

RACING WITH OR AGAINST THE MACHINE? EVIDENCE ON THE ROLE OF TRADE IN EUROPE

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Abstract

Digital technologies displace labor from routine tasks, raising concerns that labor is racing against the machine. We develop an empirically tractable task-based framework to estimate the aggregate employment effects of routine-replacing technological change (RRTC), along with the labor and product demand channels through which this aggregate effect comes about, focusing on the role of inter-regional trade. While RRTC has indeed had strong displacement effects in Europe between 1999 and 2010, it has simultaneously created new jobs through increased product demand, resulting in net employment growth. However, the distribution of gains from technological progress matters for its job-creating potential. (JEL: E24, J23, J24, O33)

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1. Introduction

In recent years, rapid improvements in digital technologies such as information and communications technology (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 one hand, there are alarmists arguing that automation will lead to the end of work. These views are fueled by reports zooming in on the automation potential of existing jobs, claiming that large shares of US 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 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, Levy, and Murnane 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, for example, 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, Benzell, and LaGarda 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

1. Although Arntz, Gregory, and Zierahn (2017) show that these “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, Manning, and Salomons (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 that 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).

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 employment by developing and estimating an empirically tractable framework. This task-based framework builds on Autor and Dorn (2013) and Goos, Manning, and Salomons (2014), and incorporates three main channels through which RRTC affects employment. First, RRTC reduces employment through *labor-saving 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 toward routine tasks, for a given level of output. Second, RRTC induces additional employment 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 employment: The increase in product demand raises incomes, which is partially spent on low-tech non-tradables, raising local employment. We further investigate how these spillovers depend on the allocation of gains from technological progress by considering the role of profits in producing these spillovers, inspired by a theoretical literature emphasizing this channel (Benzell et al. 2016; Freeman 2015; Sachs, Benzell, and LaGarda 2015). The first of these three forces acts to reduce employment, whereas the latter two go in the opposite direction. In an autarky setting, the employment effect of RRTC would be unambiguously positive. However, as we demonstrate, if regions trade, RRTC-induced improvements in terms of trade and rising demand for regional tradable output may not be sufficient to compensate direct labor savings, resulting in net negative employment effects. As such, the net employment effect of RRTC is theoretically ambiguous. We use data over the period 1999–2010 for 238 regions across 27 European countries to construct an empirical estimate of the economy-wide effect of RRTC on 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 channels outlined above.

This contributes to the literature in several ways. First, ours is the first estimate of the effect of routine-replacing technologies on economy-wide employment.⁴ As outlined in Autor, Levy, and Murnane (2003), routine-task replacement is the very nature of digital technology, making this especially relevant to study. Our approach complements work that has taken either a more narrow view by considering industrial robotics in isolation (Acemoglu and Restrepo 2017; Chiacchio, Petropoulos, and Pichler 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 also empirically quantify the relevance of the underlying transmission channels derived from our framework. As such, we study both the labor-displacing effects and the countervailing effects of RRTC highlighted in the theoretical

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

literature in an empirically tractable manner. This complements 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 employment is 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, Petropoulos, and Pichler (2018) find 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 employment effects of RRTC 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 employment changes into the three separate channels reveals a substantial decrease in 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 labor-saving 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.

Our baseline estimates are a lower bound because we abstract from rising profits feeding back into local demand. We additionally provide an upper bound where we assume that all firm profits are spent locally. The difference between these two estimates highlights that the allocation of the gains from technological progress matters for whether labor is racing with the machine.

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

2. Framework

We develop a structural model that serves as a framework to estimate the net employment effect of RRTC, and decompose this net effect into the main underlying mechanisms.

Our framework consists of $i = 1, 2, \dots, I$ regions, where each region has a non-tradable and a tradable sector (see Table 1 in Section 3.1 for our definition of sectors). Firms in the tradable sector produce goods and services by combining a set of occupational tasks that 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, Manning, and Salomons (2014).⁵ 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-intensive and have seen faster ICT-adoption than non-tradables such as personal services (see Table A.2 in Online Appendix A.3.1).⁶

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 to be potentially important,⁷ 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 regional trade.⁸ Finally, this approach allows us to compare our model's predictions to actually observed employment changes using regional variation.

We first develop our model and explain the underlying mechanisms of how RRTC affects employment, to then derive decompositions that serve to estimate (1) the overall net effect of RRTC on employment and (2) the contributions of the underlying mechanisms.

5. Note, however, that the framework in Goos, Konings, and Vandeweyer (2015) does not include a regional dimension, nor distinguishes tradables from non-tradables.

6. Furthermore, we find that only 13% of employment in non-tradables is in routine occupations, as compared to 33% in tradables.

7. 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 United States (Moretti 2010; Moretti and Thulin 2013) and Europe (Goos, Konings, and Vandeweyer 2015).

8. 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 US (Autor, Dorn, and Hanson 2013; Caliendo, Dvorkin, and Parro 2019) and German regions (Dauth, Findeisen, and Suedekum 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 over time (Autor, Dorn, and Hanson 2015).

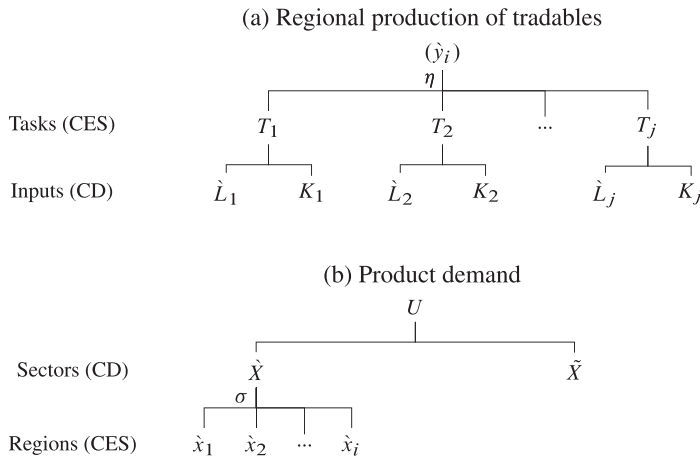


FIGURE 1. Regional production and demand structure.

