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IZA DP No. 12063

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ABSTRACT

Racing With or Against the Machine? Evidence from Europe*

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

JEL Classification: E24, J23, J24, O33

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

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

1 Introduction

In recent years, rapid improvements in digital technologies such as information and communication technologies (ICT) and artificial intelligence (AI) have led to a lively public and scientific debate on the impact of automation on jobs. As highlighted by Acemoglu and Restrepo (2018a), this debate is permeated by a false dichotomy. On the one hand, there are alarmists, foremost in public press, arguing that automation will lead to the end of work. Their views are fueled by reports zooming in on the automation potential of existing jobs, claiming that large shares of U.S. and European jobs are at risk of being eliminated in coming decades (Bowles 2014; Frey and Osborne 2017).[1] On the other hand, there are economists arguing that technological revolutions of the past have not persistently reduced labor demand, and that there is no reason to believe that this time is different. Their views are reflected in canonical skill-biased technological change (SBTC) frameworks that assume technology is complementary to (skilled) workers, thus precluding labor displacement and, ultimately, ruling out the possibility that technological change may decrease labor demand and employment (see Acemoglu and Autor 2011; Acemoglu and Restrepo 2018b for a discussion and overview of this extensive literature).

Recent theoretical studies take a more nuanced view by considering that technological change may have both labor-replacing and labor-augmenting effects. In particular, the routine-replacing technological change (RRTC)[2] hypothesis adapts canonical frameworks by explicitly allowing for labor displacement. In particular, RRTC entails that digital technologies substitute for human labor in so-called routine tasks, which follow a set protocol, making them codifiable in software (see Autor et al. 2003). Using a rich theoretical framework rooted in this approach, Acemoglu and Restrepo (2018a,c) show that technological progress may lead to decreased labor demand (along with falling wages and employment), if positive forces spurred by e.g. productivity increases are not large enough to countervail negative labor displacement effects resulting from automation.[3] Other studies have considered the theoretical conditions for more extreme scenarios, including human obsolescence and labor immiseration (Benzell et al. 2016; Nordhaus 2015; Sachs et al.

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

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

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

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

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

This contributes to the literature in several ways. Firstly, ours is the first estimate of the effect of routine-replacing technologies on economy-wide labor demand and employment.[4] As outlined in Autor et al. (2003), routine-task replacement is the very nature of digital technology,

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

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

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

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

The remainder of this paper is organized as follows. Section 3 presents our theoretical framework for analyzing the employment effect of RRTC as well as the decomposition of this effect into the three channels outlined above. Our empirical strategy for identifying the parameters of this framework is outlined in section 3.7. Section 4 describes the data and presents our parameter estimates. Section 5 outlines and discusses our results, and section 6 concludes.

2 Routinization and employment: reduced-form evidence

In this section, we provide reduced-form evidence of the relationship between Routine Task Intensity and regional employment change. Before doing so, we outline our main data sources and measurement.

2.1 Data

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

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

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.

tries (Austria, the Netherlands, and the United Kingdom), the EU LFS micro-data has been supplemented with aggregated data from Eurostat online.

We divide industries classified by one-digit Nomenclature statistique des Activités économiques dans la Communauté Européenne (NACE revision 1.1) codes into either the tradable or non-tradable sector defined, as technology-induced employment fluctuations in the former sector might spill over to the latter sector (Moretti, 2010; Moretti and Thulin, 2013; Goos et al., 2015). 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.

Occupations are coded by one-digit International Standard Classification of Occupations (ISCO-1988) codes: for each of these, we obtain a Routine Task Intensity (RTI) index from the Dictionary of Occupational Titles 1977, constructed as in Autor and Dorn (2013), converted to European occupations as in Goos et al. (2014). The measure rises with the importance

Table 2: Occupational Routine Task Intensity (RTI)

ISCO	Occupation j	RTI_j	RTI dummy (d_j^R)
100	Legislators, senior officials and managers	-0.94	0
200	Professionals	-1.01	0
300	Technicians and associate professionals	-0.28	0
400	Clerks	2.01	1
500	Service workers and shop and market sales workers	-0.75	0
700	Craft and related trades workers	0.38	0
800	Plant and machine operators and assemblers	0.48	1
900	Elementary occupations	0.10	0

Notes: RTI standardized to have a zero mean and unit standard deviation across occupations: RTI dummy is 1 for the two most routine intense occupations. Armed forces (ISCO 6) and farming professionals (ISCO 0) have been excluded from the dataset.

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 Task Intensity RTI_j of occupations j 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. In our models, we will use a routine intensity dummy d_j^R, reported in the final column, for the two most routine intense occupations: the tasks in these jobs can be automated using routine-replacing technologies. This is similar to the approach in Autor (2013), who take the top 33% most routine-task intense occupations and count their employment as routine jobs.

For a more detailed description of the data preparation and data availability for specific countries, see Appendix A.2.3.

2.2 Reduced-form evidence

Here, we first present simple reduced-form evidence on the relationship between the (initial) Routine Task Intensity of regional employment and subsequent employment growth. The models in this section closely resemble those estimated in Autor (2013), and provide insight into the raw data patterns.

We first consider how the routine intensity of employment is evolving overall. To this end, we construct a measure of the regional routine intensity of employment by weighting the occupational Routine Task Intensity dummy d_j^R (shown in Table 2) by the employment share each occupation has in each region. As such, this measure simply reflects the share of employment N each region i has in routine occupations (Clerks, and Plant and machine operators and assemblers), $s_{it}^R = \sum_{j=1}^{J} d_j^R N_{ijt} / \sum_{j'=1}^{J'} N_{ij't}$. We also construct regions' *initial* routine employment share $s_{it_0}^R$ by using occupational employment shares in the first year of data (1999 in most cases, see Table 10 in the Appendix).

Initial regional routine employment shares vary a fair amount: on average across regions, 22% of workers are employed in routine jobs, but this ranges between 13% to 34% with a standard deviation of 3.7 percentage points. Further, regressing time-varying regional routine employment shares onto a linear timetrend (controlling for region fixed effects and weighting by initial regional employment shares), we find that routine employment is decreasing by a statistically significant 0.32 percentage points annually over the period.[5] This confirms the overall pattern of routine-replacing technological change documented in the literature: the share of routine jobs in the economy is declining.

However, this need of course not imply aggregate employment is decreasing. To consider how regions that are initially more intense in routine jobs fare relative to others, we estimate the following reduced-form model:

$$Y_{it} = \beta_0 + \beta_1 s_{it_0}^R \times t + \beta_2 \times t + \nu_i + \varepsilon_{it}. \tag{1}$$

In this equation, the dependent variable Y_{it} is log employment (or log employment to working age population) in region i and year t; $s_{it_0}^R \times t$ is the initial regional routine employment share interacted with a linear timetrend t; and ν_i are region fixed effects. This regression is weighted by regional employment shares (i.e. the share of regional employment in total sample employment) in the initial year. As an alternative, we also estimate this model in first-differences. In both cases, we cluster standard errors by region. The parameter of interest is β_1, reflecting the average annual log change in employment for regions whose routine employment share is larger by 100 percentage points.

We then also separately estimate this relationship in the tradable and non-tradable sectors, by replacing the dependent variable with log regional employment in tradables and non-tradables, respectively. This is motivated by the large difference in routine intensity between industries: while 33% of employment in tradables is routine, the corresponding number is only 13% for non-tradables.

The first column of Table 3 reveals that regions' overall employment (to population) change

[5]Unweighted, this estimate is 0.28 percentage points and also statistically significant.

Table 3: Reduced-form estimates

	All employment	**Tradable sector**	**Non-tradable sector**
	A. *Dep. var.: log regional employment*		
$s^R_{it_0} \times t$	-0.019	-0.239*	0.178*
	(0.069)	(0.119)	(0.076)
N	2,704	2,704	2,704
	B. *Dep. var.: Δ log regional employment*		
$s^R_{it_0}$	0.081	-0.120	0.266***
	(0.055)	(0.106)	(0.062)
N	2,466	2,466	2,466
	C. *Dep. var.: log regional employment to population*		
$s^R_{it_0} \times t$	-0.066	-0.287*	0.129*
	(0.066)	(0.139)	(0.053)
N	2,704	2,704	2,704
	D. *Dep. var.: Δ log regional employment to population*		
$s^R_{it_0}$	0.030	-0.171	0.211***
	(0.062)	(0.127)	(0.050)
N	2,466	2,466	2,466

Notes: Coefficients reflect log point changes in employment (or in employment to working age population) for an increase in the regional routine employment share by 1. Standard errors clustered by region reported in parentheses. All models are weighted by initial regional employment shares. * p<0.05, ** p<0.01, *** p<0.001

is *not* associated with its initial routine employment share. However, this masks markedly different employment trajectories across tradable and non-tradable sectors, reported in columns 2 and 3, respectively. In particular, regions that have a 1 percentage point higher initial share of routine jobs see their tradable sector employment decline by 0.12 to 0.24% every year, and their non-tradable sector employment increase by 0.18 to 0.27% annually. Panels C and D shows that these results are similar when considering log employment to population ratios as the dependent variable, instead.

While only providing raw correlations, these results suggest important differences in how routinization impacts tradable and non-tradable sectors. It is tempting to conclude that the net effect on aggregate employment is a simple weighted average of these two relationships, as represented by the estimates in the first column of Table 2. However, this is neither realistic nor informative for two main reasons. First, these reduced-form estimates do not take into account how tradable output reallocates across regions in response to routinization, nor how any such changes in tradable output spill over onto regions' local non-tradable sector. Second, these estimates do not illuminate how any aggregate impact of routinization on employment comes about: that is, without further structure we cannot disentangle through which channels labor-replacing technological change impacts employment. The remainder of this paper attempts to remedy these shortcomings and provide insight into how aggregate employment is affected by advancing routine-replacing technology. In the next section, we set up a theoretical framework that incorporates the key distinction between tradable and non-tradable sectors, and derive a set of estimating equations allowing us to infer the employment effect of routine-replacing technological change while making explicit the channels through which this occurs.

3 Framework

In this section, we develop a structural model (1) that is consistent with the descriptive results from the last section, (2) which serves as a framework to estimate the net employment effects of RRTC, and (3) which enables us to decompose the net employment effects of RRTC into the main underlying mechanisms.

Our framework consists of $i = 1, 2, \ldots, I$ regions, where each region has a non-tradable and a tradable sector.[6] Firms in the tradable sector produce goods and services by combining a set of occupational tasks which are themselves produced by combining labor and technological capital. Hence, we differentiate labor by tasks or occupations and thus indirectly consider skill or qualification differences as long as they correspond to occupational differences. RRTC is modeled as exogenously declining costs of capital in routine tasks relative to non-routine tasks, which can alternatively be interpreted as increasing productivity of capital in routine tasks relative to non-routine tasks. This production technology and modeling of RRTC is based on Goos et al. (2014).[7] 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).

This two-sector spatial set-up enables us to consider the transmission channel of local labor demand spillovers, which a related economic geography literature (see Moretti 2011) indicates

[6] The empirical classification we implement to distinguish tradables from non-tradables is reported in Table 1 from section 2.

[7] Note, however, that the framework in Goos et al. (2015) does not include a regional dimension, nor distinguishes tradables from non-tradables.

to be potentially important,[8] and which may help explain the different responses of both sectors to RRTC (see also Autor and Dorn 2013). Moreover, this spatial framework captures the technology-induced component of interregional trade.[9] 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). Finally, this approach allows us to exploit spatial variation in regions' exposure to RRTC for empirically identifying the parameters of our model.[10]

We first develop our structural model and explain the underlying mechanisms of how RRTC affects labor demand and employment, to then derive decompositions that serve to (1) estimate the overall net effect of RRTC on labor demand and employment as well as to (2) estimate the contribution of the underlying mechanisms. Finally, we derive the empirical implementation of our framework.

3.1 Production of tradables

The production structure in the tradable sector g is depicted in Figure 1. The representative firm in the tradable sector in region i produces a variety $\grave{y}_i$ that can be traded across regions, where $\grave{}$ denotes tradable sector variables.[11] The production of tradables requires a set of different tasks $T_j, j = 1, 2, \dots, J$, some of which are routine and are thus prone to substitution by computerized capital.[12] These tasks are combined to produce tradable output $\grave{Y}_i$ with a Constant Elasticity of Substitution (CES) production technology, $\grave{Y}_i = \left[\sum_{j=1}^{J}(\grave{\beta}_{ij}T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$, where $0 < \eta < 1$ is the elasticity of substitution between tasks, reflecting to what extent firms may substitute one task for another.[13] The term $\grave{\beta}_{ij}$ captures region i's efficiency in performing task j. Each task is performed by a combination of task-specific human labor and machines (technological

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

[9] Our framework does not account for any employment effects of *exogenously* decreasing trade barriers. Previous work has shown that one such exogenous change, the accession of China to the WTO, has had an economically sizable impact on employment in U.S. (Autor et al. 2013; Caliendo et al. 2019) and German regions (Dauth et al. 2014). However, these effects were also found not to be strongly correlated with the employment effects of RRTC at the regional or occupational level, or across time (Autor et al. 2015).

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

[11] We assume monopolistic competition between firms within regions so that prices are a constant markup over marginal costs. $\grave{Y}_i$ refers to the bundle of goods of region i's firms. We present the model at the level of regions.

[12] We drop the $\grave{}$ for simplicity whenever there is no corresponding variable in the non-tradable sector.

[13] We exclude the implausible case where $\eta > 1$, since in this case a reduction in the price of routine capital would lead to such a strong reallocation that the demand for routine workers would increase, not decrease. Moreover, existing estimates of η (as well as our estimates) suggest that it is indeed well below unity.

capital). We assume a Cobb-Douglas (CD) production technology, $T_{ij} = (\grave{L}_{ij})^{\kappa}(K_{ij})^{1-\kappa}$, where the production of tasks depends on labor $\grave{L}_j$ from occupation j, task-specific capital inputs K_j, and the share of labor in the costs of producing a task, $0 < \kappa < 1$.[14]

The representative firm minimizes the costs of producing $\grave{Y}_i$, which leads to the regional task demand,

$$T_{ij} = \grave{Y}_i \grave{\beta}_{ij}^{1-\eta} \left(\frac{c_i}{\grave{w}_{ij}^{\kappa} r_j^{1-\kappa}} \right)^{\eta}, \tag{2}$$

which rises in tradable production $\grave{Y}_i$, in the efficiency of that task $\grave{\beta}_{ij}$, and in the ratio of regional marginal costs c_i relative to the task-specific costs $\grave{w}_{ij}^{\kappa} r_j^{1-\kappa}$, to the extent that tasks can be substituted (η). $\grave{w}_{ij}$ represents wages and r_j capital costs. In this setting, we think of RRTC as a decline in the costs of technological capital in routine tasks relative to non-routine tasks. Equation (2) shows that, as relative capital costs for routine tasks decrease, the representative firm shifts its tradable production towards these tasks.

The representative firm minimizes the costs of producing T_{ij}, which leads to regions' occupational employment,

$$\grave{L}_{ij} = T_{ij} \left(\frac{r_j}{\grave{w}_{ij}} \frac{\kappa}{1-\kappa} \right)^{1-\kappa}, \tag{3}$$

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 $\grave{w}_{ij}$. From Equation (3) it can be seen that occupational employment decreases with falling capital costs for routine tasks, reflecting that the firm substitutes 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.

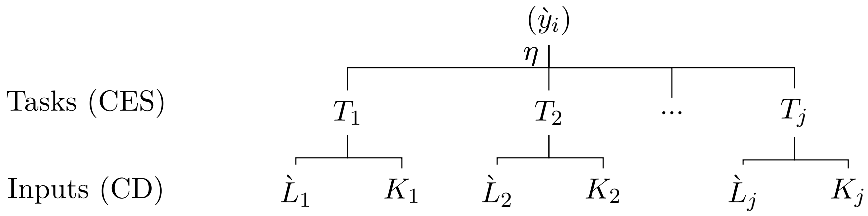
Substitution effects. The above production structure leads to our first channel: RRTC affects employment through substitution effects, where workers are replaced by machines in the production of routine tasks (direct positive relationship between r_j and $\grave{L}_{ij}$ in Equation 3).[15] This effect is further reinforced as firms shift their production technology towards routine task inputs (indirect negative relationship between r_j and $\grave{L}_{ij}$ working through T_{ij} in Equation 3).[16]

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

[15] This substitution effect covers both substitution of capital for labor in routine-intensive jobs, as well as rising labor demand in non-routine-intensive jobs.

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

Figure 1: Regional production



Overall, these two substitution effects lead to a decline in employment. The size of the negative employment effect rises in the substitutability between tasks in tradables production (η) and is more pronounced in regions with a higher initial share of routine tasks.

