	3895.5

Notes: European regions, 1999-2010. All models include region-occupation dummies and control for a linear timetrend. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1. Coefficients on RTI multiplied by 100.

ationalizations of population. These differ by their data source, which may either be aggregated Cambridge Econometrics European Regional Database (ERD) data (as in columns 1 and 2) or

Table 12: RRTC-induced labor demand changes and actual employment-to-population changes for European regions, 1999-2010

Dependent variable: actual regional change in employment-to-population ratio				
	(1)	(2)	(3)	(4)
Predicted regional labor demand change	0.179** (0.064)	0.219*** (0.064)	0.172*** (0.064)	0.173*** (0.064)
Data source	ERD	ERD	Eurostat	Eurostat
Population measure	Total	Active	Total	Working age
Number of observations	238	238	238	238
R-squared	0.032	0.048	0.030	0.030
F-statistic	7.8	11.9	7.2	7.3

Notes: European regions, 1999-2010 long difference. Independent variable is predicted labor demand change relative to 1999 regional employment level. The population measures used to construct the dependent variable are: population from ERD data in column 1; active population from ERD data in column 2; population from Eurostat data in column 3; and working age population from Eurostat data in column 4. Standardized coefficients reported. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Eurostat data (as in columns 3 and 4).[59] Furthermore, we consider the total population (in columns 1 and 3); as well as the active population– defined as the employed and unemployed[60]– (in column 2); and the working age population– defined as the population between ages 15 and 64 (in column 4). In all columns, standardized coefficients (and corresponding standard errors) are reported to ease interpretation.

This table shows that regions where RRTC is predicted to have led to a stronger increase in labor demand have indeed witnessed stronger growth in employment-to-population ratios: a one-standard deviation higher predicted labor demand corresponds to around 0.18 standard deviations faster growth in the employment to population ratio. Although the results are unsurprisingly strongest for the active population, they are quantitatively quite similar across the four models.

It should be noted that all population data are constructed based on where people live rather than where they work, and as such any commuting across regions is not taken into account. Such commuting patterns would tend to obscure any relationship between employment-to-population ratios and labor demand changes at the regional level. However, since our regions are relatively aggregated, we believe this is not a major concern in our data.

[59] All Eurostat population data are obtained from the data file demo-r-d2jan.

[60] That is, excluding children, pensioners, and the inactive population.

A.4.3 Robustness: business cycles

Our theoretical model examines how RRTC impacts long-run labor demand, and thereby 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 during 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 years. In particular, we qualify 2002-2007 as boom years, and the remainder as recessions, to capture both the bursting of the dot-com bubble in the early 2000s and the 2008-2010 Great Recession.

Table 13 shows estimates of the labor demand equation. It can be seen that the deviations from the parameter estimate for $(1-\eta)(1-\kappa)\gamma_R$ are statistically significant but economically very small.[61] Furthermore, the estimated η parameter is not significantly different in recession years.

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

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

[61] Similarly, the estimated coefficient on regional production is estimated to be higher in recession years (and this deviation is significant at the 5% level), but the difference is minor.

Table 13: Labor demand in the tradable sector

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	POLS Full sample	POLS Restricted sample	FE-IV	First stage Regional gross production	First stage Regional marginal cost index
	(1)	(2)	(3)	(4)	(5)
Standardized occupational RTI × timetrend	-1.706***	-1.731***	-1.731***	0.000	-0.000*
	(0.054)	(0.094)	(0.083)	(0.000)	(0.000)
Standardized occupational RTI × timetrend	0.000*	0.001***	0.001***	-0.000	0.000*
× recession dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log regional gross production in goods sector			0.769***		
			(0.069)		
Log regional gross production in goods sector			0.017**		
× recession dummy			(0.006)		
Log industry marginal cost index			0.603**		
			(0.185)		
Log industry marginal cost index			0.109		
× recession dummy			(0.060)		
Log regional net capital stock in goods sector				0.561***	-0.015***
				(0.036)	(0.004)
Log regional net capital stock in goods sector				-0.021***	-0.001
× recession dummy				(0.006)	(0.001)
Log counterfactual industry marginal cost index				-0.090	0.875***
				(0.151)	(0.035)
Log counterfactual industry marginal cost index				-0.447***	0.029
× recession dummy				(0.070)	(0.019)
Number of observations	28664	12416	12416	12416	12416
R-squared	0.975	0.981	0.148	0.652	0.983
F-statistic	.	.	98.9	94.2	2923.9

Notes: European regions, 1999-2010. Models (1) and (2) include region-occupation and region-year dummies. Models (3), (4) and (5) are estimated with region-occupation fixed effects and controls for a linear timetrend. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1. Coefficients on RTI multiplied by 100.