2.1. Production of Tradables

The production structure in the tradable sector is depicted in Figure 1(a). The representative firm in the tradable sector in region i produces a variety \hat{y}_i that can be traded across regions, where $\hat{\cdot}$ denotes tradable sector variables. We assume monopolistic competition between firms within regions in our baseline model, so that prices are a constant markup over marginal costs. (We relax this assumption in Section 2.6.) \hat{Y}_i refers to the bundle of tradable goods of region i 's firms. The production of tradables requires a set of tasks (equal to occupations) $T_j, j = 1, 2, \dots, J$, some of which are routine and are thus prone to substitution by computerized capital. Note that we drop the symbol $\hat{\cdot}$ over letters for simplicity whenever there is no corresponding variable in the non-tradable sector. These tasks are combined to produce tradable output \hat{Y}_i with a constant elasticity of substitution (CES) production technology, $\hat{Y}_i = [\sum_{j=1}^J (\hat{\beta}_{ij} T_{ij})^{(\eta-1)/\eta}]^{\eta/(\eta-1)}$, where $0 < \eta < 1$ is the elasticity of substitution between tasks, reflecting to what extent firms may substitute one task for another.⁹ The term $\hat{\beta}_{ij}$ captures region i 's efficiency in performing task j . Each task is performed by a combination of task-specific human labor and machines (technological capital). We assume a Cobb–Douglas (CD) production technology, $T_{ij} = (\hat{L}_{ij})^\kappa (K_{ij})^{1-\kappa}$, where the production of tasks depends on labor \hat{L}_j from occupation j , task-specific capital inputs K_j , and the share of labor in the costs of producing a task, $0 < \kappa < 1$.

9. 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 rather than decrease. Moreover, existing estimates of η (as well as our estimates) suggest that it is indeed well below unity.

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

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

which rises in tradable output \hat{Y}_i , in the efficiency of that task $\hat{\beta}_{ij}$, and in the ratio of regional marginal costs c_i relative to the task-specific costs $\hat{w}_{ij}^\kappa r_j^{1-\kappa}$, to the extent that tasks can be substituted (η). \hat{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 (1) shows that, as relative capital costs for routine tasks decrease, the representative firm shifts its tradable production toward these tasks.

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

$$\hat{L}_{ij} = T_{ij} \left(\frac{r_j}{\hat{w}_{ij}} \frac{\kappa}{1-\kappa} \right)^{1-\kappa}, \quad (2)$$

which rises in the demand for tasks in that region T_{ij} as well as in task-specific capital costs r_j relative to occupational wages \hat{w}_{ij} . From equation (2), it can be seen that occupational labor demand decreases with falling capital costs for routine tasks, reflecting that the firm substitutes capital for human labor in routine tasks.¹⁰

Labor-Saving Effects. The above production structure leads to our first channel: RRTC affects labor demand through labor saving for a given level of output, where workers are replaced by machines in the production of routine tasks, as seen from the direct positive relationship between r_j and \hat{L}_{ij} in equation (2). This effect is further reinforced as firms shift their production technology toward routine task inputs, represented by the indirect negative relationship between r_j and \hat{L}_{ij} working through T_{ij} in equation (2).¹¹ The intuition behind our labor-saving effect is that RRTC reduces the number of workers who are required to produce a given level of output. Rising output due to improving terms of trade counteracts this effect—we study this product demand response next.

2.2. Consumption

The product demand structure is depicted in Figure 1(b). We assume that the utility of households depends on the consumption of tradables \hat{X} and non-tradables $\hat{\tilde{X}}$

10. Although labor and capital are p -substitutes in the production of tasks in our framework, they can be either gross complements or gross substitutes.

11. These shifts correspond 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 part alone is unable to explain key features of automation technologies. We therefore also take into account direct capital–labor substitution.

(where $\tilde{\cdot}$ denotes non-tradable sector variables) and follows a CD utility function: $U = \tilde{X}^\mu \tilde{X}^{1-\mu}$, where $0 < \mu < 1$ is the expenditure share of tradables.¹² Non-tradables are consumed locally, and are—without loss of generality—assumed to be homogeneous. Tradables are composed of local bundles \hat{x}_i , produced by local firms, and are consumed by households from all regions worldwide. We assume that preferences for tradables follow a CES utility function, $\hat{X} = [\sum_{i=1}^I \hat{x}_i^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$, 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 ,

$$\hat{x}_{ii'} = \left(\frac{\tau_{ii'} \hat{p}_i}{\hat{P}_{i'}} \right)^{-\sigma} \mu \frac{I_{i'}}{\hat{P}_{i'}}, \quad (3)$$

where $\hat{P}_{i'}$ is an aggregated price index and \hat{p}_i are local producer prices in the tradable sector. We assume that the producer region i is too small to either affect the price index or the income in the consumer region i' —regions are too small to affect the size of the world market. $\tau_{ii'}$ are iceberg trade costs between the exporting i and importing i' regions. Equation (3) shows that consumption of tradables rises with households' real income $I_{i'}/\hat{P}_{i'}$ and with the share of income spent on these tradables μ . Moreover, consumption of tradables decreases in the relative price for these goods and services $\hat{p}_i/\hat{P}_{i'}$ 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 labor-saving effects) allows firms to reduce costs, which lowers the output prices of tradables, improving regions' terms of trade. Product demand for tradables rises as a result of lower output prices, as seen from the negative relationship between $\hat{p}_i/\hat{P}_{i'}$ and $\hat{x}_{ii'}$ in equation (3). This leads to higher output and income, inducing additional labor demand in the tradable sector. This product demand effect of RRTC thus raises labor demand.¹³

12. By relying on CD utility, we assume homothetic preferences and thus that technology-induced price declines of tradables do not affect the expenditure shares of tradables and non-tradables. We study elastic substitution in demand in Online Appendix A.5.2. In another extension (available on request), we introduce non-homothetic preferences, relaxing the restriction that $\delta_{MP} = 1$ in empirical equation (16). However, empirically, non-homothetic preferences have been found to have only small effects on relative task demand (Autor and Dorn 2013; Goos, Manning, and Salomons 2014), and our results also indicate no significant divergence, so that we do not pursue this extension further.

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

2.3. 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 $j = 1, \dots, J$, $\tilde{L}_i = [\sum_{j=1}^J (\tilde{\beta}_{ij} \tilde{L}_{ij})^{(\eta-1)/\eta}]^{\eta/(\eta-1)}$ 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 is then given by

$$\tilde{L}_{ij} = (1 - \mu) \tilde{\beta}_{ij}^{1-\eta} \left(\frac{\tilde{w}_{ij}}{\tilde{w}_i} \right)^{-\eta} \frac{I_i}{\tilde{w}_i}. \quad (4)$$

Labor demand generally decreases with average wages in the non-tradable sector \tilde{w}_i and increases with local income I_i . Occupational labor demand 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 labor demand in equation (4) only indirectly through its effect on local income.

Local income I_i is composed of the sum of income in the non-tradable and tradable sectors, $I_i = \tilde{w}_i \tilde{L}_i + \kappa \dot{p}_i \dot{Y}_i$. Tradable sector income $\kappa \dot{p}_i \dot{Y}_i$ and non-tradable sector income $\tilde{w}_i \tilde{L}_i$ consist only of labor income. We assume that tradable sector firms rent capital from the international capital market and that regions are too small to affect the size of that market. RRTC thus affects local income and, hence, labor demand in the non-tradable sector by affecting tradable sector income $\kappa \dot{p}_i \dot{Y}_i$.