3.2 Consumption

The product demand structure is depicted in Figure 2. We assume that the utility of households depends on the consumption of tradables $\grave{X}$ and non-tradables $\tilde{X}$ (where $\tilde{}$ denotes non-tradable sector variables) and follows a CD utility function: $U = \grave{X}^{\mu}\tilde{X}^{1-\mu}$, where $0 < \mu < 1$ is the expenditure share of tradables.[17] Non-tradables are consumed locally, and are – without loss of generality – assumed to be homogeneous. Tradables are composed of local bundles $\grave{x}_i$, produced by local firms, and are consumed by households from all regions. We assume that preferences for tradables follow a CES utility function, $\grave{X} = \left[\sum_{i=1}^{I} \grave{x}_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, 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 of tradables with bundles of tradables from other regions.

Individuals maximize utility by optimizing the composition of regional bundles, which leads to the demand of consumers in region i' for the local bundle of tradables produced in region i,

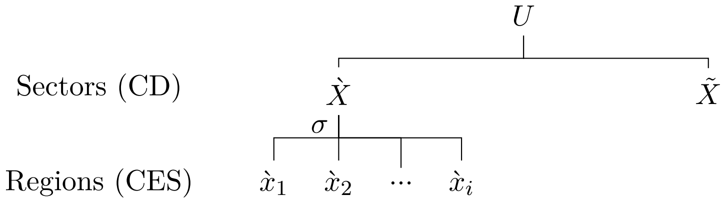
$$\grave{x}_{ii'} = \left(\frac{\tau_{ii'}\grave{p}_i}{\grave{P}_{i'}}\right)^{-\sigma} \mu \frac{I_{i'}}{\grave{P}_{i'}}, \tag{4}$$

where $\grave{P}_{i'}$ is an aggregated price index and $\grave{p}_i$ are local producer prices in the tradable sector. $\tau_{ii'}$ are iceberg trade costs between the exporting i and importing i' region. Equation 4 shows that consumption of tradables rises with households' real income $\frac{I_{i'}}{\grave{P}_{i'}}$ and with the share of income

substitution effect.

[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 $\delta_{MP} = 1$ in empirical Equation 20. However, empirically, non-homothetic preferences have been found to have only small effects on relative task demand (Autor and Dorn, 2013; Goos et al., 2014), and our results also indicate no significant divergence from homothetic preferences, so that we do not pursue this extension further.

Figure 2: Product demand



spent on these tradables μ. Moreover, consumption of tradables decreases in the relative price for these goods and services $\frac{\grave{p}_i}{\grave{P}_{i'}}$ 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 employment. The substitution of capital for labor (see substitution effects) allows firms to reduce costs, which lowers the output prices of tradables. Product demand for tradables rises as a result of lower output prices (negative relationship between $\frac{\grave{p}_i}{\grave{P}_{i'}}$ and $\grave{x}_{ii'}$ in Equation 4), leading to higher production and income, inducing additional employment in the tradable sector. This product demand effect of RRTC thus raises employment.[18] The effect increases in the substitutability between goods bundles, σ, and is stronger in regions with a higher initial share of routine tasks.

3.3 Non-tradable sector

The representative firm in the non-tradable sector produces 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 $\tilde{Y}_i = \alpha \tilde{L}_i$, where labor input $\tilde{L}_i$ is a CES-aggregate of task-specific labor inputs and α is the productivity of labor. We further assume the labor aggregate $\tilde{L}_i$ to be performed by occupations $j = 1, .., J$, $\tilde{L}_i = \left[\sum_{j=1}^{J} (\tilde{\beta}_{ij} \tilde{L}_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ with $0 < \eta < 1$.

The representative firm minimizes the costs of producing non-tradables $\tilde{Y}_i$ by minimizing the cost of obtaining the labor aggregate $\tilde{L}_i$. Occupational labor demand in the non-tradable sector

[18]The counterpart to our product demand effect is the productivity effect in the Acemoglu and Restrepo (2018a,c) framework. A major distinction, however, is that our product demand effect does not contain spillovers to other sectors, which we instead model separately in section 3.3. The sum of our product demand and spillover effects is thus similar to the productivity effect in Acemoglu and Restrepo (2018a,c).

is then given by

$$\tilde{L}_{ij} = (1-\mu)\tilde{\beta}_{ij}^{1-\eta}\left(\frac{\tilde{w}_{ij}}{\tilde{w}_i}\right)^{-\eta}\frac{I_i}{\tilde{w}_i}. \tag{5}$$

Employment generally decreases with average wages in the non-trabable sector $\tilde{w}_i$ and increases with local income I_i. Occupational employment in non-tradables rises with regions' efficiency in performing tasks ($\tilde{\beta}_{ij}$) and declines with occupational wages $\tilde{w}_{ij}$ relative to average regional wages $\tilde{w}_i$ to the extent that tasks can be substituted (η). RRTC thus affects employment in Equation 5 only indirectly through its effect on local income.

For local income I_i, we compare two alternative assumptions due to the lack of adequate data on inter-regional income flows between regions in the EU. In an **upper bound** case, we assume that 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, $I_i = \tilde{w}_i\tilde{L}_i + \grave{p}_i\grave{Y}_i - \sum_{j=1}^{J} r_j K_{ij}$.[19] Defining $\phi_{-K} = \grave{p}_i - \sum_{j=1}^{J} r_j K_{ij}/\grave{Y}_i$ as the disposable income resulting from tradable sales per unit of real output, we can express local income as follows:

$$I_i = \tilde{w}_i\tilde{L}_i + \phi_{-K}\grave{Y}_i \tag{6}$$

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

Product demand spillover effect. This framework leads to the third channel through which RRTC impacts employment. In particular, RRTC leads to higher production (see product demand effect), which results in additional income among local households (positive relationship between $\phi_{-K}\grave{Y}_i$ and I_i in Equation 6). This induces a product demand spillover effect as the additional local income is partly spent on local non-tradables (positive relationship between I_i and $\tilde{L}_{ij}$ in Equation 5), creating additional production and employment in the local economy. These spillovers are larger in regions with a higher initial share of routine tasks.

However, the product demand spillover effect is only unambiguously positive if firm owners are located in the region of production, such that additional firm profits arising from RRTC are

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

spent locally. Since we lack data on inter-regional income flows in the EU, we construct a **lower bound** for the product demand spillover effect by assuming that solely wage income flows back into local demand, whereas non-wage income is spent outside the EU. This implies that local income consists solely of wage income $I_i = \tilde{w}_i \tilde{L}_i + \sum_{j=1}^{J} \grave{w}_{ij} \grave{L}_{ij}$. The product demand spillover effect is strictly smaller (and can even turn negative) in this case. We refer to our upper bound case as the baseline, because we perceive the assumption of non-wage income not feeding back into the EU economies at all to be quite restrictive, but we compare both cases throughout to check the sensitivity of our results.

3.4 Labor and product demand

We combine Equations (2) and (3) from the production of tradables as well as Equations (5) and (6) from the production of non-tradables to derive labor demand in the tradable and non-tradable sector:[20]

$$
\begin{aligned}
\log \grave{L}_{ij} =& \log \grave{Y}_i + (\eta - 1) \log \grave{\beta}_{ij} + \eta \log c_i + (1-\kappa) \log \frac{\kappa}{1-\kappa} \\
&+ (1-\eta)(1-\kappa) \log r_j - [(1-\kappa) + \kappa\eta] \log \grave{w}_{ij} && (7) \\
\log \tilde{L}^s_{ij} =& \log \grave{Y}_i + (\eta - 1) \log \tilde{\beta}_{ij} + (\eta - 1) \log \tilde{w}_i + \log \frac{1-\mu}{\mu} \\
&- \eta^s \log \tilde{w}_{ij} + \log \phi_{-K} && (8)
\end{aligned}
$$

Note that we cannot observe task-specific capital costs r_j. In order to nevertheless empirically incorporate a decline in capital costs for routine relative to non-routine tasks, we follow the literature (starting with Autor et al. 2003) and replace log capital costs by $\rho d^R_j \times t$, where d^R_j is a dummy indicator of whether the occupation contains sufficient routine tasks to be susceptible to machine substitution. The term ρ reflects the change of capital costs for routine tasks, relative to those for non-routine tasks.[21] We expect $\rho < 0$, reflecting that computerization reduces the costs of capital for routine tasks. Note that RRTC in our framework need not only be viewed as a decline in capital costs for routine relative to non-routine tasks, but can also be interpreted as an increase in the productivity of capital for routine relative to non-routine tasks.

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

[21]This implies that we analyze the decline of capital costs for performing routine occupations relative to capital price changes for non-routine tasks as the baseline.

Labor demand depends on output in the tradable sector, $\grave{Y}_i$. We derive the product demand equation for the tradable sector from Equation (4) as the sum of demand across all destinations,

$$\log \grave{Y}_i = \log \mu - \sigma \log \grave{p}_i + \log \sum_{i'=1}^{I} \left(\frac{\tau_{ii'}}{\grave{P}_{i'}} \right)^{-\sigma} \frac{I_{i'}}{\grave{P}_{i'}}, \tag{9}$$

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

3.5 Labor demand decomposition

In order to analyze the implications of technological change, we derive decompositions for technology-driven labor demand changes in Appendix A.1.2. Our labor demand decomposition represents the shift of the labor demand curve for a given wage level. We first consider our baseline, **upper bound** estimate of RRTC-induced labor demand changes $\overline{\Delta L}$, where we assume that all non-wage income flows back into the local economies:

$$\overline{\Delta L} = \sum_{i=1}^{I} \underbrace{(1-\kappa)\rho \grave{s}_i^R \grave{L}_i}_{A_i} \left[\underbrace{1}_{B} - \underbrace{\sigma}_{C} - \underbrace{\sigma \frac{\tilde{L}_i}{\grave{L}_i}}_{D_i} \right] \tag{10}$$

where $\grave{s}_i^R = \sum_{j=1}^{J} d_j^R \grave{L}_{ij} / \grave{L}_i$ is the regional share of tradable routine jobs. Equation (10) consists of a scaling factor A_i, as well as three additive elements in the square brackets. Multiplied by the scaling factor, the elements correspond to the three channels through which RRTC affects regional labor demand: substitution effect ($\sum_i A_i B$), the product demand effect ($\sum_i A_i C$), and the product demand spillover effect ($\sum_i A_i D_i$). The size of the substitution effect increases in the capital share $(1-\kappa)$, as a larger capital share implies that production relies to a larger degree on capital so that declining capital prices have larger effects. Substitution effects are larger, the larger the decline in capital prices, ρ, and are larger in regions which have a strong focus on routine, i.e. replaceable, workers $\grave{s}_i^R$.

The substitution effects are the initial shock of RRTC on labor demand and thus also govern the sizes of the product demand and spillover responses to this shock. The size of the product demand effect, relative to the substitution effects, is governed by σ, the consumption elasticity of substitution. Product demand effects are larger when consumers respond more elastically to the

RRTC-induced price declines, generating new jobs and compensating capital-labor substitution. In particular, product demand effects compensate substitution effects in the tradable sector if $\sigma \geq 1$. This finding is similar to previous results at the regional (Cingano and Schivardi, 2004; Combes et al., 2004) and industry level (Appelbaum and Schettkat, 1999; Blien and Sanner, 2014) and has been discussed already by Neisser (1942).[22]

The size of the spillover effect, relative to the substitution effects, depends on σ and on the size of the non-tradable sector relative to the tradable sector. The larger the non-tradable sector, the larger the potential increase in labor demand due to income spillovers from the tradable sector. The size of the income spillovers, in turn, depends on output growth in tradables, which is governed by σ. The relationship between output growth and income growth is proportional, as we assume all types of income to remain in the local economy. We study the implications of non-wage income not feeding back into local demand, below. Rising income translates proportionally into employment increases, as we abstract from non-homothetic preferences and from non-constant returns to scale in the non-tradable sector.[23]

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 these channels. The net labor demand effect of technological change within a region is positive if the consumption elasticity of substitution is larger than the local employment share of the tradable sector, $\sigma > \grave{L}_i/L_i$. This result diverges from the previously described usual result that technological change generates more jobs than it destroys when $\sigma > 1$, because we take into account additional jobs created in the non-tradable sector. The requirements for RRTC to have positive labor demand effects are therefore less strict when the size of the non-tradable sector – and thus the potential to generate additional jobs via spillovers – is larger.

However, the labor demand decomposition from above is an upper-bound estimate which may be overly optimistic as it assumes that all income flows back into the local economy. We therefore compare this to a **lower-bound** estimate, where the net labor demand effect of RRTC is

$$\underline{\Delta L} = \sum_{i=1}^{I} (1-\kappa)\rho \grave{s}_i^R \grave{L}_i \left[1 - \sigma + (1-\eta)\frac{\grave{s}_i^w}{\grave{s}_i^R}\frac{\tilde{L}_i}{\grave{L}_i} + (\eta - \sigma)\frac{\tilde{L}_i}{\grave{L}_i} \right] \tag{11}$$

[22]See Blien and Sanner (2014) for a brief history of the argument. Note that in the model of Autor and Dorn (2013) the (relative) employment effects similarly depend on the consumption elasticity of substitution.

[23]Since constant returns to scale is the standard assumption in this literature, and since the effect of non-homothetic preferences on the task structure of employment has been found to be relatively small (Autor and Dorn 2013; Goos et al. 2014), we do not pursue these extensions here.

where $\grave{s}_i^w = \sum_{j=1}^J d_j^R \grave{w}_{ij} \grave{L}_{ij} / \sum_{j=1}^J \grave{w}_{ij} \grave{L}_{ij}$ is the local tradable sector wage bill share of routine jobs.

In this alternative labor demand decomposition, less income flows back into the local economy (namely, only wage income) and hence solely the product demand spillover effect is affected. The condition for RRTC to locally have positive labor demand effects now is stricter:

$$\sigma > \frac{\grave{L}_i}{L_i} + \frac{\tilde{L}_i}{L_i} \left[\frac{\grave{s}_i^w}{\grave{s}_i^R} + \eta \left(1 - \frac{\grave{s}_i^w}{\grave{s}_i^R} \right) \right] \tag{12}$$

To understand the implications of this equation, let us assume that wages of routine and non-routine jobs do not differ, in which case the wage bill shares and employment shares of tradable routine jobs are identical, $\grave{s}_i^w = \grave{s}_i^R$ and the equation reduces to $\sigma > 1$, as in previous studies. The reason is that when $\sigma > 1$, the substitution effects of RRTC are overcompensated by product demand effects within the tradable sector. Only then does RRTC raise wage income in the tradable sector, which is the pre-condition for positive spillovers to the non-tradable sector in our lower-bound case.

More generally, the condition for RRTC to have positive labor demand effects is stricter when the ratio of routine to non-routine wages in the tradable sector is larger, as this implies a stronger decline of tradable wage-income due to substitution effects. Moreover, the condition for positive labor demand effects of RRTC is stricter (less strict) the larger is η when routine wages exceed non-routine wages $\grave{s}_i^w > \grave{s}_i^R$ (non-routine wages exceed routine wages $\grave{s}_i^w < \grave{s}_i^R$) due to occupational restructuring.