Table 14: Product demand in the tradable sector

Dependent variable: log regional production of tradables (in region-year cells)	FE	FE-IV	First stage Market potential	First stage Regional marginal cost index
	(1)	(2)	(3)	(4)
Log market potential	1.195***	1.351***		
	(0.096)	(0.115)		
Log market potential	-0.010	-0.021		
× recession dummy	(0.010)	(0.012)		
Log industry marginal cost index	-0.418*	-0.661**		
	(0.167)	(0.205)		
Log industry marginal cost index	-0.078	-0.054		
× recession dummy	(0.063)	(0.075)		
Log spatially weighted net capital stock			1.346***	0.039*
			(0.040)	(0.017)
Log spatially weighted net capital stock			0.007	-0.004**
× recession dummy			(0.004)	(0.001)
Log counterfactual industry marginal cost index			0.457***	0.892***
			(0.039)	(0.027)
Log counterfactual industry marginal cost index			-0.292***	0.036*
× recession dummy			(0.022)	(0.016)
Number of observations	2048	2048	2048	2048
R-squared	0.638	0.635	0.945	0.982
F-statistic	122.9	118.9	4359.7	4691.1

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Standard errors clustered by region reported in parentheses. ***p<0.01, **p<0.05, *p<0.1

A.5 Theoretical extensions and additional empirical results

This Appendix shows some theoretical extensions of our model and additional results when we relax some of our assumptions. In particular, we can additionally 1) relax the assumption that non-wage earners reside in the region where their income is generated; and 2) incorporate agglomeration externalities in our model in a reduced-form way.

A.5.1 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 multiplier 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 multiplier 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 multiplier effect.

Assume that local income is only composed of wage income:

$$I_i = w_i^s L_i + \sum_{j=1}^{J} w_j N_{ij}^g \tag{36}$$

Then, labor demand in the non-tradable sector is

$$N_{ij}^s = \frac{1-\mu}{\mu} {\beta_{ij}^s}^{1-\eta^s} w_j^{-\eta^s} {w_i^s}^{\eta^s - 1} \sum_{j=1}^{J} w_j N_{ij}^g \tag{37}$$

or in logs,

$$\log N_{ij}^s = \log \sum_{j=1}^{J} w_j N_{ij}^g + (1-\eta^s) \log \beta_{ij}^s + (\eta^s - 1) \log w_i^s - \eta^s \log w_j + \log(1-\mu)/\mu \tag{38}$$

This implies that labor demand in the non-tradable sector depends on the employment and wage structures in the tradable sector. The labor demand change in the non-tradable sector is now given by

$$\frac{\partial \log N^s_{ijt}}{\partial \log r_{j't}} = \frac{\partial \log \sum_{j=1}^J w_{jt} N^g_{ijt}}{\partial \log r_{j't}} = \sum_{j=1}^J \frac{\partial \log N^g_{ijt}}{\partial \log r_{j't}} \frac{w_{jt} N^g_{ijt}}{\sum_{j=1}^J w_{jt} N^g_{ijt}} \tag{39}$$

$$= (1-\eta)(1-\kappa) s^w_{j'|it} + (\eta - \sigma)(1-\kappa) s_{j'|it} \tag{40}$$

where we have used the definition $s^w_{j|it} = \frac{w_{jt} N^g_{ijt}}{\sum_{j=1}^J w_{jt} N^g_{ijt}}$. Hence, labor demand responds to changes in individual capital prices as follows:

$$\frac{\partial N_{it}}{\partial \log r_{j't}} = (1-\eta)(1-\kappa)\left(N^g_{ij't} + s^w_{j'|it} N^s_{it}\right) + (\eta - \sigma)(1-\kappa) s_{j'|it}(N^g_{it} + N^s_{it}) \tag{41}$$