Product Demand Spillover Effect. This leads to the third channel through which RRTC impacts labor demand. In particular, RRTC affects income in the tradable sector, which results in a demand spillover effect as changes in local income affect demand for local non-tradables. This can be seen from the positive relationship between I_i and \tilde{L}_{ij} in equation (4). Changes in demand for local non-tradables affect output and labor demand in the local non-tradable sector. These spillovers are larger in regions with a higher initial share of routine tasks. If RRTC raises (reduces) local tradable income, this induces positive (negative) spillovers to the non-tradable sector.

2.4. Labor and Product Demand

We combine equations (1) and (2) from the production of tradables as well as equation (4) from the production of non-tradables to derive labor demand in the tradable and non-tradable sectors (see Online Appendix A.1.1 for details on these

derivations):

$$\begin{aligned} \log \dot{\tilde{L}}_{ij} = & \log \dot{Y}_i + (\eta - 1) \log \dot{\beta}_{ij} + \eta \log \frac{c_i}{\dot{w}_{ij}} + (1 - \kappa) \log \frac{\kappa}{1 - \kappa} \\ & + (1 - \eta)(1 - \kappa) \log \frac{r_j}{\dot{w}_{ij}}, \end{aligned} \quad (5)$$

$$\begin{aligned} \log \tilde{L}_{ij} = & \log \dot{p}_i \dot{Y}_i + (\eta - 1) \log \tilde{\beta}_{ij} + (\eta - 1) \log \tilde{w}_i + \log \frac{1 - \mu}{\mu} \\ & - \eta \log \tilde{w}_{ij}. \end{aligned} \quad (6)$$

Note that we do not observe task-specific capital costs r_j . In order to empirically incorporate a decline in the capital-to-labor factor price ratio for routine relative to non-routine tasks, we replace relative log capital costs by $\rho d_j^R \times t$, where d_j^R is a dummy indicator for the occupation containing sufficient routine tasks to be susceptible to machine substitution.¹⁴ This approach follows a literature that uses trends in routine task intensity (RTI) as a proxy for falling computer costs or, analogously, rising efficiency of computers (see e.g. Autor and Dorn 2009, 2013; Goos, Manning, and Salomons 2014). The approach is motivated by empirical evidence showing that RTI is strongly predictive of subsequent computer adoption (see Autor, Levy, and Murnane 2003). The term ρ reflects the change of the capital-to-labor factor price ratio for routine tasks, relative to non-routine tasks. This implies that we analyze the decline of relative capital costs for performing routine occupations compared to relative capital price changes for non-routine tasks as the baseline. 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.

Labor demand depends on output in the tradable sector, \dot{Y}_i . We derive the product demand equation for the tradable sector from equation (3) as the sum of demand across all destinations¹⁵ assuming monopolistic competition:

$$\log \dot{Y}_i = \log \mu - \sigma \log c_i + \log \sum_{i'=1}^{I'+RoW} \left(\frac{\tau_{ii'}}{\dot{P}_{i'}} \right)^{-\sigma} \frac{I_{i'}}{\dot{P}_{i'}}, \quad (7)$$

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 $\tau_{ii'}/\dot{P}_{i'}$ between region i and its trading partner i' .

14. While we find a negative coefficient using a continuous routine task intensity measure also, its effect is much more difficult to interpret or implement in our decomposition, because for a continuous measure, there is no clear way to construct a routine employment share.

15. That is, all E.U. regions as well as the rest of the world (RoW).

2.5. Net Employment Effects

So far, we have only modeled labor demand L . To study employment effects, we need to incorporate labor supply N . In particular, we follow Acemoglu and Restrepo (2017) and specify the supply of labor as follows:

$$\dot{N}_{ij} = \tilde{N}_{ij} \dot{w}_{ij}^{\varepsilon} \text{ and } \tilde{N}_{ij} = \bar{\tilde{N}}_{ij} \tilde{w}_{ij}^{\varepsilon}. \quad (8)$$

This specification implies that $\varepsilon \geq 0$ 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 E.U. 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. 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 through changing relative occupational labor demand. Moreover, it induces changes in the local price index, inducing output and labor demand changes for all occupations.

To understand how RRTC can lead to net negative employment effects in our model, it is instructive to compare our setting to the case of autarky. In autarky, the tradable sector sells its goods solely to the local economy, and local consumers consume only local tradables. Here, the wage bill—and thus labor demand—is proportional to output, $L_i w_i / p_i = (\mu\kappa + 1 - \mu)Y_i$, because there is a constant share of tradables in consumption (μ), and homogeneous labor shares across occupations in tradables (κ).¹⁶ The size of the economy is defined by the resource constraints, that is, by labor supply and by the costs of renting technological capital. RRTC reduces the costs of renting technological capital, thereby expanding the production frontier. The economy grows, and labor demand (the wage bill) expands proportionally and unambiguously. In autarky, RRTC thus never reduces labor demand on net.

In contrast to the autarky case, our model assumes that regions trade, although demands for their outputs need not rise in proportion with their production capabilities.¹⁷ Net negative employment effects then occur if the expansion of tradable output is insufficient to compensate for the reduced number of workers who are needed to produce this output as a result of RRTC. This is the key mechanism that allows for potential net negative employment effects in our model. To capture this, we assume that regions sell their goods to the global market but are too small to affect the world price index or the size of the global market. Then, RRTC leads to a decline in the price of regions' tradable output, which induces an expansion in global demand for

16. The labor share in non-tradables equals unity as there is no capital in this sector. w_i , p_i , L_i , and Y_i are local wages, prices, employment, and output across both sectors, respectively.

17. Note however, that we assume that production equals income equals consumption, which implies that trade balances in each region.

their output, depending on the elasticity of substitution between regions, σ . If the price elasticity of demand for tradables exceeds unity ($\sigma > 1$), RRTC induces an expansion of local income and a proportional increase in the demand for labor. Conversely, if $\sigma < 1$, local income declines and so do labor demand and employment. RRTC therefore affects the local economy by altering its terms of trade. This mechanism is similar to previous results on the role of productivity shocks at the regional (Cingano and Schivardi 2004; Combes, Magnac, and Robin 2004) and industry (Appelbaum and Schettkat 1999; Blien and Sanner 2014) levels and has been discussed already by Neisser (1942).¹⁸

2.6. Decomposition

We decompose RRTC-induced net changes in aggregate employment (across all regions) ΔN into labor-saving, product demand, and spillover effects as follows:

$$\Delta N = (1 - \kappa)\rho s^R \tilde{N} \frac{\varepsilon}{\varepsilon + 1 - \kappa + \kappa\sigma} \left[1 - \sigma + (1 - \sigma) \frac{\tilde{N}}{N} \right], \quad (9)$$

where we drop the index i as the variables now refer to E.U. aggregates. \tilde{N} and \tilde{N} are E.U.-level employment in tradables and non-tradables, and s^R is the E.U. share of routine jobs.