3.6 Employment decomposition

So far, we have only modeled labor demand: however, we are interested in effects on employment. By taking into account wage adjustments via labor supply responses, we can derive two analogous employment decompositions. To do so, we follow Acemoglu and Restrepo (2017) and specify the supply of labor as follows:

$$\grave{N}_{ij} = \bar{\grave{N}}_{ij} \grave{w}_{ij}^{\epsilon} \quad \text{and} \quad \tilde{N}_{ij} = \bar{\tilde{N}}_{ij} \tilde{w}_{ij}^{\epsilon}, \tag{13}$$

This specification implies that $\epsilon \geq 0$ is the wage elasticity of labor supply. We do not directly model movements of workers between occupations, sectors, and regions due to lack of adequate data at the EU level. However, this mobility is implicitly included in ϵ, meaning that ϵ measures both labor supply at the intensive and extensive margins, and workers' mobility between labor market segments. The labor supply responses create interdependencies between labor market segments in our model. In particular, unless labor supply is perfectly elastic, a labor demand shock from RRTC will induce wage adjustments in the region and occupation where the shock occurs. This alters the local occupational wage structure and thus indirectly affects all other occupations in the region via changing relative occupational labor demand. Moreover, it induces changes in the local price index, inducing output and labor demand changes for all occupations. In Appendix A.1.3, we show that the employment effects of RRTC can be obtained from the labor demand shock by scaling all effects to correct for labor supply responses. The baseline, **upper-bound** estimate for the employment change, $\overline{\Delta N}$, predicted from our model is

$$\overline{\Delta N} = \frac{\epsilon}{\epsilon + 1 - \kappa(1-\sigma)} \sum_{i=1}^{I} (1-\kappa)\rho \grave{s}_i^R \grave{N}_i \left[1 - \sigma - \frac{\epsilon + 1 - \kappa(1-\sigma)}{\epsilon + 1} \sigma \frac{\tilde{N}_i}{\grave{N}_i} \right] \tag{14}$$

The decomposition is analogous to the labor demand decomposition, although the employment changes are scaled-down versions of the labor demand changes due to wage adjustments. The amount of scale-down depends on the size of wage responses, which in turn depend on the wage elasticity of labor supply ϵ. If labor supply was perfectly elastic ($\epsilon \to \infty$), employment responses correspond to labor demand responses. If labor supply is perfectly inelastic ($\epsilon = 0$), employment does not respond and RRTC-induced labor demand shocks result solely in wage changes. The **lower-bound** estimate for the employment change follows analogously:

$$\begin{aligned} \underline{\Delta N} = \frac{\epsilon}{\epsilon + 1 - \kappa(1-\sigma)} \sum_{i=1}^{I} (1-\kappa)\rho \grave{s}_i^R \grave{N}_i \Bigg[& 1 - \sigma + \frac{\epsilon + 1 - \kappa(1-\sigma)}{\epsilon + 1 - \kappa(1-\eta)} (1-\eta) \frac{\grave{s}_i^w}{\grave{s}_i^R} \frac{\tilde{N}_i}{\grave{N}_i} \\ & + \frac{\epsilon + 1 - \kappa(\eta - \sigma)}{\epsilon + 1 - \kappa(1-\eta)} (\eta - \sigma) \frac{\tilde{N}_i}{\grave{N}_i} \Bigg] \end{aligned} \tag{15}$$

3.7 Empirical implementation

We estimate the labor demand equation for the tradable sector (Equation 7) and the product demand equation (Equation 9) in order to get estimates for the key parameters of our framework (ρ, η, κ, and σ). We obtain the labor supply parameter (ϵ) from the literature. We then use these parameters jointly with the data to predict the labor demand and employment effects of

RRTC, using the decompositions above.[24]

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

$$\log \grave{L}_{ijt} = \beta_0 + \beta_Y \log \grave{Y}_{it} + \beta_c \log \grave{c}_{it} + \beta_R d_j^R \times t + \theta t + \beta_w \grave{w}_{it} + \upsilon_{ij} + \varepsilon_{ijt} \tag{16}$$

where the number of employed workers for each region i, occupation j, and year t in the tradable sector ($\grave{L}_{ijt}$) depends on the real regional production of tradables ($\grave{Y}_{it}$) and on real regional marginal costs of tradables production ($\grave{c}_{it}$). Technological change is modeled by a dummy for routine occupations interacted with a linear time trend $d_j^R \times t$ to reflect changes in the cost of capital for routine relative to non-routine tasks. To ensure that our measure of technological change does not capture trends that are unrelated to technological improvements, we further incorporate a linear time trend (t). Moreover, in order to control for differences in regional production technologies and resulting differences in the efficiencies of regions to utilize certain tasks ($\grave{\beta}_{ij}$ in the theoretical framework), we include region-occupation fixed effects (υ_{ij}). These fixed effects also capture unobserved factors related to the occupation-region cells. ε_{ijt} corresponds to the remaining error term.

Based on the estimates of Equation (16), we obtain our estimated elasticity of substitution between job tasks, $\eta = \beta_c$. The coefficient on the routine-dummy interacted with the time trend, β_R, is an estimate of $(1-\eta)(1-\kappa)\rho$. Lastly, we use the coefficient on wages, $\beta_w = -(1-\kappa+\kappa\eta)$,[25] jointly with the RTI coefficient, $\beta_R = (1-\eta)(1-\kappa)\rho$, and the elasticity of substitution between tasks, $\eta = \beta_c$, to back out both κ and ρ from our estimated parameters. Note that besides providing all our labor demand parameters, this procedure provides a check on these estimates: a reasonable value for the labor share κ would be close to two-thirds (Karabarbounis and Neiman, 2014), and our empirical model is in no way constrained to produce this.

IV strategy. To account for endogeneity in the labor demand equation, we follow an IV strategy. For regional production of tradables, we use the following Bartik (1991) IV as our

[24] We do not need to estimate labor demand in the non-tradable sector (Equation 8) since it is only indirectly affected by RRTC and its parameter estimates do not enter in our decomposition.

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

preferred instrument (i=region, c=country, k=industry, t_0=initial time period):

$$\log \grave{Y}_{it}^{IV} = \log \left(\sum_{k=1}^{Y} \frac{N_{kit_0}}{N_{kct_0}} \grave{Y}_{kct} \right), \tag{17}$$

where annual national industry production of tradables ($\grave{Y}_{kct}$) is reweighted by regional (N_{kit_0}) to national employment shares (N_{kct_0}) such that national aggregates are distributed among the regions according to the relative size of the region. We thereby use the weights of the starting year for each country so that our instrument captures changes in industry production at the national level only. To further check for the robustness of our results, we alternatively use industry capital stocks ($\grave{K}_{kct}$) instead of production in Equation 17.

For regional marginal costs, we calculate a similar Bartik (1991) IV as our preferred IV:

$$\log \grave{c}_{it}^{IV} = \log \left(\sum_{k=1}^{K} \frac{N_{kit_0}}{N_{it_0}} c_{kct} \right), \tag{18}$$

where annual national industry marginal costs (c_{kct}) are reweighted by industry employment shares within regions of the starting year. Compared to the IV for the absolute measures, we thus distribute the industry marginal costs to regions according to the industry employment shares within regions as a more proper approach for relative measures. As an alternative, we construct an IV based on the predicted components, $\log \grave{c}_{it}^{IV} = \log \left(\frac{\grave{Y}_{it}^{IV} - N\grave{O}S_{it}^{IV}}{rea\grave{l}Y_{it}^{IV}} \right)$, where $N\grave{O}S_{it}^{IV}$, $rea\grave{l}Y_{it}^{IV}$ and $\grave{Y}_{it}^{IV}$ are calculated as in Equation 17. The basic idea of this alternative IV is to use allocate industry-specific national-level information to the regions using industry-specific regions' shares within countries.[26]

For more transparency of the Bartik instruments, we calculate Rotemberg weights for the preferred specifications as proposed by Goldsmith-Pinkham et al. (2018). The weights show which industries and years are driving its variation (for details, see Appendix A.3.4). The top five Rotemberg weights suggest that our instruments for regional production and marginal costs are driven by events related to manufacturing, transport and real estate as well as events related to the years after 2006. The large role of manufacturing is as expected, since manufacturing dominates the tradable sector. The large role of the pre-crisis years might indicate sensitivity to business cycles. However, we show in Appendix A.4.2 that our estimates are robust to business cycle interactions.

[26] Note that, for data reasons, marginal costs on the industry-level, c_{kct}, are defined differently compared to the regional-level, c_{it}. See section 4.1.

We instrument regional wages with local female labor supply shocks calculated as follows (f=female):

$$\log \grave{w}_{it}^{IV} = \log \left(\frac{\grave{N}_{ic,t_0}^{f}}{\grave{N}_{c,t_0}^{f}} \grave{N}_{c,t}^{f,-i} \right), \tag{19}$$

where annual national female employment ($\grave{N}_{c,t}^{f,-i}$) is reweighted by regional ($\grave{N}_{ic,t_0}^{f}$) to national ($\grave{N}_{c,t_0}^{f}$) female employment shares of the starting year. The superscript $-i$ indicates a leave-own-out strategy, where national female employment is lowered by the female employment in region i.[27]

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

$$\log \grave{Y}_{it} = \delta_0 + \delta_c \log \grave{c}_{it} + \delta_{MP} \log MP_{it} + \nu_i + \varepsilon_{it} \tag{20}$$

where the real regional production of tradables ($\grave{Y}_{it}$) depends on real regional marginal costs of producing tradable output ($\grave{c}_{it}$)[28] as well as on a region's market potential (MP_t). Market potential for any one region ($MP_{it} = \left(\sum_{i'=1}^{I'} \tau_{ii'} Y_{i't} \right)$) is the sum of real income (tradables and non-tradables) in all other regions, discounted by the transport costs towards these regions ($\tau_{ii'}$). It represents the size of the market which can be potentially accessed by region i. In order to control for further regional factors, we include a set of regional fixed effects (ν_i). Finally, ε_{it} captures the remaining error term.

Based on the estimates in Equation 20 we can then obtain $\sigma = -\delta_c$, the elasticity of substitution between regional bundles of tradables.

IV strategy. To account for the endogeneity of regional marginal costs c_{it}, we follow the same IV strategy as for the labor demand equation, that is we use the Bartik IV in Equation (18) based on the re-weighted national industry marginal costs as well as the alternative IV based on the predicted components.

For regional market potential, we construct an analogous instrument as for the labor demand estimations by using the sum of predicted income (Y_{it}^{IV}) in all other regions, discounted by the

[27] Note that we can not perform a similar leave-own-out strategy for production and marginal costs, since we only observe the later data either on the industry level (STAN data) or regional level (Cambridge Econometrics data), but not for industry-region cells (ELFS data).

[28] Product demand depends on prices $\grave{p}_{it}$, which we replace with regional marginal costs c_{it}, since prices are a constant mark-up over marginal costs in our model.

transport costs towards these regions:

$$\log MP_{it}^{IV} = \log\left[\left(\sum_{i'=1}^{I'} \tau_{ii'} Y_{i't}^{IV}\right) - Y_{it}^{IV}\right] \tag{21}$$

As an alternative, we use the predicted capital stock (K_{it}^{IV}) in Equation (21).

The Rotemberg weights for the preferred Bartik IVs suggest that our instruments are driven by events related to manufacturing, transport, real estate and financial intermediation as well as events in the years after 2006 (see Appendix A.3.4). We thus perform similar robustness checks, as for labor demand, showing that our results are robust to specifications with business cycle interactions (see Appendix A.4.2).

(C) Labor demand decomposition. Using our estimated parameters $\hat{\eta}$, $\hat{\kappa}$, $\hat{\rho}$ and $\hat{\sigma}$ jointly with an estimate of ϵ from the literature, we calculate the components of equations (10) and (11), i.e. the effects of the three channels on labor demand in the upper and lower bound cases. All other variables in these equations, i.e. $\grave{s}_i^R$, $\grave{s}_i^w$, $\grave{L}_i$, and $\tilde{L}_i$, are calculated from the data.[29] The sum over all three effects reflects the net effect of RRTC on labor demand.

(D) Employment decomposition. Lastly, we scale the labor demand effects by their labor supply terms (see equations 14 and 15). These terms are obtained by backing out labor supply (resp. wage) responses and the related interdependencies between the labor market segments. The terms depend on the elasticity of labor supply, ϵ. This then gives us the three components of the employment decomposition, and their sum reflects the net effect of RRTC on employment.

4 Data and parameter estimates

4.1 Additional data sources

Estimating our labor and product demand equations requires some additional data than what what was described for reduced-form estimation in section 2.1. In particular, we obtain data for regional wages, regional marginal costs and regional production from the Cambridge Econometrics European Regional Database (ERD)[30]. For wages, we divide annual compensation of

[29] We calculate the decomposition for each year separately, using the start-of-year values of these variables, and then calculate the sum across all years.

[30] 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.

employees in 2005 Euros by ERD employment figures to obtain annual wages per employee at the regional level. We define regional marginal costs as [(compensation of employees + gross fixed capital formation) / gross value added] at the regional level in the tradable industry.[31]

For our IV strategy, we further use industry-level data on production and marginal costs obtained from the OECD Database for Structural Analysis (STAN). Following Goos et al. (2014), we define marginal costs for our alternative IV in the data as [(nominal production - nominal net operating surplus) / real production]. For real production, we divide the sector-specific production values by the sector specific deflator provided in STAN.

A region's market potential is calculated as the sum of income across all other regions, lowered by the trading costs towards these trading partners. We derive transport costs from German data on trade flows between regions (see Appendix A.3.2 for details). The market potential thus represents the potential market which a region can serve, depending on the trading costs with these partners and the partners' market sizes.

Not all data are available for all countries and time periods. For our labor demand estimations, we are left with a sample including Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Italy, Norway, Poland, Spain, Sweden, and the United Kingdom. This leaves 142 (rather than 238) regions to be considered. For the product demand estimations, we additionally have data for Austria, Greece, Hungary, Luxembourg, the Netherlands, Portugal and Slovakia, but loose Denmark. This leaves 180 regions to be considered there. When constructing our model predictions in section 5, we will expand the sample to cover all 238 regions.

4.2 Parameter estimates

Following Step A in section 3.7, Table 4 shows the estimates of labor demand in the tradable sector from Equation 16. Column (1) is an OLS estimate containing all observations and with a set of region-year fixed effects to capture variation in output and regional marginal costs. Column (2) shows the same estimates but restricted to the set of country-years for which all variables are available. Column (3) then adds the latter variables to replace the region-year fixed effects. Column (4) finally shows the IV specification with the preferred instruments outlined in

[31] Unfortunately, ERD aggregates do not distinguish occupations, but they do vary by six broad industries from which we define "industry" and "financial business services" as tradable industries and conduct robustness checks with an alternative definition including "wholesale, retail, transport & distribution, communications, hotels & catering". Besides "agriculture" which we exclude, the remaining (non-tradable) industries include "construction" and "non-market services", although there are some slight deviations from these categories across the variables.

Table 4: Labor demand in the tradable sector

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	FE Full sample (1)	FE Restricted sample (2)	FE (3)	FE-IV 1 (4)	FE-IV 2 altern. IV for prod. (5)	FE-IV 3 altern. IV for MC (6)	FE-IV 4 altern. IV for prod. and MC (7)
Dummy for routine occupations	-0.025***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
× linear time trend	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log regional production			0.476***	0.704***	0.860***	0.806***	0.966***
			(0.053)	(0.123)	(0.259)	(0.127)	(0.217)
Log regional marginal costs			0.286***	0.615***	0.676***	0.312	0.476*
			(0.054)	(0.222)	(0.240)	(0.226)	(0.279)
Log regional wages			-0.387***	-0.733***	-0.556***	-0.773***	-0.546***
			(0.065)	(0.133)	(0.174)	(0.133)	(0.180)
Constant			-21.540***				
			(2.573)				
N	21,632	12,096	12,096	12,096	12,096	12,096	12,096
R-squared	0.980	0.981	0.140	0.125	0.120	0.125	0.120

Notes: European regions, 1999-2010. Models (1) and (2) include region-occupation and region-year fixed effects. Models (3) to (7) are estimated with region-occupation fixed effects and control for a linear timetrend. Model 4 is our preferred specification. Standard errors clustered by region reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. First stage estimates in Table 12. Business cycle tests in Table 16.

section 3.7. The remaining columns show models with the alternative instruments for regional production (column 5) and regional marginal costs (column 6), and both (column 7).

Overall, all coefficients as well as the first stage estimates (see Appendix Table 12) have the expected sign and impact and are robust to business cycles (see Appendix Table 16). In particular, the negative and significant coefficient for the routine occupations dummy interacted with a linear time trend, which we refer to as the routinization coefficient, is almost identical across specifications, suggesting that job growth is 2.8 percent lower in routine occupations relative to non-routine occupations. The precisely estimated positive effect of output varies between 0.70 and 0.97 across IV models: this is very close to the theoretically expected value of one, supporting the assumption of constant returns to scale.

The effect of regional marginal costs provides our estimate for η – the substitution elasticity between tasks. This estimate lies in the range of 0.31-0.68 across the IV specifications. The estimate is larger when using our preferred marginal costs IV as compared to the alternative one, and the first stage is not strong for the alternative instrument (see Appendix Table 12). Nevertheless, all estimates are within the expected range between 0 (perfect complements) and 1 (unit-elasticity). To our knowledge, there are no estimates of our η coefficient in the literature, but the size is similar to the elasticity of substitution between tasks within industries of 0.9 estimated by Goos et al. (2014).[32] Intuitively, the estimate suggests that firms do have some

[32]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,

scope for substituting between tasks as a reaction to a relative price change, although with limits. As such, the estimate may reflect that firms' production steps require very different and/or specialized tasks which can not be easily substituted: indeed, Cortés and Salvatori (2015) find that firms are highly specialized in their task content along routine versus non-routine lines. Finally, we find a negative wage elasticity ranging between 0.55 and 0.73. Our estimates are close to the estimates of Beaudry et al. (2018) for the US who find an estimate of -0.3 at the city-level and -1.0 at the industry-city-level, whereas our wage elasticity refers to the regional level in tradables.