Then, our decomposition is given by:

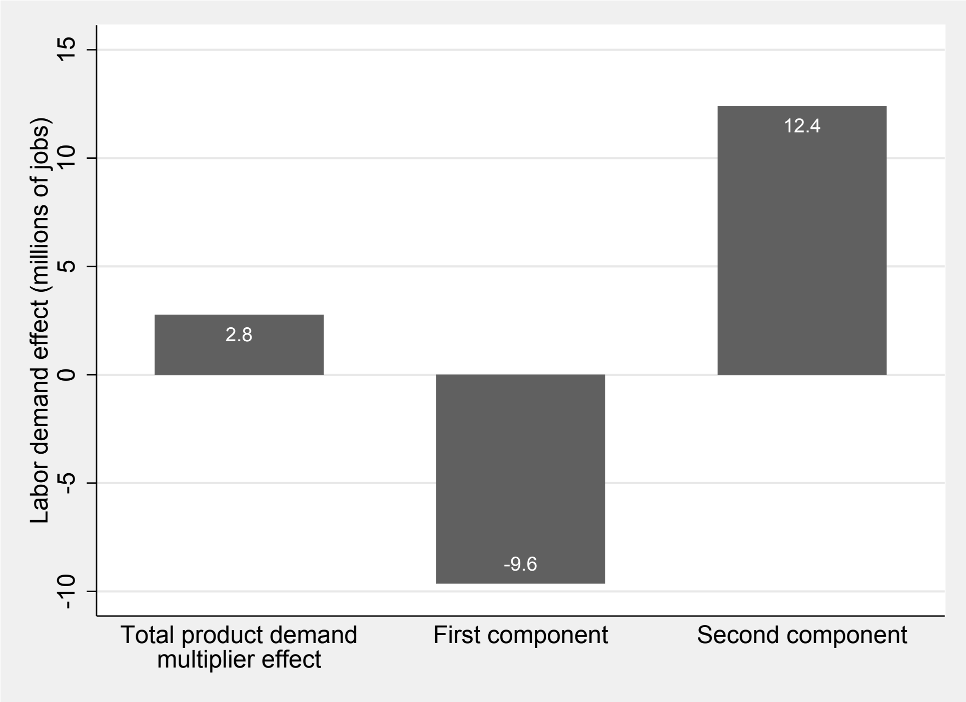
$$\Delta N_{it} = (1-\eta)(1-\kappa)\gamma_R \left[\sum_{j=1}^J R_j N^g_{ijt} + \frac{\eta}{1-\eta} R^I_{it} N^g_{it} - \frac{\sigma}{1-\eta} R^I_{it} N^g_{it} + \left(R^w_{it} N^s_{it} + \frac{\eta - \sigma}{1-\eta} R^I_{it} N^s_{it}\right)\right] \tag{42}$$

where we have used the definition $R^w_{it} = \sum_{j=1}^J s^w_{j|it} R_j$.

This shows that the first two effects (i.e. the substitution and product demand effects) remain the same, but the third effect (i.e. the multiplier effect) changes, as in the baseline model it was $\frac{-\sigma}{1-\eta} R^I_{it} N^s_{it}$. The multiplier effect can now be either positive or negative, depending on how RRTC affects the wage structure (R^w_{it}) and depending on whether employment losses in tradables from the increased usage of routine tasks in production are overcompensated by employment gains in tradables from the product demand effect, i.e. whether $\sigma > \eta$. The results from this overall decomposition are shown in Figure 6 in the main text: it can be seen that the multiplier effect is still positive (2.8 million jobs), but much smaller as compared to the baseline model (12.4 million jobs).