We obtain this decomposition by multiplying the derivative of employment with respect to capital prices by the estimated capital price changes and summing across all regions, as shown in Online Appendix A.1.2. We expect that RRTC reduces the costs for routine capital, such that $\rho < 0$. In this case, the multiplier in front of the square brackets is negative. The first element in the square brackets then represents the labor-saving effect: Conditional on the level of output, demand for labor declines in RRTC as fewer workers are needed to produce the same level of output. The labor-saving effect is multiplied by a fraction that depends on the labor supply elasticity ε , reflecting that wages absorb part of the shock depending on the wage elasticity of labor supply. The second element represents the product demand effect: RRTC induces a decline in the costs of production and a decline in prices, which raises demand and thus output. The net effect of the two is positive if $\sigma > 1$, and negative if $\sigma < 1$. The net effect spills over to the local non-tradable sector, denoted by the third element in the square brackets.

We pursue several extensions of this baseline decomposition. The most important one concerns the role of profit income and mark-ups. Since we lack data on the regional allocation of firm profits, we assume that no firm profits feed back into the local economy in our baseline model. Specifically, we abstract from rising firm profits by assuming monopolistic competition: This means we do not model a potential source of demand arising through the allocation of firm profits. Since this may lead

18. In Autor and Dorn (2013), the (relative) employment effects similarly depend on the consumption elasticity of substitution.

to an underestimation of net employment effects, we also construct an upper bound estimate, where we relax the assumption of constant mark-ups and instead assume all additional profits accrue locally. In this setting, the response of real output to RRTC remains unchanged, but local income changes by a larger amount because the rising wedge between prices and marginal costs induces additional profits. Product demand spillovers to the non-tradable sector are thus larger in the upper bound, depending on firms' mark-ups. Comparing the upper and lower bound estimates is informative given recent evidence of rising firm mark-ups (see e.g. De Loecker, Eeckhout, and Unger 2020), suggesting that firms have not passed on all of the decline in marginal costs to lower prices.

The corresponding decomposition, which takes into account firm profits as a source of local demand, is as follows (derived as equation A.27 in Online Appendix A.1.2):

$$\Delta N = (1 - \kappa)\rho s^R \dot{N} \frac{\varepsilon}{\varepsilon + 1 - \kappa + \kappa\sigma} \left[1 - \sigma + (\theta - \sigma) \frac{\tilde{N}}{N} \right], \quad (10)$$

where $\theta = \partial \ln \hat{p}_i / \partial \ln c_i < 1$ is the rate at which firms pass on changes in marginal costs to prices. Actual employment effects likely lie somewhere in the range between our baseline and upper-bound estimates.

We also use this extension to simulate what would have happened had firms not raised their mark-ups, such that prices would have declined at the same pace as marginal costs. This results in the following counterfactual decomposition (derived as equation A.28 in Online Appendix A.1.2):

$$\Delta N = (1 - \kappa)\rho s^R \dot{N} \frac{\varepsilon}{\varepsilon + 1 - \kappa + \kappa\sigma} \left[1 - \frac{\sigma}{\theta} + \left(1 - \frac{\sigma}{\theta} \right) \frac{\tilde{N}}{N} \right]. \quad (11)$$

This counterfactual illustrates the role of rising mark-ups for the employment effects of RRTC and thereby contributes to recent research on the relationship between technological change and rising mark-ups. We discuss these extensions in Section 4.3.

Lastly, in Section 4.2, we extend our baseline model by allowing for additional mechanisms through which RRTC could produce net disemployment effects.

3. Data and Parameter Estimates

3.1. Employment Data

Employment data for European regions are 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 onward, and there are classification breaks in 2011: We therefore analyze the period 1999–2010.

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.

We have data for 27 European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Latvia, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. For most countries, regional information is available at the level of two-digit or one-digit Nomenclature des Unités Territoriales Statistiques (NUTS-2006) codes. For five small countries (Estonia, Iceland, Latvia, Luxembourg, and Malta), we only observe employment at the national level. For some countries (Austria, the Netherlands, and the United Kingdom), the EU-LFS micro-data have 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, as technology-induced employment fluctuations in the former sector may spill over to the latter (Goos, Konings, and Vandeweyer 2015; Moretti 2010; Moretti and Thulin 2013). 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 Online Appendix A.3.1 for details). The resulting division is outlined in Table 1. 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 an RTI index from

TABLE 2. Occupational 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.

the Dictionary of Occupational Titles 1977, constructed as in Autor and Dorn (2013), converted into European occupations as in Goos, Manning, and Salomons (2014). The measure rises with the importance of routine tasks in each occupation and declines with the importance of manual and abstract tasks. Note that the index is standardized to have a zero mean and unit standard deviation across occupations. The routine 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 an RTI dummy d_j^R , reported in the final column, for the two most routine-intense occupations: The tasks in these jobs can be most easily 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. We conduct robustness checks with alternative definitions for routine intensity in Online Appendix A.4.3.

For a more detailed description of the data preparation and data availability by country, see Online Appendix A.2.

3.2. Additional Data Sources

Estimating our labor and product demand equations requires some additional data. In particular, we obtain data for regional wages, regional marginal costs, and regional output from the Cambridge Econometrics European Regional Database (ERD).¹⁹ For wages, we divide annual compensation of employees in 2005 euros by ERD employment figures to obtain annual wages per employee at the regional level. We

19. 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.

define regional marginal costs as [(compensation of employees + gross fixed capital formation) / gross value added] at the regional level in the tradable industry.²⁰

For our instrumental variable (IV) strategy, discussed below, we further use industry-level data on output and marginal costs obtained from the OECD Database for Structural Analysis (STAN). Following Goos, Manning, and Salomons (2014), we define marginal costs in the data as [(nominal value added—nominal net operating surplus) / real value added]. For real value added—henceforth referred to as output—we divide sector-specific value added by the sector specific deflator provided in STAN.²¹ We also calculate the labor share from the STAN data as labor compensation divided by the sum of labor compensation and consumption of fixed capital.