In line with Step B in section 3.7, Table 5 reports estimates of product demand in the tradable sector from Equation (20). The first column shows results including region-occupation fixed effects, whereas column (2) shows our preferred model which additionally instruments for market potential and marginal costs. The first stages are reported in Table 13 in the Appendix, where instruments are statistically significant and have the expected sign. The estimates are also robust to business cycles (see Appendix Table 17).

The coefficient on regional marginal costs, which reflects our parameter estimate for σ (the elasticity of substitution in consumption between regional bundles of tradables), varies somewhat across models. Our preferred model in column (2) finds $\sigma = -1.5$, a value in the middle of the range, such that the demand for regional goods bundles is neither very elastic, nor very inelastic. Again, the estimated effect is smaller when using the alternative IV for marginal costs, although again the first stage is weaker for this instrument. Nevertheless, the coefficients of all IV models lie within the range of estimates for the elasticity of international trade by Imbs and Mejean (2010), who find values between 0.5 to 2.7 at the country level for 30 countries worldwide. The coefficient on regional market potential is around 1 across IV models, suggesting that larger market potentials increase local product demand in the same proportion and indicating homothetic preferences, consistent with the theory.

Table 6 summarizes the baseline parameter estimates that we use to construct predictions for the overall employment effects in section 5. In particular, it includes the following estimates from our preferred labor demand model (column 4 in Table 4): (1) the routinization coefficient, $\beta_R = (1-\eta)(1-\kappa)\rho$; (2) the elasticity of substitution between tasks, η; and (3) the wage elasticity of labor demand. It also includes (4), the elasticity of substitution in consumption between regional bundles of tradables, σ, obtained from our preferred product demand model

but also since we include a larger set of EU countries and consider a different time period.

Table 5: Product demand in the tradable sector

Dependent variable: log regional production of tradables (in region-year cells)	FE	FE-IV 1	FE-IV 2 altern. IV for marg. costs	FE-IV 3 altern. IV for market pot.	FE-IV 4 altern. IV for marg. costs and market pot.
	(1)	(2)	(3)	(4)	(5)
Log regional marginal costs	-0.288***	-1.505***	-0.521**	-2.175***	-1.094***
	(0.059)	(0.547)	(0.248)	(0.783)	(0.323)
Log regional market potential	1.229***	1.098***	1.115***	1.021***	1.021***
	(0.063)	(0.131)	(0.075)	(0.186)	(0.098)
Constant	3.468***				
	(0.297)				
N	2,080	2,080	2,080	2,080	2,080
R-squared	0.628	-0.209	0.594	-1.385	0.254

Notes: European regions, 2001-2010. All models are estimated with region-occupation fixed effects. Model 2 is our preferred specification. Standard errors clustered by region reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. First stage estimates in Table 13. Business cycle tests in Table 17.

(column 2 in Table 5).

Moreover, Table 6 shows two additional parameters: (5), the labor share, κ, which can be backed out from the wage coefficient (given by $-[(1-\kappa)+\kappa\eta]$). We find a labor share of 69%, which is very close to the aggregate labor share as usually measured (see e.g. Karabarbounis and Neiman (2014)). Further, we show a sixth parameter, the relative decline in capital costs, ρ, which is implied by the routinization coefficient (given by $(1-\eta)(1-\kappa)\rho$). This parameter suggests that a decrease in the price of capital indeed leads to a stronger substitution of routine compared to non-routine labor by capital. Hence, as shown in the literature on job polarization (e.g. see Autor and Dorn 2013; Goos and Manning 2007; Goos et al. 2014), there is a shift in employment away from occupations that are more routine towards those that are less routine. The size of this estimate suggests routine-replacing capital prices are declining by some 23.7% per year, on average. For comparison, Byrne and Corrado (2017) report annual price declines of around 25% over 2004-2014 for several high-tech products including personal computers, computer storage and computers servers. These plausible implied values for κ and ρ increase confidence in the validity of our parameter estimates.[33] Additionally, we check the sensitivity of our results to variations of the parameter estimates in the next section.

There is one remaining parameter which we do not empirically estimate: the (Hicksian macro) labor supply elasticity (denoted by ϵ in our model). Here, we follow Acemoglu and

[33] The standard errors on κ and ρ are large, whereas the routinization coefficient, which is composed of these estimates, is very precisely estimated. This suggests that we have high statistical confidence on the size of the overall effect of RRTC on relative employment, but less confidence on whether this effect is driven by large capital shares and small capital price declines, or vice versa.

Table 6: Parameter estimates

Parameter	Description	Estimate
$(1-\eta)(1-\kappa)\rho$	routinization coefficient	-0.028***
		(0.002)
η	substitution elasticity between tasks	0.615***
		(0.222)
σ	substitution elasticity between bundles of tradables	-1.505***
		(0.547)
$-[(1-\kappa)+\kappa\eta]$	wage elasticity of labor demand	-0.733***
		(0.133)
κ	labor share	0.694
		(0.552)
ρ	change of capital costs for routine relative to non-routine tasks	-0.237
		(0.544)

Notes: Standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. All estimates are obtained from column 4 in Table 4, except for the σ estimate which is obtained from column 2 in Table 5. Standard errors reported in parentheses.

Restrepo (2017) in assuming a value of 0.50 from Chetty et al. (2011) as a baseline. This is best suited to our purpose since we use macro data and are interested in a long-term steady-state effect. In Appendix A.4.1, we explore the sensitivity of our results to this parameter choice.

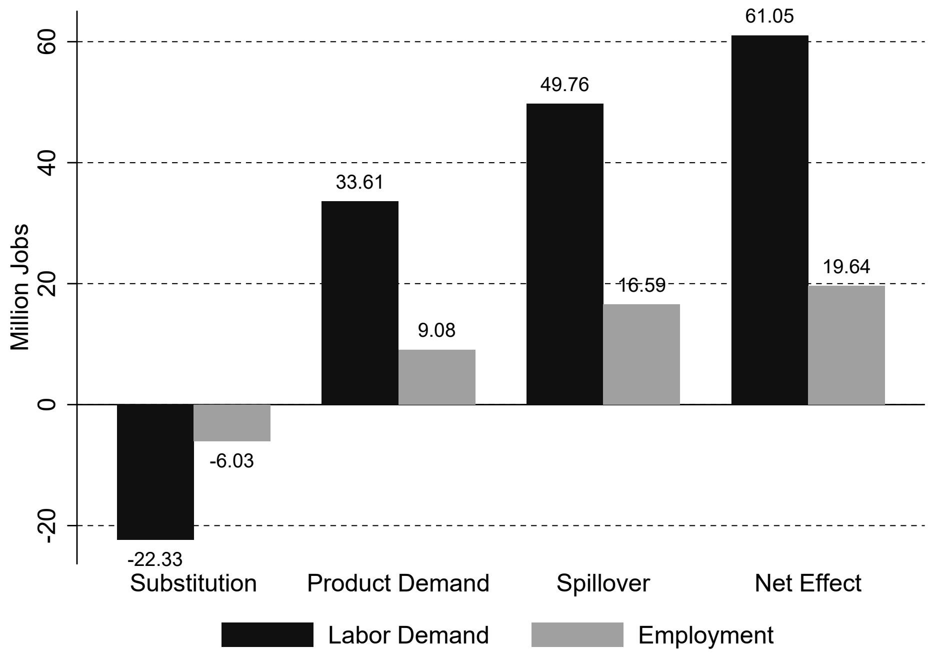
5 Results

5.1 European labor demand and employment effects

Using the decomposition outlined in section 3.7, we construct an estimate of the labor demand and employment impacts of RRTC. Specifically, we obtain predicted labor demand and employment effects for each of the three distinct channels from our framework, for Europe over 1999-2010. We choose the upper-bound decomposition as our baseline estimate, since this decomposition takes into account non-wage income feeding back into the local economies. However, we check the sensitivity of our results to the extreme assumption that none of the non-wage income remains in the EU in section 5.2: this reflects a lower bound.

Figure 3 shows the results at the European level. It can be seen that all three channels are empirically relevant and have the expected signs. The substitution effects are negative, suggesting that labor demand has decreased by 22.33 million jobs as technology substitutes for labor in routine tasks, and as production has restructured towards routine tasks. These are the direct substitution effects that have played a central role in the public debate. However, the product demand and local demand spillover effects on labor demand are positive and larger in absolute value, respectively implying an increase in labor demand of 33.61 and 49.76 million

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



jobs across Europe. These arise because lower goods prices lead to higher demand for tradables, increasing labor demand; and because the rise in product demand spills over to the non-tradable sector so that additional labor demand is created. As a result, labor demand *increases* by 61.05 million jobs, on net.

These labor demand effects only correspond to employment effects if labor supply is assumed to be perfectly elastic, which is inconsistent with a large literature finding finite supply elasticities. Implementing a supply elasticity of 0.5 in our employment decomposition model produces employment effects which are identically signed but more muted than their labor demand counterparts, as illustrated by the second set of bars in Figure 3. In particular, after accounting for labor supply rigidities, substitution effects within the tradable sector produce an employment loss of 6.03 million jobs, which is outweighted by employment gains from product demand effects of 9.08 million jobs. This implies our model predicts a small increase in employment for those sectors directly affected by routinization. On net, employment *increases* by 19.64 million jobs, mostly because of positive spillover effects (amounting to 16.59 million jobs) occurring in the non-tradable sector.

Table 7 additionally reports the confidence intervals for these labor demand and employment results, reflecting sensitivity to our parameter estimates. In particular, we create 10,000 bootstrapped predictions from our model, as such varying our key parameter estimates (σ, η,

Table 7: Confidence intervals for predicted labor demand and employment changes

	Point Est.	5th pctile	95th pctile	p-value
Labor demand change (in millions of jobs)				
Substitution	-22.33	-89.86	-10.67	0.029
Product Demand	33.61	11.10	180.53	0.034
Spillover	49.76	16.25	267.72	0.034
Net Effect	61.05	12.52	365.98	0.036
Employment change (in millions of jobs)				
Substitution	-6.03	-18.71	-2.68	0.018
Product Demand	9.08	4.44	26.96	0.014
Spillover	16.59	5.42	89.09	0.034
Net Effect	19.64	4.13	102.01	0.036

Notes: Distribution of predicted effects obtained by bootstrapping predictions with 10,000 draws. Bootstrap clustered by region-occupation for labor demand parameter estimates; and by region for the product demand parameter estimate. The p-value is the percentile of the zero in the distribution of the estimated and bootstrapped effects or one minus this value if the effect's point estimate is negative.

κ and ρ; reported in Table 6). Table 7 reports the point estimate, the 5th, and 95th percentile of the resulting distribution of predictions, for each of the three channels of our model as well as for the net labor demand and employment effects. In addition, we compute the percentile of the estimate which is closest to zero within the distribution of estimates as an indicator for the significance of the estimated effect ("p-value").[34] Note that we compute the capital share as $\kappa = (1 + \beta_w)/(1 - \beta_c)$, so that we get extreme values whenever the estimate of β_c is close to unity. Therefore, we obtain fat-tailed distributions for our effects, as visible from the confidence intervals. While this implies that there is some uncertainty about the exact size of our effects, all four effects retain their sign within the confidence interval despite the fat-tailed distributions. Since the signs of the effects of the three channels are as expected, this increases confidence in our overall conclusion of net positive labor demand and employment effects of RRTC. Our p-values further suggest that all of our predicted effects are statistically significant.

In addition, appendix A.4.1 provides extensive robustness checks on our findings. In particular, we rely on estimates from other specifications reported in Tables 4 and 5 for all parameters. Using these to construct alternative predictions, we find very similar results.

Finally, Table 8 compares our predictions to regions' actual employment evolutions. In particular, it shows regressions of actual employment-to-population changes onto the employment-to-population change predicted from our model. Each region is one observation, and observations

[34]We compute one minus this value, if the point estimate is negative to ease interpretation.

Table 8: Actual versus predicted employment-to-population change

Dependent variable: actual regional employment-to-population change	(1)	(2)	(3)	(4)
Predicted regional employment-to-population change	0.419*** (0.092)	0.302*** (0.048)	0.459*** (0.048)	0.309*** (0.042)
Number of observations	230	230	208	208
Sample	All regions		5th-95th percentile	
Fixed effects	None	Country	None	Country
R-squared	0.083	0.890	0.309	0.765

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

are weighted by the initial regional employment size to ensure that the results aggregate up to the total change. We find that our model of routine-replacing technological change is predictive of actual regional employment rate changes: across specifications, the coefficients are positive and statistically significant. Further, our model can help explain regions' employment rate evolutions both within and across countries, as can be seen by comparing the models with and without country fixed effects. Further, results are robust to excluding outlier regions in terms of the actual employment change.[35]

The results reported in this section highlight four main findings. Firstly, we provide the first estimate in the literature of the overall effect of RRTC on the number of jobs, finding that the net labor demand and employment effects of routine-replacing technologies are positive. This implies there is no support for the scenario of overall routinization leading to a net displacement of humans from the labor market. Of course, this does not rule out that there could be individual (automation) technologies which produce net aggregete disemployment effects, such as those found for industrial robots in the U.S. (Acemoglu and Restrepo 2017); nor the displacement of individual workers from their jobs (Bessen et al. 2019). Further, our results suggest that technological progress is a key driver of job growth: while the estimated employment increases of 19.64 million jobs over 1999-2010 across Europe reflects an upper bound, it is large compared to the total employment growth of 23 million jobs observed across these countries over the period considered (see Appendix Figure 5).

[35]These outliers are in part the result of imputing actual employment evolutions for countries which have limited data coverage over 1999-2010, such as Denmark – see Table 10 in the Appendix. Regression results are similar when weighting by initial population size, or when giving all regions equal weight; and from an alternative model specification regressing actual employment changes to predicted employment changes while controlling for regions' initial employment size.

The second important finding is that all three channels are quantitatively relevant: there are substantial substitution effects at the task level, leading to decreases in labor demand and employment, but these are countervailed by product demand effects and local spillovers. As such, the positive overall employment effect of RRTC is *not* the result of a negligible amount of substitution of capital for labor: rather, product market effects dominate these substitution effects. This highlights the importance of considering the interactions between labor and product markets when thinking about the employment effects of technological change, as also pointed out by Autor (2015) and Acemoglu and Restrepo (2018a,c).[36] These interactions cannot be studied in canonical SBTC models, which typically only consider a single final consumption good; or in reduced-form empirical approaches which do not uncover the channels through which aggregate effects come about.

Third, the product demand effect offsets the employment decline resulting from the substitution of capital for labor and the reorganization of task production: even within the tradable sector, there is no decline in employment as a result of routine-replacing technological change, consistent with Autor et al. (2015)'s findings for the U.S.[37] However, most job growth is in non-tradables, industries which are not directly affected by technological progress: this reallocation of employment to technologically lagging sectors has been documented since Baumol (1967). These predictions from our model match the overall patterns seen in the European labor market: employment is strongly reallocating towards non-tradables (see also Figure 5 in the Appendix).

The fourth result is that localized spillover effects to industries which are not directly affected by technological progress play a quantitatively important role for understanding the total labor demand and employment effects of RRTC. Although we are the first to model and estimate product demand spillovers in the RRTC context, we can compare our estimates with related studies on local multipliers. In particular, the findings shown in Figure 3 imply that each job generated in the local tradable industry as a result of increased product demand results in an additional employment effect of 16.59 million/9.08 million=1.83 jobs in the local non-tradable industry. This employment multiplier is similar to the one found by Moretti (2010),

[36] 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.

[37] 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.

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 workers from routine task intense jobs to non-routine service jobs.