Decomposing the product demand multiplier effect In Figure 13, we additionally decompose the product demand multiplier effect into its two separate components [1) $R^w_{it} N^s_{it} + \frac{\eta}{1-\eta} R^I_{it} N^s_{it}$ and 2) $\frac{-\sigma}{1-\eta} R^I_{it} N^s_{it}$], which are respectively triggered by the substitution and product demand effects from the original decomposition. As for the first component, we find a negative effect: since substitution effects lead to a decline in tradable sector labor demand and the associated wage income, it lowers the potential spillovers to non-tradables. This lowers the previously

Figure 13: Decomposition of the alternative demand multiplier effect, 1999-2010



estimated product demand multiplier effect by 9.6 million jobs. Nevertheless, additional labor income through the product demand effect ($\frac{-\sigma}{1-\eta}R^I_{it}$) still increase labor demand by 12.4 million jobs as before and thus a positive spillover effect of 2.8 million jobs remains.

A.5.2 Extension: Agglomeration externalities

There is an extensive literature analyzing the role of agglomeration externalities in regional development (Moretti 2011; Buch et al. 2014), arguing that such externalities are important for employment growth in big cities such as national capitals. Although this is not the focus of our paper, our model can accommodate such externalities for employment in a reduced-form way. As an extension to our baseline model, we assume that there are positive agglomeration externalities in tradables production. For this, we adjust the production function for tradables as follows:

$$Y_i^g(T_{i1}, T_{i2}, ..., T_{iJ}) = \left[\sum_{j=1}^{J}(\beta_{ij}T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} A_i \tag{43}$$

where A_i is a region-specific productivity shifter which is exogenous to firms. Due to this exogeneity, it does not affect optimal firm behavior. Conditional task demand is now given by

$$T_{ij} = Y_i^g \beta_{ij}^{1-\eta} \left(\frac{c_i^I}{c_{ij}^T} \right)^{\eta} A_i^{\eta-1} \tag{44}$$

Assume that there are technological spillovers between firms at the regional level. Firms learn from each other, so that productivity A_i increases as the regional level of production increases, namely $A_i = (Y_i^g)^{\alpha_g}$. Hence, task demand is:

$$T_{ij} = (Y_i^g)^{1-\alpha_g(1-\eta)} \beta_{ij} \left(\frac{c_i^I}{c_{ij}^T} \right)^{\eta} \tag{45}$$

where we define $\tilde{\alpha}_g = (1 - \alpha_g(1 - \eta))$ for brevity. Accordingly, conditional labor demand in the tradable sector is

$$\begin{aligned} \log N_{ij}^g =& \tilde{\alpha}_g \log Y_i^g + (1-\eta) \log \beta_{ij}^g + \eta \log \frac{c_i^I}{P^g} + (1-\kappa) \log \frac{\kappa}{1-\kappa} \\ &+ (1-\eta)(1-\kappa) \log \frac{r_j}{P^g} - [(1-\kappa) + \kappa\eta] \log \frac{w_{ij}}{P^g} \end{aligned} \tag{46}$$

$$\tag{47}$$

The response of employment to changes in capital prices is now

$$\frac{\partial N_{ijt}^g}{\partial \log r_{j't}} = (1-\eta)(1-\kappa) + (\eta - \tilde{\alpha}_g \sigma) \frac{\partial \log c_{it}^I}{\partial \log r_{j't}} \text{ for } j = j' \tag{48}$$

$$= (\eta - \tilde{\alpha}_g \sigma) \frac{\partial \log c_{it}^I}{\partial \log r_{j't}} \text{ for } j \neq j' \tag{49}$$

and our decomposition changes to

$$\Delta N_{it} = (1-\eta)(1-\kappa)\gamma_R \left[\sum_{j=1}^{J} R_j N_{ijt}^g + \frac{\eta}{1-\eta} R_{it}^I N_{it}^g - \frac{\tilde{\alpha}_g \sigma}{1-\eta} R_{it}^I N_{it}^g - \frac{\sigma}{1-\eta} R_{it}^I N_{it}^s \right] \tag{50}$$

As such, the existence of agglomeration externalities would reduce the size of the product demand effect. Our empirical estimates lend some support to the existence of agglomeration externalities, as the coefficient on log regional gross production in the tradable sector in the labor demand equation is estimated to be 0.766 (see Table 3, in the main text), i.e. smaller than one.