A region's market potential is calculated as the sum of income across all other regions, lowered by the trading costs toward these trading partners. We derive transport costs from German data on trade flows between regions (see Online Appendix A.3.2 for details). The market potential thus represents the potential market that 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 the labor demand estimations, we are left with 13 countries (Belgium, the Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Italy, Norway, Poland, Sweden, and the United Kingdom) and 142 rather than 238 regions.²² For our final product demand estimations, we are left with 16 countries (Belgium, the Czech Republic, Germany, Estonia, Spain, Finland, France, Greece, Hungary, Italy, Luxembourg, Norway, Poland, Portugal, Sweden, and Slovakia), and further remove 4 countries (Estonia, Finland, Luxembourg, and Slovakia) with five or fewer regions as this may violate the share assumption of the Bartik IVs.²³ This leaves us with 153 regions for the product demand estimates. When constructing our model predictions in Section 4, we expand the sample to cover all 238 regions.

20. ERD aggregates vary by six broad industries from which we define Industry and Financial business services as tradable industries. Besides Agriculture, which we exclude, the remaining (non-tradable) industries are Construction; Wholesale and retail trade; Transport storage, and communications; Hotels and restaurants; and Non-market services.

21. The main difference is thus that our regional-level marginal cost variable contains investments (through gross fixed capital formation), whereas our industry-level marginal cost indicator relies on consumption of fixed capital and thus is corrected for investments. This can be seen from the definition of output, which consists of employees' compensation, consumption of fixed capital, net operating surplus, and taxes less subsidies. With our IV strategy, we ensure that variations in investments are not used for identifying the coefficients on marginal costs, as investments are not included in our IV for marginal costs.

22. We conduct robustness checks dropping countries with fewer or equal to five regions, including Denmark, Estonia, and Finland.

23. This problem applies especially to the product demand equation, which is estimated in region-year cells. (In contrast to the labor demand equation, where we additionally have occupation-level variation.) However, our estimates are robust to these sample selections. In particular, our product demand estimates are similar when leaving countries with five or fewer regions in the sample and the labor demand estimates are virtually identical when dropping these countries.

3.3. Empirical Implementation

We estimate the labor demand equation for the tradable sector (equation (5)) and the product demand equation (equation (7)) in order to get estimates for the key parameters of our framework (ρ , η , and σ). We directly observe the labor share (κ) in the data and obtain the labor supply elasticity (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

Estimating Labor Demand. First, we estimate the labor demand equation for the tradable sector (equation (5)),

$$\log \hat{L}_{ijt} = \beta_0 + \beta_Y \log \hat{Y}_{it} + \beta_c \log \frac{\hat{c}_{it}}{\hat{w}_{it}} + \beta_R d_j^R \times t + \theta t + v_{ij} + \varepsilon_{ijt}, \quad (12)$$

where the number of employed workers for each region i , occupation j , and year t in the tradable sector (\hat{L}_{ijt}) depends on the real regional output of tradables (\hat{Y}_{it}), and on real regional marginal costs relative to wages in tradable production ($\hat{c}_{it}/\hat{w}_{it}$). Wages are only available at the regional level in our data, although our estimates are robust to using occupation-country wages or fixed effects (see Online Appendix A.4.2). As noted in Section 2.4, 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 also include a linear time trend (t). Furthermore, in order to control for differences in regional production technologies and resulting differences in the efficiencies of regions to utilize certain tasks (β_{ij} in the theoretical framework), we include region-occupation fixed effects (v_{ij}). These fixed effects also capture unobserved factors related to the occupation-region cells. We measure occupations' routine intensity using the 1977 US Dictionary of Occupational Titles, which reflects a period before the introduction of the computer revolution. The assumption here is that the effect of task-specific time trends on labor demand purely captures the effect of RRTC.²⁵

Based on the estimates of equation (12), 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 obtain an estimate of ρ by using the labor share κ (observed in our data), as well as our estimate of η .

24. We do not need to estimate labor demand in the non-tradable sector (equation (6)) since it is only indirectly affected by RRTC and its parameter estimates do not enter in our decomposition.

25. This assumption could be violated if initial routinization has a direct impact on employment changes (not levels as those are removed by region-occupation fixed effects) other than through RRTC. One example could be offshoring, if this also reduces labor demand of routine intensive occupations relative to non-routine ones. We cannot easily rule this out: Given the low number of occupations, a dummy for a subset of occupations subject to offshoring will likely be highly collinear with the routinization dummy. Previous work has, however, suggested that the impacts of offshoring are much smaller than those of routinization (Goos, Manning, and Salomons 2014).

IV Strategy for Labor Demand. A concern with estimating equation (12) with ordinary least-squares (OLS) is that output and marginal costs are endogenous. Specifically, as regions' output structure changes from routinization, it may endogenously experience other demand shocks that impact output and/or marginal costs.

To instrument output in the labor demand equation, we follow a Bartik (1991) approach that exploits variation only related to regions' initial industry specialization. In doing so, we follow Goldsmith-Pinkham, Sorkin, and Swift (2020), arguing that exogenous variation is coming from the shares, that is, assuming regions randomly specialize in certain industries (random shares).²⁶ In particular, we define the Bartik instrument as follows (i = region, c = country, k = industry, and t_0 = initial time period):

$$\log \hat{Y}_{it}^{IV} = \log \left(\sum_{k=1}^K \frac{N_{kit_0}}{N_{kct_0}} \hat{Y}_{kct} \right), \quad (13)$$

where annual national industry output in tradables (\hat{Y}_{kct}) are reweighted by regional (N_{kit_0}) to national employment shares (N_{kct_0}) such that regions are exposed to the national industry shocks according to the relative size of the region's industry compared to the national level. As such, we use the time-constant weights of the starting year for each country, so that our industry shares capture differential exogenous exposures to the common shocks. Our results are robust to using industry capital stocks in tradable industries (\hat{K}_{kct}) instead of industry output of tradables in equation (13) (see Online Appendix A.4.1).

To tackle the endogeneity of marginal costs, we construct a similar Bartik IV:

$$\log \hat{c}_{it}^{IV} = \log \left(\sum_{k=1}^K \frac{N_{kit_0}}{N_{it_0}} \hat{c}_{kct} \right), \quad (14)$$

where annual national industry marginal costs in tradables (\hat{c}_{kct}) are reweighted by industry employment shares within regions of the starting year.²⁷ Compared to the IV for the absolute measures, regions are thus exposed to the national industry shocks according to the relative size of the industry within regions as a more proper approach for relative measures. Our estimates are robust to using an alternative instrument based on the predicted components, $\log \hat{c}_{it}^{IV} = \log[(\hat{Y}_{it}^{IV} - N\hat{O}S_{it}^{IV})/\hat{real}Y_{it}^{IV}]$, where $N\hat{O}S_{it}^{IV}$, $\hat{real}Y_{it}^{IV}$, and \hat{Y}_{it}^{IV} are calculated as in equation (13). The basic idea of this alternative component-based IV is that, as with output, regions are exposed to the national industry

26. In contrast, Borusyak, Hull, and Jaravel (2019) emphasize the possibility of exploiting exogenous variation coming from the shocks, that is, assuming that industry growth is random (random shocks). The latter approach requires a large number of industries. Since we observe many regions, but few industries and time periods, we follow Goldsmith-Pinkham, Sorkin, and Swift (2020) and focus on the share approach.