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

5.2 The role of non-wage income

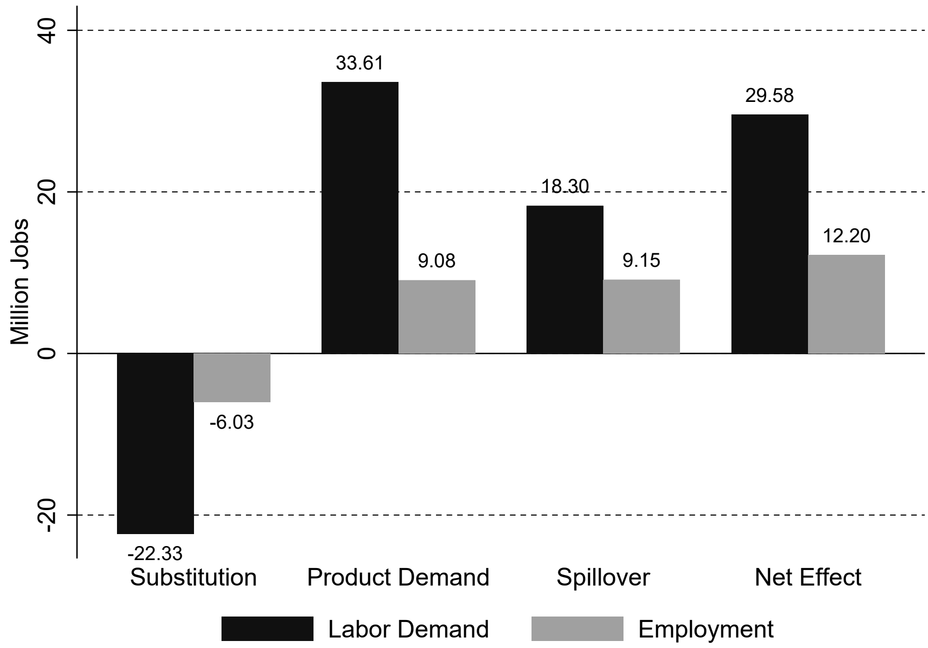
To consider the role of non-wage income in the spillover effect, we relax the assumption that non-wage income earners spend their income locally by assuming the other extreme: namely, that non-wage income does not feed back into consumption at all.[38] Conceptually, this represents the case where non-wage earners do not reside in Europe.[39] As such, we calculate product demand spillovers resulting from changes in wage income only, providing a lower-bound estimate of the spillover effect.

Figure 4 shows the empirical results from this alternative decomposition for both labor demand and employment. Note that the first two channels are unaltered: only the product demand spillover effect has changed. In particular, the predicted spillover effect is markedly smaller, reflecting an employment increase of 9.15 million instead of 16.59 million jobs. This smaller prediction for the demand spillover effect is the result of less tradable income being spent on non-tradables, since we now exclude any non-wage income. As such, our original estimate represents an upper bound for the spillover effect, whereas the estimate shown here is a lower bound. Note that the local employment spillover implied by this lower bound is 1.01 (=9.15/9.08). Given that completely abstracting from non-wage income is rather extreme, and that our upper bound is closer to the value of the spillover found in the literature, we interpret the larger spillover as our baseline result. Most importantly, we find a positive employment

[38] See Appendix A.1 for a derivation of this alternative model, where we also show that this assumption does not affect the first two channels in our framework.

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

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



effect even in this lower-bound scenario. However, the spillover and net effects are now at the border of statistical significance (see Table 9), although the point estimates are still positive and non-negligible in size. We thus conclude that the effect is smaller in the lower-bound case, but does not turn negative.

Our 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 roughly half as much – 12.2 million instead of 19.64 million jobs. This empirical prediction is in line with recent theoretical models which stress that the labor market effects of technological change depend on the allocation of the gains from these innovations (Benzell et al., 2016; Sachs et al., 2015).

6 Conclusion

There are long-standing public concerns about technological change destroying jobs, invoking images of labor racing against the machine. These concerns are echoed in a recent crop of theoretical models which allow technology to be labor-replacing, showing conditions under which labor-displacement occurs on aggregate as a result of technological change. However, empirical

Table 9: Confidence intervals for predicted labor demand and employment changes (lower bound)

	Point Est.	5th pctile	95th pctile	p-value
Labor demand change (in millions of jobs)				
Substitution	-22.33	-89.86	-10.67	0.029
Product Demand	33.61	11.10	180.53	0.034
Spillover	18.30	-9.79	142.91	0.121
Net Effect	29.58	-176.59	238.39	0.130
Employment change (in millions of jobs)				
Substitution	-6.03	-18.71	-2.68	0.018
Product Demand	9.08	4.44	26.96	0.014
Spillover	9.15	-3.64	63.72	0.101
Net Effect	12.20	-6.04	75.42	0.111

Notes: Distribution of predicted effects obtained by bootstrapping predictions with 10,000 draws. Bootstrap clustered by region-occupation for labor demand parameter estimates; and by region for the product demand parameter estimate. The p-value is the percentile of the zero in the distribution of the estimated and bootstrapped effects or one minus this value if the effect's point estimate is negative.

evidence on such aggregate effects is scarce, as most existing studies have focused on the relative effects of technological progress across worker skill levels and job types; or on very specific technologies such as industrial robots. Furthermore, the body of empirical evidence considering absolute labor demand and employment effects uses reduced-form specifications, thus remaining largely silent on the countervailing transmission channels highlighted in theoretical models. This paper contributes by developing and estimating an empirically tractable framework modeling the key job-creating and job-destroying channels of technological change and quantifying their empirical relevance for the overall effect. Our approach complements work focusing solely on industrial robots by studying routine-replacing technologies (RRTC) as a whole: unlike robotics, these technologies have already permeated many jobs and sectors.

We find that routine-replacing technologies substantially increased employment in Europe over the 1999-2010 period. Breaking down these employment effects into the underlying transmission channels, we show that this is not due to an absence of displacement effects. To the contrary, our results suggest that, in the absence of any countervailing mechanisms, employment would fall by some 6 million jobs as a result of machines replacing workers in performing routine tasks. These are the substitution effects ignored in canonical frameworks where technology is thought of as strictly factor-augmenting. However, our study also shows that these job losses are more than outweighed by the job-creating effects of RRTC. These countervailing effects result both from lower product prices and from growing local incomes, both of which raise local product demand and thereby employment.

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

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

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A For Online Publication: Appendix

This supplemental appendix contains 1) a more detailed description of our theoretical model and decompositions; 2) a data overview; 3) more detailed information on our empirical implementation; and 4) further robustness checks on our baseline results.

A.1 Theoretical model

A.1.1 Main model

This Appendix provides a more formal description of the model outlined in the paper. In our model, the representative firm in region i in the tradable sector produces output $\grave{Y}_i$ by combining tasks T_{ij} via a CES production technology $\grave{Y}_i = \left[\sum_{j=1}^{J} \left(\grave{\beta}_{ij} T_{ij}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta-1}{\eta}}$ with $0 < \eta < 1$. Firms minimize costs, which yields demand for tasks

$$T_{ij} = \grave{Y}_i \grave{\beta}_{ij}^{\eta-1} \left(\frac{c_i}{c_{ij}}\right)^{\eta} \tag{22}$$

where $c_i = \left[\sum_{j=1}^{J} \left(\frac{c_{ij}}{\grave{\beta}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}$ is the CES index for marginal costs. Each task is a CD combination of task-specific capital and labor, $T_{ij} = \grave{L}^{\kappa} K^{1-\kappa}$ with the labor share $0 < \kappa < 1$. Firms minimize costs, from which we derive demand for labor $\grave{L}_{ij} = T_{ij} \frac{c_{ij}}{\grave{w}_{ij}} \left(\frac{1-\kappa}{\kappa}\right)^{\kappa-1}$, where $c_{ij} = \grave{w}_{ij}^{\kappa} r_j^{1-\kappa}$ are the marginal costs for task j. We combine to obtain labor demand in tradables

$$\grave{L}_{ij} = \grave{Y}_i \grave{\beta}_{ij}^{\eta-1} c_i^{\eta} r_j^{(1-\eta)(1-\kappa)} \grave{w}_{ij}^{(1-\eta)\kappa-1} \left(\frac{1-\kappa}{\kappa}\right)^{1-\kappa} \tag{23}$$

Consumers have CD utility over tradables $\grave{X}$ and non-tradables $\tilde{X}$, $U = \grave{X}^{\mu} \tilde{X}^{1-\mu}$ with $0 < \mu < 1$. The expenditure shares of tradable and non-tradable goods are $\grave{X} = \mu \frac{I}{\grave{P}}$ and $\tilde{X} = (1-\mu)\frac{I}{\tilde{P}}$. Tradable goods are a CES bundle of the local varieties, $\grave{X} = \left[\sum_{i=1}^{I} \grave{x}_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, where $0 < \sigma < 1$ is the consumption elasticity of substitution between regional goods. Consumers pay iceberg transport costs $\tau_{ii'}$ between origin i and destination i' region. They minimize the costs of attaining $\grave{X}$, from which we derive the demand of consumers in destination i' for goods produced in origin i:

$$\grave{x}_{ii'} = \left(\frac{\tau_{ii'} \grave{p}_i}{\grave{P}_{i'}}\right)^{-\sigma} \mu \frac{I_{i'}}{\grave{P}_{i'}} \tag{24}$$

where $\grave{P}_{i'} = \left[\sum_{i=1}^{I} \left(\tau_{ii'} \grave{p}_i\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is the CES consumer price index.

The representative firm in the non-tradable sector produces non-tradable output $\tilde{Y}_i$ in region i under perfect competition with a linear production function, $\tilde{Y}_i = \alpha\tilde{L}_i$. The labor input $\tilde{L}_i$ is a CES aggregate of task-specific labor inputs, $\tilde{L}_i = \left[\sum_{j=1}^{J}\left(\tilde{\beta}_{ij}\tilde{L}_{ij}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ with the elasticity of substitution between occupations $0 < \eta < 1$. Firms minimize the costs of attaining the labor input, from which we derive the occupation-specific demand for labor

$$\tilde{L}_{ij} = \tilde{L}_i\tilde{\beta}^{\eta-1}\left(\frac{\tilde{w}_i}{\tilde{w}_{ij}}\right)^{\eta} \tag{25}$$

Average wages $\tilde{w}_i = \left[\sum_{j=1}^{J}\left(\frac{\tilde{w}_{ij}}{\tilde{\beta}_{ij}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}$ are a CES wage cost index. In the local equilibrium, non-tradable production equals non-tradable demand, $\tilde{Y}_i = \tilde{X}_i$, which implies

$$\tilde{Y}_i = (1-\mu)\frac{I_i\alpha}{\tilde{w}_i} \tag{26}$$

where prices $\tilde{P}_i$ for non-tradables equal their marginal costs $\tilde{w}_i/\alpha$ due to perfect competition.

We compare two alternative assumptions. In the first case **(upper bound)**, income in the local economy consists of labor income in non-tradables (there is no other income in this sector) as well as labor income and firm profits in the local tradable sector. We assume that capital is produced with a real resource costs r_j in a competitive capital sector, such that there is no capital income, but only firm profits. Local tradable sector income thus is output $\grave{Y}_i$ less of capital costs $\sum_{j=1}^{J} r_j K_{ij}$. Local income thus is $I_i = \tilde{w}_i\tilde{L}_i + \grave{p}_i\grave{Y}_i - \sum_{j=1}^{J} r_j K_{ij}$. We define the amount of income per unit of output in the tradable sector as $\phi_{-K} = \grave{p}_i - \sum_{j=1}^{J} r_j K_{ij}/\grave{Y}_i$. We thus express local income as

$$I_i = \tilde{w}_i\tilde{L}_i + \phi_{-K}\grave{Y}_i \tag{27}$$

We plug this definition of income and the production function into the definition of the non-tradable sector equilibrium to obtain $\tilde{L}_i = \frac{1-\mu}{\mu}\tilde{w}_i^{-1}\phi_{-K}\grave{Y}_i$. Occupation-specific labor demand thus is

$$\tilde{L}_{ij} = \frac{1-\mu}{\mu}\tilde{w}_i^{\eta-1}\tilde{w}_{ij}^{-\eta}\phi_{-K}\grave{Y}_i\tilde{\beta}^{\eta-1} \tag{28}$$

In the second case **(lower bound)**, we rely on wage income for defining local income, only. That is, we take into account solely wage income feeding back into local demand. Local income then is $I_i = \tilde{w}_i\tilde{L}_i\sum_{j=1}^{J}\grave{w}_{ij}\grave{L}ij$. We plug this definition of income jointly with the non-tradable production function into the local equilibrium condition to obtain:

$$\tilde{L}_i = \tilde{w}_i^{-1} \frac{1-\mu}{\mu} \sum_{j=1}^{J} \grave{w}_{ij} \grave{L}_{ij} \tag{29}$$

Local occupation-specific labor demand then is

$$\tilde{L}_{ij} = \frac{1-\mu}{\mu} \tilde{w}_i^{\eta-1} \tilde{w}_{ij}^{-\eta} \phi_{-K} \tilde{\beta}^{\eta-1} \sum_{j=1}^{J} \grave{w}_{ij} \grave{L}_{ij} \tag{30}$$

For the labor supply side of our model, we follow Acemoglu and Restrepo (2017) and assume that there is a constant wage elasticity of labor supply ϵ, such that labor supply in each segment of the labor market is

$$\grave{N}_{ij} = \bar{\grave{N}}_{ij} \grave{w}_{ij}^{\epsilon} \text{ and } \tilde{N}_{ij} = \bar{\tilde{N}}_{ij} \tilde{w}_{ij}^{\epsilon}, \tag{31}$$

Labor supply-induced wage responses in one occupation create labor demand responses in all other occupations due to the dependence of labor demand on local average marginal costs. This creates interdependences between labor market segments.

A.1.2 Labor demand decomposition

We first derive the **upper bound** for the labor demand effect of RRTC by assuming that all income feeds back into local demand. We analyze shifts of labor demand holding constant wages. Local employment is the sum across employment in both sectors, $L_i = \sum_{j=1}^{J} \left(\grave{L}_{ij} + \tilde{L}_{ij} \right)$. The total change in labor demand is the sum of labor demand changes across all regions, $\Delta L = \sum_{i=1}^{I} \Delta L_i$. We are interested in RRTC-induced local labor demand changes

$$\Delta L_i = \sum_{j'=1}^{J'} \frac{\partial L_i}{\partial \ln r_{j'}} \Delta \ln r_{j'} \tag{32}$$

Note that we replace log capital price changes in the empirical implementation as $\Delta \ln r_{j'} = \rho d_{j'}^{R}$. Total labor demand change thus is

$$\Delta L = \sum_{j'=1}^{J'} \sum_{i=1}^{I} \frac{\partial L_i}{\partial \ln r_{j'}} \rho d_{j'}^{R} \tag{33}$$

The employment responses of regions to log capital price changes are

$$\frac{\partial L_i}{\partial \ln r_{j'}} = \sum_{j=1}^{J} \left[\frac{\partial \ln \grave{L}_{ij}}{\partial \ln r_{j'}} \grave{L}_{ij} + \frac{\partial \ln \tilde{L}_{ij}}{\tilde{\ln} r_{j'}} \tilde{L}_{ij} \right] \tag{34}$$

Total labor demand changes thus are

$$\Delta L = \sum_{j'=1}^{J'} \sum_{i=1}^{I} \sum_{j=1}^{J} \left[\frac{\partial \ln \grave{L}_{ij}}{\partial \ln r_{j'}} \grave{L}_{ij} + \frac{\partial \ln \tilde{L}_{ij}}{\tilde{\ln} r_{j'}} \tilde{L}_{ij} \right] \rho d^R_{j'} \tag{35}$$

To get at total labor demand changes, we need to derive the responses of tradable and non-tradable labor demand to capital price changes. The response of tradable labor demand to capital price changes is (using the tradable labor demand equation)

$$\frac{\partial \ln \grave{L}_{ij}}{\partial \ln r_{j'}} = \frac{\partial \ln \grave{Y}_i}{\partial \ln r_{j'}} + \eta \frac{\partial \ln c_i}{\partial \ln r_{j'}} + (1-\eta)(1-\kappa)\ \mathbf{1}(j=j') \tag{36}$$

where $\mathbf{1}(j = j')$ represents the indicator function and which is 1 if $j = j'$ and zero otherwise. The response of output to RRTC is (using the product demand equation)

$$\frac{\partial \ln \grave{Y}_i}{\partial \ln r_{j'}} = -\sigma \frac{\partial \ln c_i}{\partial \ln r_{j'}} \tag{37}$$

For the response of marginal costs to RRTC, we have

$$\begin{aligned} \frac{\partial \ln c_i}{\partial \ln r_{j'}} =& \frac{\partial \ln \left[\sum_{j=1}^{J} (c_{ij}/\grave{\beta}_{ij})^{1-\eta} \right]^{1/(1-\eta)}}{\partial \ln r_{j'}} & (38) \\ =& \sum_{j=1}^{J} \grave{s}^C_{j|i} \frac{\partial \ln c_{ij}}{\partial \ln r_{j'}} & (39) \\ =& \grave{s}^C_{j|i}(1-\kappa) & (40) \end{aligned}$$

where $\grave{s}^C_{j|i}$ is the cost share of task j in the tradable sector in region i which we approximate by the employment share of occupation j, $\grave{s}^L_{j|i} = \grave{L}_{ij} / \sum_{j'=1}^{J'} \grave{L}_{ij'}$. We combine the above to get:

$$\frac{\partial \ln \grave{L}_{ij}}{\partial \ln r_{j'}} = (1-\kappa)(\eta-\sigma)\grave{s}^L_{j|i} + (1-\eta)(1-\kappa)\ \mathbf{1}(j=j') \tag{41}$$