27. For data reasons and as explained in Section 3.2, marginal costs at the industry level, c_{kct} , are defined differently compared to the regional level, c_{it} .

shocks according to the relative size of the region's industry compared to the national level.

The identifying assumption for the Bartik instruments for output and marginal costs is that the differential effect of higher exposure of one industry (compared to another) only affects the change in the outcome through the endogenous variable of interest, and not through any potential confounding channel, conditional on observables. Since we control for region-occupation fixed effects in our regressions, our assumption is that the shares are exogenous to mean-deviations in the error term (i.e. mean-deviations in the outcome variable). Note that we also conduct robustness checks based on a first difference model where the assumption only requires that the shares are exogenous to *changes* in the error term (rather than exogenous to mean-deviations in the error term; see Online Appendix A.4.4). This strategy is also valid if the shares are correlated with the levels of the outcomes.

We conduct robustness tests, including dropping the country dimension in the exogenous share part, that is, using local to E.U. rather than local to national shares (see Online Appendix A.4.5). Furthermore, for more transparency on the instruments, we follow Goldsmith-Pinkham, Sorkin, and Swift (2020) and calculate Rotemberg weights for each instrument. The weights show which industries and years are driving the instrumental variation (for details, see Online Appendix A.4.6). Overall, the analysis suggests that our instruments for regional output and marginal costs relative to wages are driven by events related to manufacturing as well as events in years 2007 and 2010. The large role of manufacturing is as expected, since manufacturing is routine-intensive and dominates the tradable sector. The large role of the years around the financial crisis could indicate sensitivity to business cycles. However, we show that our estimates are robust to including business cycle interactions (see Online Appendix A.4.7), to controlling for local manufacturing shares, as well as to dropping the years 2007 and 2010 (see Online Appendix A.4.6).

Finally, we also instrument regional wages, since wage developments may be endogenous to employment changes. Specifically, our instrument uses local female labor supply shocks calculated as follows (f denotes female):

$$\log \hat{w}_{it}^{IV} = \log \left(\frac{\hat{N}_{ict_0}^f \hat{N}_{ct}^{f,-i}}{\hat{N}_{ct_0}^f} \right), \quad (15)$$

where annual national female employment ($\hat{N}_{ct}^{f,-i}$) is reweighted by regional ($\hat{N}_{ict_0}^f$) to national ($\hat{N}_{ct_0}^f$) 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 .²⁸ The assumption here is that initial period local female employment shares are exogenous conditional on observables. Note that this

28. We cannot perform a similar leave-own-out strategy for output and marginal costs, since we only observe the latter data either at the industry level (STAN data) or at the regional level (Cambridge Econometrics data), but not for industry-region cells (as in the EU-LFS data).

instrument, in contrast to the other instruments, is not a Bartik IV in the spirit of Goldsmith-Pinkham, Sorkin, and Swift (2020).

Estimating Product Demand. Next, we estimate the product demand equation (equation (7))

$$\log \dot{Y}_{it} = \delta_0 + \delta_c \log \dot{c}_{it} + \delta_{MP} \log MP_{it} + v_i + \varepsilon_{it}, \quad (16)$$

where the real regional output of tradables (\dot{Y}_{it}) depends on the real regional marginal costs of producing tradable output (\dot{c}_{it}) as well as on a region's market potential (MP_{it}).²⁹ Market potential for any one region ($MP_{it} = (\sum_{i'=1}^{I'} \tau_{ii'} Y_{i't})$) is the sum of real income (tradables and non-tradables) in all other regions, discounted by the transport costs toward these regions ($\tau_{ii'}$). It represents the size of the market that can be potentially accessed by region i . In order to control for further regional factors, we include a set of regional fixed effects (v_i). Finally, ε_{it} captures the remaining error term.

Based on the estimates of equation (16), we can then obtain $\sigma = -\delta_c$, the elasticity of substitution between regional bundles of tradables.

IV Strategy for Product Demand. To account for the endogeneity of regional marginal costs in tradables \dot{c}_{it} , we follow the same IV strategy as for the labor demand equation, that is, we use the Bartik IV in equation (14).

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 transport costs toward these regions:

$$\log MP_{it}^{IV} = \log \left[\left(\sum_{i'=1}^{I'} \tau_{ii'} Y_{i't}^{IV} \right) - Y_{it}^{IV} \right]. \quad (17)$$

As an alternative, we use the predicted capital stock (K_{it}^{IV}) in equation (17), leading to similar results.

The Rotemberg weights for the preferred Bartik IVs suggest that our instruments are mainly driven by events related to manufacturing as well as events in the years 2008 and 2010 (see Online Appendix A.4.6). We perform similar robustness checks to those for labor demand, showing that our results are robust to specifications with business cycle interactions (see Online Appendix A.4.7), controlling for local manufacturing shares, as well as to dropping the years 2008 and 2010 (see Online Appendix A.4.6).

Remaining Error Terms. Our IV strategy for both labor and product demand assumes that the error term does not contain region-specific productivity shocks (other than RRTC) that are correlated to regions' initial industry specialization, that is, the shares

29. Product demand depends on prices \hat{p}_{it} , which we replace with regional marginal costs c_{it} , since prices are a constant mark-up over marginal costs in our baseline model. We relax this assumption in Section 4.3.

from our Bartik IVs. While we cannot test this assumption directly, we can estimate our models in first-differences to relax this assumption: In a first-differenced specification, the error term is only a function of the t and $t - 1$ errors, rather than all time periods as in fixed effects. Results of this exercise are reported in Online Appendix A.4.4 for both labor and product demand. Our finding is that while this leads to similar results, the estimated elasticities (η and σ) tend to be somewhat larger as compared to the fixed effects models: Especially the estimated substitution elasticity between tradables in consumption (σ) increases. This suggests that, if routine-intensive regions experience other productivity shocks, these tend to bias our estimated elasticities downward, but leave their relative size unaffected. The fixed effect estimates used below represent a more conservative set of estimates: Implementing the first-differenced estimates instead would lead to the same qualitative results, but quantitatively bigger effects. Below, we therefore show model predictions for a range of parameter values.

Baseline Employment Decomposition. Using our estimated parameters $\hat{\eta}$, $\hat{\rho}$, and $\hat{\sigma}$ jointly with $\hat{\kappa}$ from the data and an estimate of ε from the literature, we calculate the components of equation (9), that is, the effects of the three channels on employment in our baseline prediction. All other variables in these equations, that is, s^R , \tilde{N} , and \tilde{N} , are calculated from the data.³⁰ The sum over all three effects reflects the net effect of RRTC on employment. Empirical implementations of model extensions are discussed together with results in Sections 4.2 and 4.3.

3.4. Parameter Estimates

Table 3 shows the estimates of labor demand in the tradable sector from equation (12). 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 relative to wages. Column (2) shows the same estimates but restricted to the set of region-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 as outlined above.

Overall, all coefficients as well as the first stage estimates (see Online Appendix Table A.3) have the expected sign and impact, and are robust to business cycles (see Online Appendix Table A.18), alternative IV sets (see Online Appendix A.4.1), using occupational wages (see Online Appendix A.4.2) as well as estimation in first differences (see Online Appendix A.4.4). 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% lower in routine occupations relative to non-routine occupations.

30. 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.

TABLE 3. Labor demand in the tradable sector.

Dependent variable: log employment in tradable sector (in region-occupation-year cells)				
	FE Full sample (1)	FE Restricted sample (2)	FE (3)	FE-IV (4)
Dummy for routine occupations × time trend	−0.025*** (0.002)	−0.028*** (0.002)	−0.028*** (0.002)	−0.028*** (0.002)
Log regional output			0.465*** (0.052)	0.631*** (0.104)
Log regional marginal costs relative to wages			0.330*** (0.049)	0.761*** (0.126)
<i>N</i>	22,848	12,096	12,096	12,096

Notes: European regions and occupations, 1999–2010. Models 1 and 2 include region-occupation and region-year fixed effects. Models 3 and 4 are estimated with region-occupation fixed effects and control for a linear time trend. Model 4 is our preferred (i.e. baseline) specification. Standard errors clustered by region reported in parentheses. First stage estimates are reported in Online Appendix Table A.3. *** $p < 0.01$.

The precisely estimated positive effect of output is 0.631, which is somewhat lower than the theoretically expected value of 1 (assumption of constant returns to scale). We therefore test the sensitivity of our results by allowing for increasing returns to scale in Online Appendix A.5.2 and find our results to be robust.

The effect of regional marginal costs relative to wages provides our estimate for η —the substitution elasticity between tasks. With an estimate of $\eta = 0.76$, the estimate lies 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, Manning, and Salomons (2014).³¹ Intuitively, the estimate suggests that firms do have some 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 that cannot be easily substituted: Indeed, Cortes and Salvatori (2015) find that firms are highly specialized in their task content along routine versus non-routine lines.

Table 4 reports estimates of product demand in the tradable sector from equation (16). The first column shows results including region-occupation fixed effects, whereas column (2) shows our preferred model that additionally instruments for market potential and marginal costs. The first stages are reported in Online Appendix Table A.4: Instruments are statistically significant and have the expected sign. The estimates are also robust to business cycles (see Online Appendix Table A.19).

31. However, the estimate in Goos, Manning, and Salomons (2014) cannot be directly compared to ours, not only because we estimate the substitution of tasks across tradables production within regions instead of tasks between industries, but also because we include a larger set of E.U. countries and consider a different time period.

TABLE 4. Product demand in the tradable sector.

Dependent variable: log regional output of tradables (in region-year cells)		
	FE (1)	FE-IV (2)
Log regional marginal costs	− 0.275*** (0.052)	− 1.625*** (0.297)
Log regional market potential	1.188*** (0.066)	1.020*** (0.075)
<i>N</i>	1,836	1,836

Notes: European regions, 1999–2010. All models are estimated with region fixed effects. Model 2 is our preferred (i.e. baseline) specification. Robust standard errors in parentheses. First stage estimates in Online Appendix Table A.4. *** $p < 0.01$.

TABLE 5. Parameter estimates.

Parameter	Description	Estimate
$(1 - \eta)(1 - \kappa)\rho$	Routinization coefficient	− 0.028*** (0.002)
η	Substitution elasticity between tasks	0.761*** (0.126)
κ	Labor share	0.650
ρ	Change of capital costs for routine relative to non-routine tasks	− 0.335* (0.180)
σ	Substitution elasticity between bundles of tradables	1.625*** (0.297)
ε	Labor supply elasticity	0.500

Notes: Standard errors in parentheses. Estimates for $(1 - \eta)(1 - \kappa)\rho$ and η are obtained from column (4) in Table 3 and the σ estimate is obtained from column (2) in Table 4. Parameters without standard error: The labor share κ is calculated directly from STAN data, and the labor supply elasticity ε is taken from Chetty et al. (2011). The estimate for ρ is calculated based on the other parameter values. * $p < 0.10$, *** $p < 0.01$.

The coefficient on regional marginal costs gives our parameter estimate for σ , the elasticity of substitution in consumption between regional bundles of tradables. In our preferred model in column (2), this estimate is 1.6, indicating that the demand for regional tradable goods bundles is neither very elastic nor very inelastic. Coefficients of alternative IV models also lie within the range of estimates for the elasticity of international trade by Imbs and Mejean (2010), who find values between 0.5 and 2.7 at the country level for 30 countries worldwide.

The coefficient on regional market potential is around 1 in column (2), suggesting that larger market potentials increase local product demand in the same proportion and indicating homothetic preferences, consistent with our theoretical assumption.

Table 5 summarizes the baseline parameter estimates that we use to construct predictions for the overall employment effects in the next section. From our preferred labor demand model (column (4) in Table 3), it reports the routinization coefficient, β_R

$= (1 - \eta)(1 - \kappa)\rho$; and the elasticity of substitution between tasks, η . We also report the labor share from the data, κ . We find a labor share of 65%, which is very close to the aggregate labor share as usually measured (see e.g. Karabarbounis and Neiman 2014).

Furthermore, Table 5 shows the estimated relative decline in capital costs, ρ , which is implied by the routinization coefficients, κ and η . The negative value suggests that a decrease in the price of capital indeed leads to a stronger substitution of routine compared to non-routine labor by capital. As shown in the literature on job polarization (see e.g. Autor and Dorn 2013; Goos and Manning 2007; Goos, Manning, and Salomons 2014), there is a shift in employment away from occupations that are more routine toward those that are less routine. The size of this estimate suggests routine-replacing capital prices are declining by some 33.5% 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, and larger declines between 1994 and 2004. This plausible implied value for ρ increases confidence in the validity of our parameter estimates.

The fifth parameter reported in Table 5 is the elasticity of substitution in consumption between regional bundles of tradables, σ , obtained from our preferred product demand model (column (2) in Table 4). Lastly, we report one remaining parameter that we do not empirically estimate: the (Hicksian macro) labor supply elasticity (denoted by ε in our model). Here, we follow Acemoglu and 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, taking into account both intensive and extensive labor supply margins. In Online Appendix A.5.4, we explore the sensitivity of our results to this parameter choice.