For the non-tradable sector, we have

$$\frac{\partial \ln \tilde{L}_{ij}}{\partial \ln r_{j'}} = \frac{\partial \ln \grave{Y}_i}{\partial \ln r_{j'}} = -\sigma(1-\kappa)\grave{s}^L_{j|i} \tag{42}$$

Plugging the above into the definition of ΔL, we obtain

$$\begin{aligned}\overline{\Delta L} = &\sum_{j'=1}^{J'}\sum_{i=1}^{I}\sum_{j=1}^{J}\left[(\eta-\sigma)(1-\kappa)\grave{s}^L_{j|i}\grave{L}_{ij} - \sigma(1-\kappa)\grave{s}^L_{j|i}\tilde{L}_{ij}\right]\rho d^R_{j'} \\ &+ \sum_{i=1}^{I}\sum_{j=1}^{J}(1-\eta)(1-\kappa)\grave{L}_{ij}\rho d^R_{j'} \end{aligned} \tag{43}$$

We define the share of routine jobs in the local tradable sector $s^R_i = \sum_{j=1}^{J} d^R_j \grave{L}_{ij}/\grave{L}_i$ and simplify to get:

$$\overline{\Delta L} = (1-\kappa)\rho\sum_{i=1}^{I}\left[1-\sigma-\sigma\frac{\tilde{L}_i}{\grave{L}_i}\right] \tag{44}$$

We next derive the **lower bound** for our labor demand effect, assuming that solely wage income feeds back into local demand. This affects only the response of non-tradable employment to RRTC:

$$\frac{\partial \ln \tilde{L}_{ij}}{\partial \ln r_{j'}} = \frac{\partial \ln \sum_{j=1}^{J}\grave{w}_{ij}\grave{L}_{ij}}{\partial \ln r_{j'}} = \sum_{j=1}^{J}\grave{s}^w_{j|i}\frac{\partial \ln \grave{L}_{ij}}{\partial \ln r_{j'}} \tag{45}$$

$$= (1-\eta)(1-\kappa)\grave{s}^w_{j'|i} + (1-\kappa)(\eta-\sigma)\grave{s}^L_{j'|i} \tag{46}$$

Using this and the above in the definition of total labor demand changes, we get:

$$\underline{\Delta L} = (1-\kappa)\rho\sum_{i=1}^{I}s^R_i\grave{L}_i\left[1-\sigma+(1-\eta)\frac{\grave{s}^w_i}{s^R_i}\frac{\tilde{L}_i}{\grave{L}_i}+(\eta-\sigma)\frac{\tilde{L}_i}{\grave{L}_i}\right] \tag{47}$$

A.1.3 Employment decomposition

In the employment decompositions, we take into account labor supply respones via wage adjustments into our model. This creates interdependence between the labor market segments. For the **upper bound** employment decomposition, we build on the labor demand decomposition from above, but take into account wage changes due to labor supply responses. The tradable sector employment response to RRTC now is:

$$\begin{aligned}\frac{\partial \ln \grave{N}_{ij}}{\partial \ln r_{j'}} =&(1-\eta)(1-\kappa)\ \mathbf{1}(j=j') + (1-\kappa)(\eta-\sigma)\grave{s}^N_{j'|i} - (1-\kappa+\kappa\eta)\frac{\partial \ln \grave{N}_{ij}}{\partial \ln r_{j'}}\frac{1}{\epsilon} \\ &+ \kappa(\eta-\sigma)\sum_{j''=1}^{J''}\grave{s}^N_{j''|i}\frac{\partial \ln \grave{N}_{ij''}}{\partial \ln r_{j'}}\frac{1}{\epsilon}\end{aligned} \tag{48}$$

We simplify to get

$$\begin{aligned}\frac{\partial \ln \grave{N}_{ij}}{\partial \ln r_{j'}}\left(1+\frac{1-\kappa+\kappa\eta}{\epsilon}\right) =&(1-\eta)(1-\kappa)\ \mathbf{1}(j=j') + (1-\kappa)(\eta-\sigma)\grave{s}^N_{j'|i} \\ &+ \frac{\kappa(\eta-\sigma)}{\epsilon+1-\kappa+\kappa\sigma}\Big[(1-\eta)(1-\kappa)\grave{s}^N_{j'|i} + (1-\kappa)(\eta-\sigma)\grave{s}^N_{j'|i}\Big]\end{aligned} \tag{49}$$

The total employment change in the tradable sector across all regions and occupations then is:

$$\overline{\Delta \grave{N}} = \sum_{j'=1}^{J'}\sum_{i=1}^{I}\sum_{j=1}^{J}\frac{\partial \ln \grave{N}_{ij}}{\partial \ln r_{j'}}\grave{N}_{ij}\rho d^R_{j'} \tag{50}$$

$$=\frac{\epsilon}{\epsilon+1-\kappa+\kappa\sigma}\rho(1-\kappa)\sum_{i=1}^{I}s^R_i\grave{N}_i\left[1-\sigma\right] \tag{51}$$

Employment responses in the non-tradable sector are:

$$\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}} =(\eta-1)\frac{\partial \ln \tilde{w}_i}{\partial \ln r_{j'}} - \eta\frac{\partial \ln \tilde{w}_{ij}}{\partial \ln r_{j'}} + \frac{\partial \ln \grave{Y}_i}{\partial \ln r_{j'}} \tag{52}$$

$$=(\eta-1)\frac{\sum_{j''=1}^{J''}\tilde{s}^w_{j''|i}}{\partial \ln r_{j'}} - \eta\frac{\partial \ln \tilde{w}_{ij}}{\partial \ln r_{j'}} - (1-\kappa)\sigma\grave{s}^N_{j'|i} \tag{53}$$

$$=\frac{\eta-1}{\epsilon}\sum_{j''=1}^{J''}\tilde{s}^w_{j''|i}\frac{\partial \ln \tilde{N}_{ij''}}{\partial \ln r_{j'}} - \frac{\eta}{\epsilon}\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}} - (1-\kappa)\sigma\grave{s}^N_{j'|i} \tag{54}$$

$$=\frac{\eta-1}{\epsilon+\eta}\sum_{j''=1}^{J''}\tilde{s}^w_{j''|i}\frac{\partial \ln \tilde{N}_{ij''}}{\partial \ln r_{j'}} - \frac{\epsilon}{\epsilon+\eta}(1-\kappa)\sigma\grave{s}^N_{j'|i} \tag{55}$$

We simplify to get

$$\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}} = -(1-\kappa)\sigma\grave{s}^N_{j'|i}\frac{\epsilon}{\epsilon+1} \tag{56}$$

Total employment changes in the non-tradable sector then are:

$$\overline{\Delta \tilde{N}} = \sum_{j'=1}^{J'}\sum_{i=1}^{I}\sum_{j=1}^{J}\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}}\tilde{N}_{ij}\rho d^R_{j'} \tag{57}$$

$$= \sum_{j'=1}^{J'}\sum_{i=1}^{I}\sum_{j=1}^{J} -(1-\kappa)\sigma\rho\grave{s}^N_{j'|i}\frac{\epsilon}{\epsilon+1}\tilde{N}_{ij}d^R_{j'} \tag{58}$$

Aggregating across tradable and non-tradable sector employment changes, total employment effects of RRTC in the **upper bound** scenario are:

$$\overline{\Delta N} = \rho(1-\kappa)\sum_{i=1}^{I} s_i^R \grave{N}_i \left[\frac{\epsilon}{\epsilon+1-\kappa+\kappa\sigma}(1-\sigma) - \frac{\epsilon}{\epsilon+1}\sigma\frac{\tilde{N}_i}{\grave{N}_i}\right] \tag{59}$$

For the **lower bound**, the tradable sector responses to RRTC remain the same, but the non-tradable sector responses change. We now have:

$$\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}} =(\eta-1)\frac{\partial \ln \tilde{w}_i}{\partial \ln r_{j'}} - \eta\frac{\partial \ln \tilde{w}_{ij}}{\partial \ln r_{j'}} + \frac{\partial \ln \sum_{j''=1}^{J''} \grave{w}_{ij''}\grave{N}_{ij''}}{\partial \ln r_{j'}} \tag{60}$$

$$=(\eta-1)\sum_{j''=1}^{J''} \tilde{s}^w_{j''|i}\frac{\partial \ln \tilde{w}_{ij''}}{\partial \ln r_{j'}} - \eta\frac{\partial \ln \tilde{w}_{ij}}{\partial \ln r_{j'}} + \sum_{j''=1}^{J''} \grave{s}^w_{j''|i}\frac{\partial \ln \grave{N}_{ij''}}{\partial \ln r_{j'}}\frac{\epsilon+1}{\epsilon} \tag{61}$$

using the same steps to solve inter-occupational dependences as before, we get:

$$\frac{\partial \ln \tilde{N}_{ij}}{\partial \ln r_{j'}} =\frac{\epsilon}{\epsilon+1}\sum_{j''=1}^{J''} \grave{s}^w_{j''|i}\frac{\partial \ln \grave{N}_{ij''}}{\partial \ln r_{j'}}\frac{\epsilon+1}{\epsilon} \tag{62}$$

$$=\frac{\epsilon}{\epsilon+1-\kappa+\kappa\eta}(1-\kappa)(1-\eta)\left[\grave{s}^w_{j'|i} + \grave{s}^N_{j'|i}\frac{\kappa(\eta-\sigma)}{\epsilon+1-\kappa+\kappa\sigma}\right] + \frac{\epsilon}{\epsilon+1-\kappa+\kappa\eta}(1-\kappa)(\eta-\sigma)\grave{s}^N_{j'|i} \tag{63}$$

We use this to derive non-tradable employment changes

$$\underline{\Delta\tilde{N}} =(1-\kappa)\rho\sum_{i=1}^{I} s_i^R \grave{N}_i \left[\frac{\epsilon}{\epsilon+1-\kappa+\kappa\eta}(1-\eta)\frac{\grave{s}_i^w}{s_i^R}\frac{\tilde{N}_i}{\grave{N}_i} + \frac{\epsilon}{\epsilon+1-\kappa+\kappa\eta}\frac{\epsilon+1-\kappa\eta+\kappa\sigma}{\epsilon+1-\kappa+\kappa\sigma}(\eta-\sigma)\frac{\tilde{N}_i}{\grave{N}_i}\right] \tag{64}$$

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 10 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[40] 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[41], and all 1-digit NACE revision 2 codes correspond to NACE revision 1.1 codes within either the tradable or the non-tradable group. We remove employment in industries Agriculture, Hunting and Forestry; Fishing; as well as Extraterritorial Organisations and Bodies from the dataset. Figure 5 shows the development of employment separately for the tradable and non-tradable sectors. It can be seen that employment has grown in both, but much more strongly so in the non-tradable sector.

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

Although occupation and industry data are typically available from 1993 onwards in the EU LFS, regional information only starts in 1999 for most countries. Furthermore, there are some countries (namely the Czech Republic, Germany, Denmark, Malta, Poland and Slovenia), where consistent regional data is only available in a later year: see Table 10. In Figures 3, 4, 5, 8, and 6, and Table 8, 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

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

Kingdom with aggregate Eurostat data[42], 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[43], which provide EU LFS employment data aggregated by Eurostat to the region-industry-year level.[44] 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.[45] Specifically, we use the following imputation method for regional employment in tradables over time (and analogously for regional employment in non-tradables over time):

$$N^g_{ijt} = N^g_{it} \times N^g_{j|\widetilde{it}}$$

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

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

Figure 6 shows the actual changes in employment shares[46] 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,

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

[43]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.

[44]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.

[45]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.

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

Table 10: Employment data coverage by country

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

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

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

A.2.2 Routine Task Intensity

The definition and data for the Routine Task Intensity (RTI) measure is described in section 2.1 in the main text. Table 2 in the main text shows the Routine Task Intensity of occupations: note that agricultural professionals (ISCO 6) and armed forces (ISCO 0) have been excluded from the dataset.

Further, Figure 7 shows that the decrease in the routine intensity of European employment documented in the paper is observed both in the sub-sample of 15 countries covered in Goos et al. (2014) and the 12 countries not included in the analysis in Goos et al. (2014).[47]

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

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

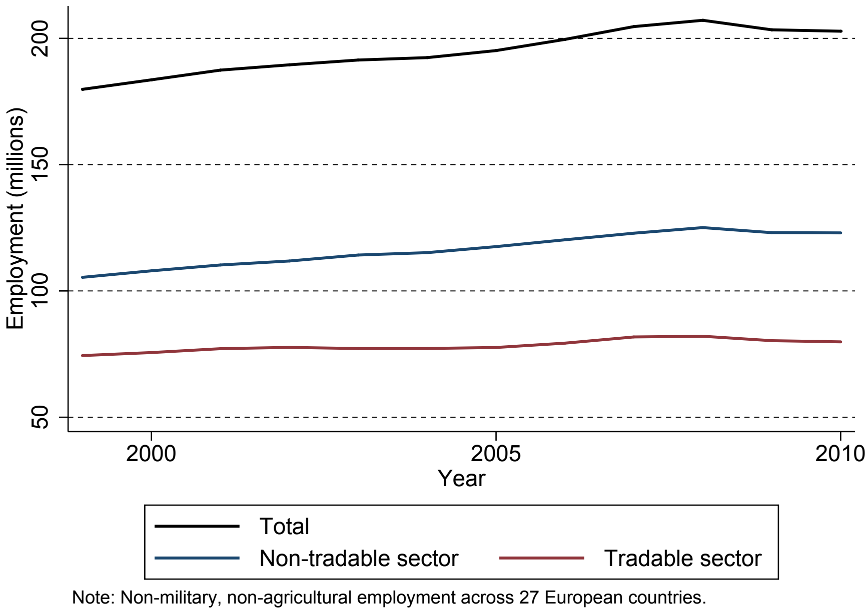
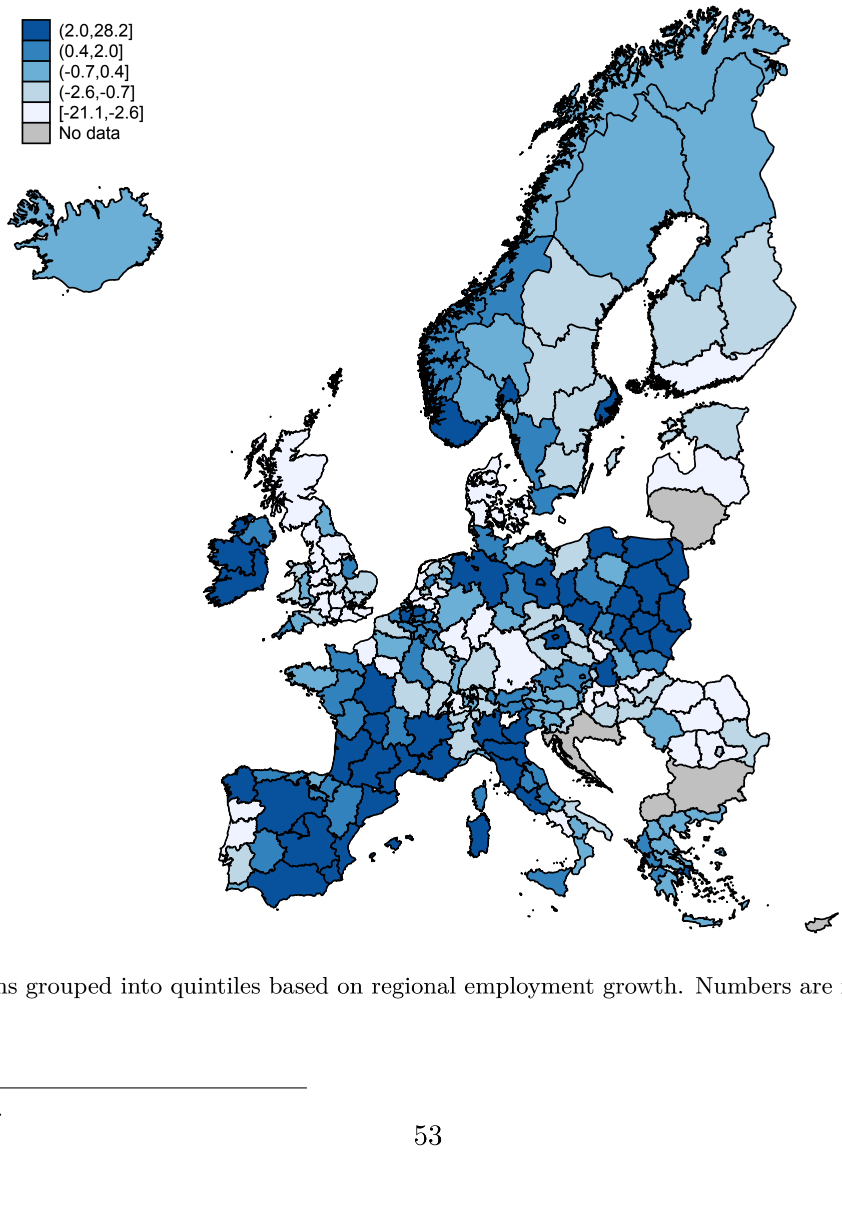


Figure 6: European regional employment growth, 1999-2010



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

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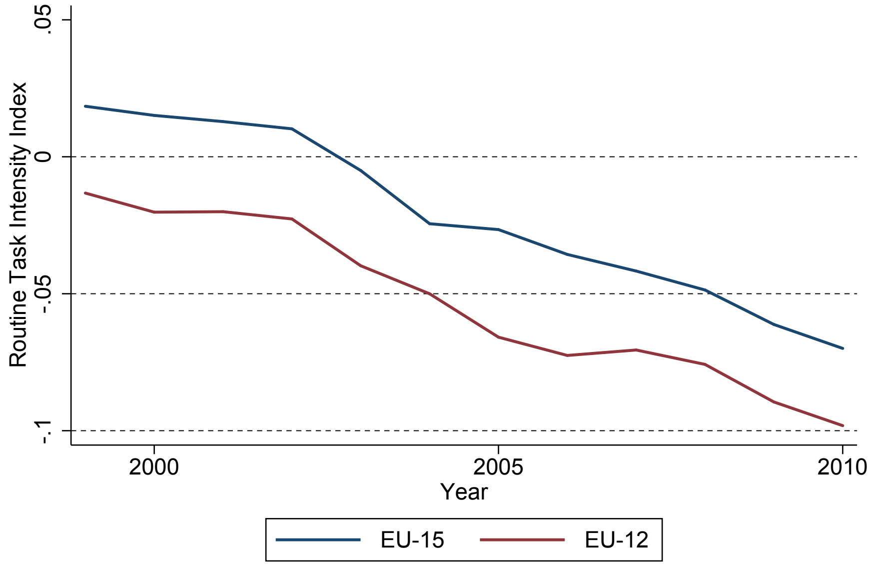
and Switzerland.

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

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



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

A.2.3 Output, marginal costs and capital stock

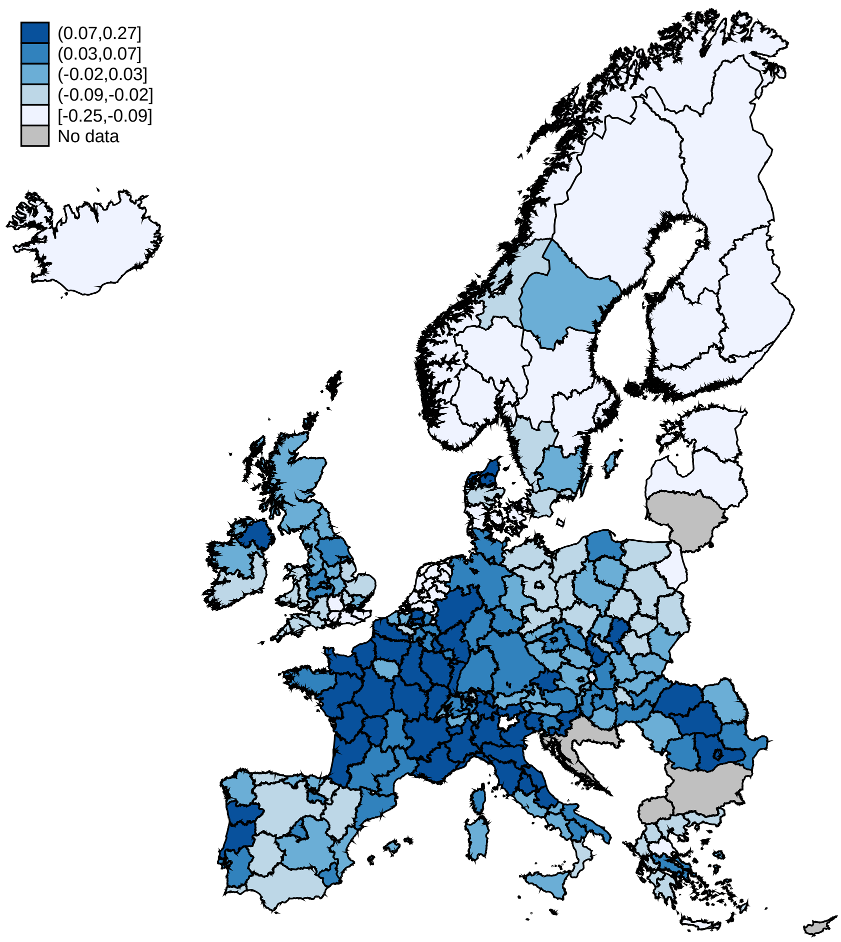
We construct measures of regional wages, marginal costs and production (in tradables) from the Cambridge Econometrics European Regional Database (ERD). This data is available for all 27 European countries mentioned in section 2.1 except Switzerland and Iceland.

For the construction of the instruments, we take industry-specific national data on marginal costs, production and capital stocks from OECD's structural analysis database (OECD STAN).[48] 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.[49] This requires resetting the baseyear from 2005 to 2000 in the revision 4 database,

[48] Available at `http://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm`.

[49] This is typically for years 2009 and 2010.

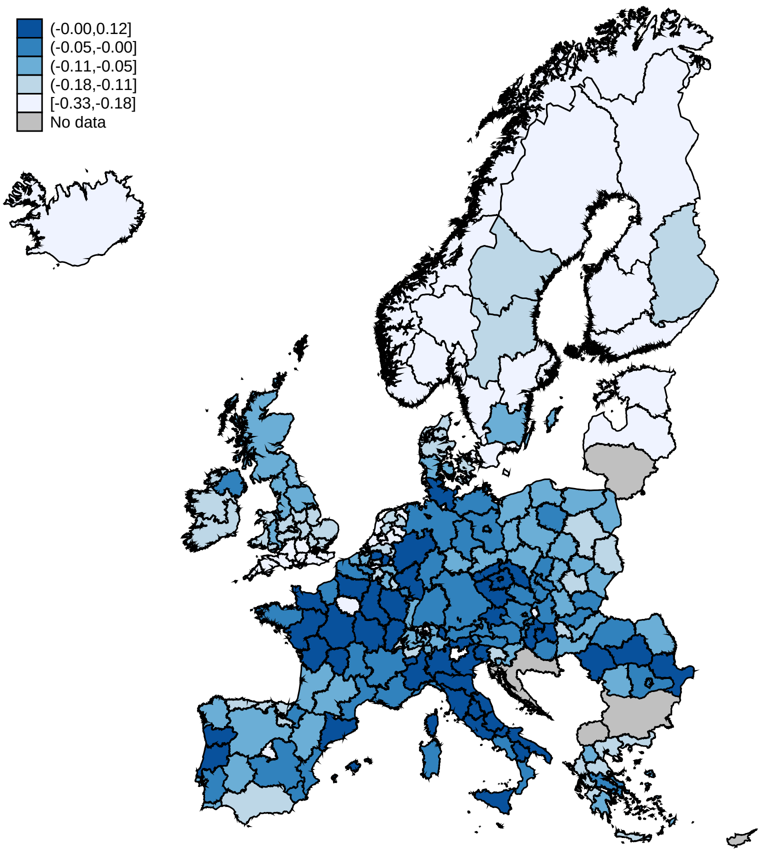
Figure 8: Spatial distribution of Routine Task Intensity (RTI) across European regions, 1999



Notes: Regions grouped into quintiles based on their RTI-index (see section 2.1 for more details on the construction of the RTI index.).

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 nominal production by industry-country-year varying deflators. Capital stock is defined as real net capital stock summed across all industries, deflated by country-year varying deflators.

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



Notes: Regions grouped into quintiles based on their RTI-index (see section 2.1 for more details on the construction of the RTI index.).

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.[50] 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.[51] These are reported in column 1 of Table 11. 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 11, which provide the level and change in ICT intensity for 15 Western European countries based on EUKLEMS data. These results are stable across countries.

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

[51]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 11: 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 and ERD, we do not know the trade costs to these regions. However, we have information on trade flows between all regions in Germany,[52] 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:

$$\grave{Y}_i = \grave{p}_i^{-\sigma} \sum_{i'=1}^{I'} \left(\frac{\tau_{ii'}}{\grave{P}_{i'}} \right)^{-\sigma} \mu \frac{I_{i'}}{\grave{P}_{i'}}, \tag{65}$$

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

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

$$\log \grave{Y}_i = -\sigma \log \grave{p}_i + \log \sum_{i'=1}^{I'} \left(\frac{\tau_{ii'}}{\grave{P}_{i'}} \right)^{-\sigma} \mu \frac{I_{i'}}{\grave{P}_{i'}} \tag{66}$$

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:

$$\log \grave{x}_{ii'} = -\sigma \log \grave{p}_i - \sigma \log \frac{\tau_{ii'}}{\grave{P}_{i'}} + \log \mu + \log \frac{I_{i'}}{\grave{P}_{i'}} \tag{67}$$

We translate this into a fixed-effects model:

$$\log \grave{x}_{ii't} = \beta_0 + \beta_{ii'} + \beta_1 timetrend + \beta_2 \log \frac{I_{i't}}{\grave{P}_{i't}} + \beta_3 \log c_{it} + \epsilon_{ii't} \tag{68}$$

We use the total real income of private households as a measure for $\frac{I_{i't}}{\grave{P}_{i't}}$[53] and we replace the regional price level $\grave{p}_{it}$ with regional marginal costs c_{it}.The trade-pair fixed effects $\beta_{ii'}$ in this equation contain estimates of $-\sigma \log \tau_{ii'}/\grave{P}_{i'}$, 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 real 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:[54]

$$\log \tilde{\tau_{ii'}} = \beta_0 + \beta_1 \log \text{distance}_{ii'} + \varepsilon_{ii'} \tag{69}$$

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

[53]Source: Statistical Offices of the Länder and the Federal Statistical Office of Germany.

[54]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:

$$\hat{\tau_{ii'}} = \frac{\hat{\tau^*_{ii'}}}{\sum_{i'=1}^{I}\sum_{i=1}^{I}\hat{\tau^*_{ii'}}} \tag{70}$$

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

$$\text{MP}_{it} = \sum_{i'=1}^{I} \hat{\tau_{ii'}} \frac{I_{i't}}{\grave{P}_{i't}} \tag{71}$$

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 as a measure for $I_{i'}$. To construct our IV for market potential, we replace $I_{i'}$ with predicted regional income or with the regional net capital stock, see section 3.7.

A.3.3 First-stage estimates

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

Table 12: Labor demand in the tradable sector: first stages

Dependent variable:	Log regional production	Log regional marginal costs	Log regional wage
	(1)	(2)	(3)
FE-IV 1			
Bartik IV for regional production	0.571***	0.133**	0.469***
	(0.059)	(0.067)	(0.056)
Bartik IV for regional marginal costs	-0.112	0.492***	-0.036
	(0.135)	(0.141)	(0.180)
Female labor supply shock	0.108	0.002	-0.563***
	(0.094)	(0.098)	(0.126)
F-Test of excl. instruments	74.819	6.477	49.426
Sanderson-Windmeijer F-Test of excl. instruments	25.590	10.044	36.764
FE-IV 2			
Bartik IV for regional production (based on capital stock)	0.212**	-0.029	0.331***
	(0.100)	(0.078)	(0.113)
Bartik IV for regional marginal costs	-0.210	0.497***	-0.173
	(0.146)	(0.145)	(0.185)
Female labor supply shock	0.351***	0.066	-0.375***
	(0.101)	(0.090)	(0.131)
F-Test of excl. instruments	8.016	5.141	14.658
Sanderson-Windmeijer F-Test of excl. instruments	12.697	7.335	8.360
FE-IV 3			
Bartik IV for regional production	0.569***	0.169**	0.467***
	(0.060)	(0.069)	(0.063)
Bartik IV for regional marginal costs (based on components)	-0.030	0.458***	-0.026
	(0.155)	(0.156)	(0.153)
Female labor supply shock	0.091	0.011	-0.565***
	(0.092)	(0.101)	(0.119)
F-Test of excl. instruments	79.661	5.869	44.093
Sanderson-Windmeijer F-Test of excl. instruments	20.059	5.598	30.322
FE-IV 4			
Bartik IV for regional production (based on capital stock)	0.216**	0.005	0.344***
	(0.102)	(0.082)	(0.122)
Bartik IV for regional marginal costs (based on components)	-0.251	0.408**	-0.252*
	(0.165)	(0.161)	(0.149)
Female labor supply shock	0.349***	0.095	-0.371***
	(0.097)	(0.092)	(0.122)
F-Test of excl. instruments	8.509	3.676	14.457
Sanderson-Windmeijer F-Test of excl. instruments	15.605	4.932	6.342

Notes: First stage estimates of models in columns (4)-(7) in Table 4. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 13: Product demand in the tradable sector: first stages

Dependent variable:	Log regional market potential (1)	Log regional marginal costs (2)
	FE-IV 1	
IV for log regional marginal costs	0.322***	-0.037***
	(0.120)	(0.012)
IV for log regional market potential	-0.366***	0.820***
	(0.112)	(0.014)
F-Test of excl. instruments	5.363	18344.425
Sanderson-Windmeijer F-Test of excl. instruments	7.049	18.577
	FE-IV 2	
IV for log regional marginal costs	0.491***	0.184***
	(0.125)	(0.019)
IV for log regional market potential (based on capital stocks)	-0.563***	0.588***
	(0.111)	(0.020)
F-Test of excl. instruments	13.217	5906.440
Sanderson-Windmeijer F-Test of excl. instruments	19.537	89.085
	FE-IV 3	
IV for log regional marginal costs (based on components)	0.294**	-0.010
	(0.121)	(0.011)
IV for log regional market potential	-0.334***	0.797***
	(0.111)	(0.013)
F-Test of excl. instruments	4.559	22120.386
Sanderson-Windmeijer F-Test of excl. instruments	5.881	20.097
	FE-IV 4	
IV for log regional marginal costs (based on components)	0.453***	0.144***
	(0.132)	(0.020)
IV for log regional market potential (based on capital stocks)	-0.519***	0.628***
	(0.118)	(0.021)
F-Test of excl. instruments	10.069	7155.010
Sanderson-Windmeijer F-Test of excl. instruments	13.915	82.263

Notes: N=2020 in all models. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. First stage estimates of models in columns (2)-(5) in Table 5.

A.3.4 Rotemberg Weights

Bartik estimators combine many instruments using a particular weight matrix. In our case, the Bartik estimator uses 72 instruments (12 years x 6 tradable industries). In order to make transparent, which of these instruments is driving the results, we follow the suggestion by Goldsmith-Pinkham et al. (2018) and calculate Rotemberg weights (which sum up to one) that allow to asses the contribution of single instruments in driving the overall variation of the Bartik IV. For this, Table 14 shows the Rotemberg weights (column 1) of the top five instruments related to regional production and regional marginal costs from the labor demand estimates. Column (2) shows the national industry shift, g_k, column (3) the coefficient from the just-identified regression, β_k, and column (4) the share of α_k among its sum (over all positive weights), $\hat{\alpha_k}$.

The results show that the Bartik IV for regional production is driven by events in manufacturing and real estate as well as events related to the years 2006, 2007 and 2008. The top five instruments account for 65% of the the positive weights. For the regional marginal costs, the top five instruments contain manufacturing, transport and real estate as well as the years 1999, 2009 and 2010, accounting for 63% of the positive weights. Table 14 shows that similar events are driving the variation of the Bartik instruments for regional marginal costs and regional market potential in the product demand equation.

The large weights for manufacturing are as expected, since manufacturing is dominating the tradable sector and thus should also play a large role in the IVs. The large role of the pre-crisis years, however, might indicate sensitivity of our results to business cycles. We therefore check the robustness of our results to business cycle interactions in Appendix A.4.2 and find that our results remain robust.

Table 14: Labor demand in the tradable sector: rotemberg weights

Top five Rotemberg weight industries	α_k (1)	g_k (2)	β_k (3)	$\hat{\alpha_k}$ (4)
Regional production		in bil.		
D Manufacturing, 2007	3.095	191.184	0.203	0.217
D Manufacturing, 2008	1.839	186.488	0.161	0.129
K Real estate, renting and business activities, 2007	1.792	114.012	0.166	0.126
D Manufacturing, 2006	1.577	188.774	0.088	0.111
K Real estate, renting and business activities, 2008	1.031	117.669	0.066	0.072
Total (top five):				0.655
Regional marginal costs				
D Manufacturing, 2010	122.309	1.274	0.320	0.350
I Transport, storage and communications, 2010	29.300	1.138	0.349	0.084
D Manufacturing, 2009	27.952	1.089	-0.288	0.080
K Real estate, renting and business activities, 2010	24.915	0.931	0.466	0.071
D Manufacturing, 1999	15.941	0.896	2.579	0.046
Total (top five):				0.630

Notes: Table reports the top five industries according to the Rotemberg weights. The g_k is the national industry shift, β_k is the coefficient from the just-identified regression and $\hat{\alpha_k}$ is the share of α_k among its sum over all positive weights.

Table 15: Product demand in the tradable sector: rotemberg weights

Top five Rotemberg weight industries	α_k (1)	g_k (2)	β_k (3)	$\hat{\alpha_k}$ (4)
Regional marginal costs				
D Manufacturing, 2010	9.266	1.046	0.342	0.404
I Transport, storage and communications, 2010	3.208	1.075	0.412	0.140
K Real estate, renting and business activities, 2010	2.287	0.978	0.712	0.100
D Manufacturing, 2009	1.389	1.023	1.732	0.061
J Financial intermediation, 2010	0.841	0.853	0.667	0.037
Total (top five):				0.741
Regional market potential		in bil.		
D Manufacturing, 2008	0.660	146.480	1.362	0.148
D Manufacturing, 2007	0.552	141.688	1.464	0.124
D Manufacturing, 2010	0.414	134.874	1.060	0.093
K Real estate, renting and business activities, 2008	0.312	68.996	1.366	0.070
D Manufacturing, 2006	0.274	133.352	1.424	0.062
Total (top five):				0.497

Notes: Table reports the top five industries according to the Rotemberg weights. The g_k is the national industry shift, β_k is the coefficient from the just-identified regression and $\hat{\alpha_k}$ is the share of α_k among its sum over all positive weights.

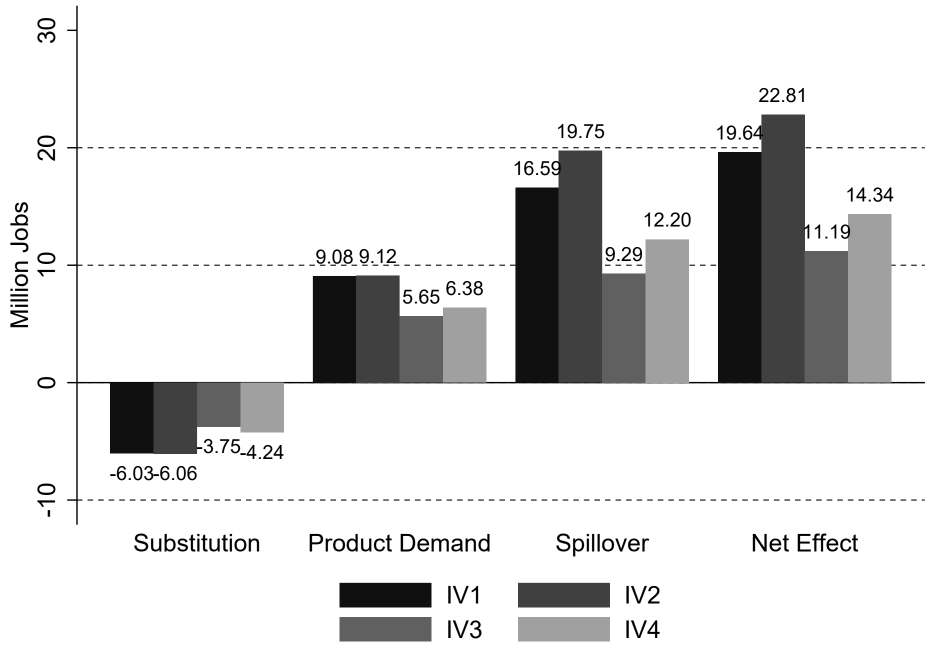
A.4 Empirical robustness checks

This appendix provides further empirical robustness checks.

A.4.1 Alternative parameter estimates

This section presents robustness checks using parameter estimates from our specifications with alternative IVs. We first consider the parameters obtained from the labor demand equation, i.e.

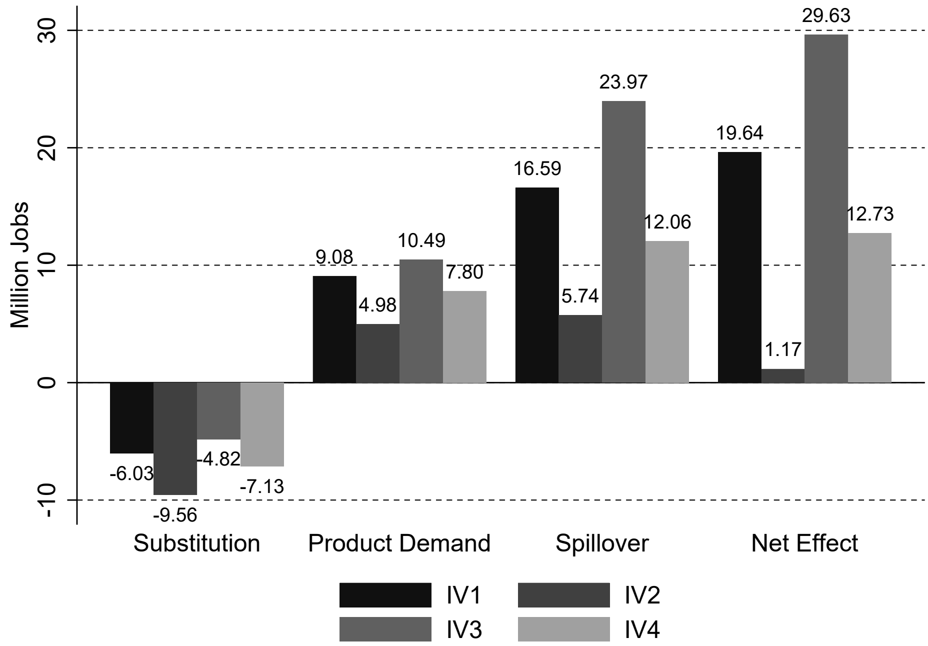
Figure 10: Robustness check: alternative labor demand estimates



ρ, κ and η. These parameter estimates are computed from the four IV specifications in Table 4, including the baseline and three alternative IV specifications. Firstly, note that the routinization coefficient $(1-\eta)(1-\kappa)\rho$ is identical across all IV specifications and thus remarkably stable. The estimated substitution elasticity between tasks, η, varies between 0.321 (IV3) and 0.676 (IV2), whereas it is 0.615 in the baseline (IV1). While all values lie within the expected range, the estimates are much smaller when using our alternative IV for marginal costs (IV3 and IV4). This is potentially due to the alternative IV for marginal costs being less able to capture variations in actual marginal costs due to differences in definitions. We nevertheless check the robustness of our results to using this alternative IV. The wage elasticity of labor demand varies between -0.546 (IV4) and -0.773 (IV3), whereas it is -0.733 in our baseline (IV1).

Figure 10 reports point estimates for the net employment effects and all three channels using our baseline (IV1), as well as the three alternatives (IV2, IV3, and IV4) in the labor demand equation. Note that all predictions shown in this figure still use our baseline product demand elasticity (σ) of 1.505 for now. The predicted net employment effect is both qualitatively identical and quantitatively similar for all four parameter sets, ranging between 11.19 (IV3) and 22.81 (IV2) million jobs compared to 19.64 in the baseline. Our effects thus are robust despite variations of the wage elasticity of labor demand and of the elasticity of substitution between tasks. This is because of the remarkable stability of our main estimate, the routinization effect

Figure 11: Robustness check: alternative product demand estimate

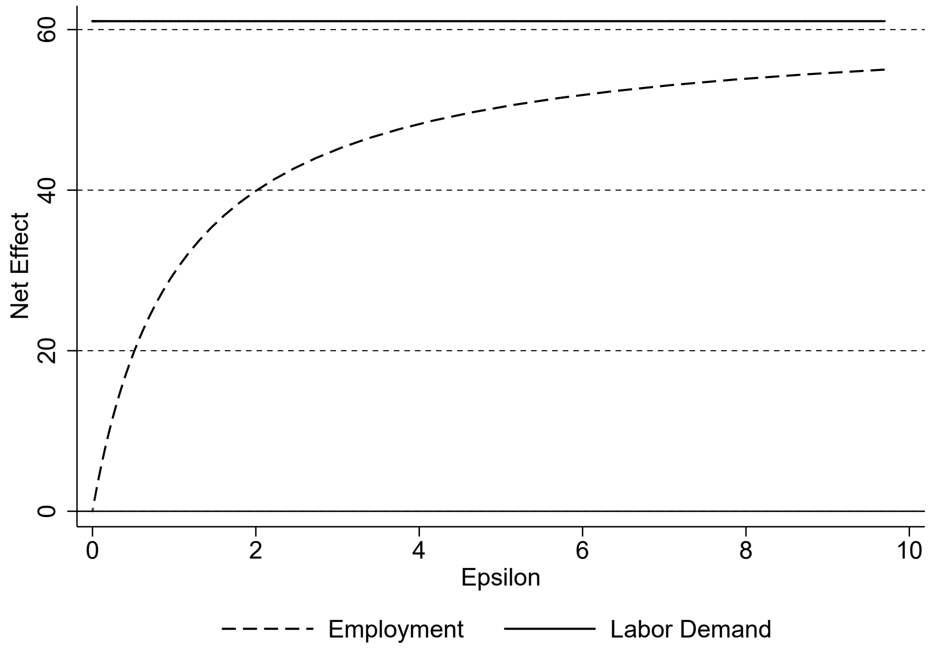


$(1-\eta)(1-\kappa)\rho$, across all specifications.

We additionally take alternative values for σ, the product demand elasticity parameter estimated in Table 5. We again compare three alternative constellations of IVs to our baseline specification (IV1). The estimated elasticity ranges between 0.521 (IV2) and 2.175 (IV3), as compared to 1.505 (IV1) in our baseline. The estimates again are smaller when using the alternative IV for marginal costs, which relies on a different definition of marginal costs and thus likely is worse at predicting actual marginal costs. We nevertheless use these estimates to check for the robustness of our results. Figure 11 implements the three alternative specifications (IV2-IV4) along with the baseline specification (IV1) from the product demand equation. For this figure, we rely on the baseline specification from the labor demand equation. Due to the wide range of the estimate for σ, also the estimated employment effects vary. However, they remain positive in all specifications. In fact, all effects remain their sign, so that our results remain qualitatively the same. This highlights the robustness of our results even when using a less-suited IV for marginal costs.

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

Figure 12: Robustness check: labor supply elasticity



of ϵ from 0 to 10. Lastly, Appendix A.4.2 shows that our labor and product demand parameter estimates do not vary substantially across the economic cycle.

All in all, the results presented here show that our baseline effects (reported in section 5) are robust to alternative parameter configurations.

A.4.2 Business cycles

Our theoretical model examines how RRTC impacts long-run labor demand, and does not consider business cycles. Indeed, we model technological progress as a task measure interacted with a linear timetrend to capture a steady secular process, implying we should pool information across the economic cycle. Indeed, there have been both booms and recessions over our observation window 1999-2010, and as a robustness check we examine whether our parameter estimates are significantly different across different parts of the economic cycle. This appendix therefore presents estimates of our labor and product demand equations where our respective independent variables have been interacted with a dummy for recession and/or boom years. In particular, we obtain country-specific business cycle indicators from the OECD, which classifies years as peaks, troughs, or neither, for each country in our sample: around 20 percent of years are peak years, 20 percent are troughs, and the remainder is neither.[55]

[55]The OECD does not have indicators for Iceland, Latvia, and Romania– for these countries, we use indicators for the UK, Estonia, and Hungary, respectively. Results are robust to alternatively constructing a business cycle

Table 16: Labor demand in the tradable sector: business cycle interactions

Dependent variable: log employment in tradable sector (in region-occupation-year cells)	FE (1)	FE-IV 1 (2)	FE-IV 2 (3)	FE-IV 3 (4)	FE-IV 4 (5)
Dummy for routine occupations × linear time trend	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dummy for routine occupations × linear time trend × trough dummy	0.000*	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dummy for routine occupations × linear time trend × peak dummy	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log regional production	0.487***	0.363	0.280	0.655**	-0.139
	(0.055)	(0.332)	(0.584)	(0.310)	(7.638)
Log reginoal marginal costs	0.276***	0.728**	-0.116	0.310	-7.540
	(0.053)	(0.371)	(1.678)	(0.443)	(70.225)
Log regional marginal costs × trough dummy	0.016	-0.005	0.938	0.240	7.128
	(0.019)	(0.272)	(1.881)	(0.305)	(59.608)
Log regional marginal costs × peak dummy	0.024	0.487	-0.282	0.031	-4.437
	(0.033)	(0.612)	(0.877)	(0.597)	(38.394)
Log regional wages	-0.396***	-0.856***	-0.731**	-0.693***	-0.355
	(0.064)	(0.288)	(0.310)	(0.241)	(2.931)
Log regional wages × trough dummy	0.002	0.079	0.422	0.139	2.869
	(0.005)	(0.071)	(0.690)	(0.097)	(24.724)
Log regional wages × peak dummy	0.009	0.317	0.040	0.104	-1.323
	(0.008)	(0.298)	(0.225)	(0.273)	(12.626)
Trough dummy	-0.024	-0.829	-4.298	-1.415	-29.152
	(0.049)	(0.719)	(7.026)	(0.989)	(251.331)
Peak dummy	-0.108	-3.250	-0.447	-1.092	13.337
	(0.078)	(3.034)	(2.274)	(2.780)	(127.594)
Constant	-20.850***				
	(2.684)				
N	12096	12096	12096	12096	12096
R-squared	0.141	-0.037	-0.236	0.106	-32.653

Notes: European regions, 1999-2010. This table plots models from columns (3)-(7) from Table 4, where parameters of interest are interacted with peaks and troughs. Standard errors clustered by region reported in parentheses.

Table 16 shows estimates of the labor demand equation, allowing our parameters of interest including the routinization coefficient ($(1-\eta)(1-\kappa)\rho$) as well as the coefficient on regional marginal cost (η) and regional wages ($-[(1-\kappa)+\kappa\eta]$) to differ during peaks and troughs. Overall, it can be seen that our parameters of interest are not significantly different in recession or trough years. Moreover, the coefficients for all parameters of interest in our preferred specification (column 2) that we use for our main employment effects are very similar compared to our non-interacted results in Table 4.

Table 17 contains the corresponding product demand estimates: also here, we do not find statistically significant deviations for our estimated σ parameter during peaks or troughs. Also, σ is very similar in size compared to Table (5).

In conclusion, we do not find evidence to suggest our parameter estimates are affected by

indicator common across countries, where a year is classified as a peak or trough if it is classified as such for at least half of all countries in our sample.

Table 17: Product demand in the tradable sector: business cycle interactions

Dependent variable: log regional production of tradables (in region-year cells)	FE (1)	FE-IV 1 (2)	FE-IV 2 (3)	FE-IV 3 (4)	FE-IV 4 (5)
Log regional marginal costs	-0.288***	-1.620**	-0.903	-0.990	-0.524
	(0.059)	(0.735)	(0.628)	(0.604)	(0.440)
Log regional marginal costs × trough dummy	-0.012	0.511	0.479	-1.262	-1.048*
	(0.016)	(1.008)	(0.816)	(0.818)	(0.586)
Log regional marginal costs × peak dummy	-0.007	-0.970	-0.568	-1.507	-0.936
	(0.012)	(0.728)	(0.588)	(1.518)	(1.309)
Log regional market potential	1.222***	1.058***	1.065***	1.199***	1.163***
	(0.063)	(0.145)	(0.115)	(0.139)	(0.088)
Peak dummy	-0.011***	-0.022**	-0.015**	-0.024	-0.020
	(0.003)	(0.009)	(0.007)	(0.020)	(0.016)
Trough dummy	-0.001	0.034	0.020	0.037	0.021
	(0.002)	(0.033)	(0.025)	(0.043)	(0.036)
Constant	3.503***				
	(0.301)				
N	2080	2080	2080	2080	2080
R-squared	0.630	-1.393	-0.027	-2.008	-0.495

Notes: European regions, 2001-2010. This table plots all models from Table 5, where parameters of interest are interacted with peaks and troughs.Standard errors clustered by region reported in parentheses.

pooling both recession and boom years.