4. The Employment Effects of Routine-Replacing Technologies in Europe

4.1. Baseline Results

Using the decomposition outlined in Section 2.6, we construct an estimate of the employment impact of RRTC. Specifically, we obtain predicted employment effects for each of the three distinct channels from our framework, for Europe over 1999–2010. We choose the lower-bound decomposition as our baseline estimate, since we do not have sufficient information on the reallocation of profits across E.U. regions.

The first column in Table 6 shows the results at the European level. It can be seen that all three channels are empirically relevant and have the expected signs. The labor-saving effects are negative, suggesting that employment has decreased by 9.44 million jobs as technology substitutes for labor in routine tasks, and as production has restructured toward routine tasks. These are the direct labor-saving effects that have played a central role in the public debate. However, the product demand and local demand spillover effects on employment are positive and larger in absolute value,

TABLE 6. Predicted European employment changes and bootstrapped confidence intervals.

	Estimate	5th percentile	95th percentile	<i>p</i> -value
<i>Employment change (in millions of jobs)</i>				
Labor-saving effect	− 9.44	− 31.20	− 5.53	0.007
Product demand effect	15.34	8.04	46.14	0.008
Spillover effect	8.73	0.75	25.99	0.029
Net effect	14.63	1.26	43.55	0.029

Notes: Distribution of predicted effects obtained by bootstrapping predictions with 1,000 draws. Bootstrap clustered by region-occupation for labor demand parameter estimates. The *p*-value is the percentile of the 0 in the distribution of the estimated and bootstrapped effects or 1 minus this value if the point estimate is negative.

respectively, implying an increase in employment by 15.34 and 8.73 million jobs across Europe. These arise because RRTC improves regions' terms of trade, lowering goods prices and raising demand for their tradable output, increasing employment; and because the rise in product demand spills over to the non-tradable sector so that additional employment is created. As a result, employment *increases* by 14.63 million jobs, on net. These estimates are based on a labor supply elasticity of $\varepsilon = 0.5$, obtained from the literature. We show in Online Appendix Figure A.8 how our results vary with the choice of ε : While this impacts the size of the net effect, its sign is unaffected.

Table 6 also reports confidence intervals for these results, reflecting sensitivity to our parameter estimates. In particular, we create 1,000 bootstrapped predictions from our model, as such varying our key parameter estimates (σ , η , and ρ). We report the point estimate along with 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 employment effect. In addition, we compute the percentile of the estimate that is closest to zero within the distribution of estimates, as an indicator for the significance of the estimated effect ("*p*-value"). To ease interpretation, Table 6 reports 1 minus the *p*-value whenever the point estimate is negative. The signs of the effects of the three channels are as expected within their respective confidence intervals: This increases confidence in our overall conclusion of net positive employment effects of RRTC. Our *p*-values further suggest that all of our predicted effects are statistically significant.

Of particular importance for a positive net employment effect are the findings that $\eta < 1$ and $\sigma > 1$: In Figure 2, we show the underlying distribution of bootstrapped estimates for these two parameters. The figure shows that there is a 0.7% chance that η exceeds unity, and a 2.2% chance that σ is smaller than unity, explaining why our baseline estimates robustly predict positive net employment changes.

We further provide extensive robustness checks for the estimation of our parameters in Online Appendix A.4. While these parameter estimates differ from our baseline, they are well within the confidence intervals of our baseline estimates. Therefore, the decomposition of the employment effects using the parameter estimates from our robustness checks also falls within the confidence intervals provided in Table 6, implying that our baseline results are robust to the checks performed in Online Appendix A.4.

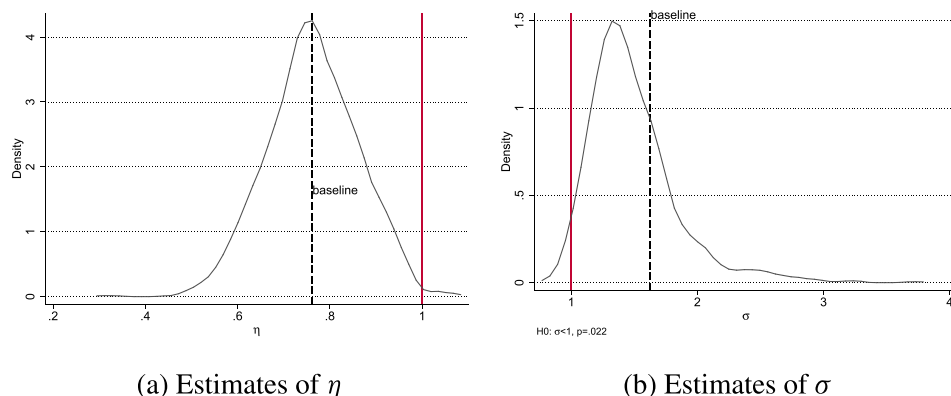


FIGURE 2. Bootstrapped parameter distributions for η and σ . The dashed lines indicated mean baseline estimates. The solid vertical lines indicate a value of 1. η is below 1 in 99.3% of sample draws. σ exceeds 1 in 97.8% of sample draws.

TABLE 7. Actual versus predicted employment-to-population change.

	Dependent variable: actual regional employment-to-population change			
	(1)	(2)	(3)	(4)
Predicted regional employment-to-population change	0.535*** (0.072)	0.342*** (0.069)	0.614*** (0.127)	0.319*** (0.082)
N	230	230	206	206
Sample	All regions		5th–95th percentile	
Fixed effects	None	Country	None	Country
R ²	0.170	0.867	0.117	0.868

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. Robust standard errors in parentheses. *** $p < 0.01$.

Finally, Table 7 compares our predictions to regions' actual employment evolutions. In particular, it shows regressions of actual employment-to-population changes onto the employment-to-population change predicted from our model. Each region is one observation, and observations are weighted by the initial regional employment size to ensure that the results aggregate up to the total change. We find that our model of RRTC is predictive of actual regional employment rate changes: Across specifications, the coefficients are positive and statistically significant. Furthermore, 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. Lastly, results are robust to excluding outlier regions in terms of the actual employment change.³²

32. These outliers are in part the result of imputing actual employment evolutions for countries that have limited data coverage over 1999–2010, such as Denmark—see Online Appendix Table A.1 Online. Regression results are similar when weighting by initial population size, or when giving all regions equal

We further compute predicted changes in regional tradable marginal costs, wages, output, and labor productivity, as well as changes in regional routine and tradable employment shares, and regress actual changes on predicted changes for these outcomes, analogous to the exercise in Table 7. These regressions serve to test the predictive power of our model for variables that it was not directly constructed to address. We find that our model is largely predictive of these outcomes as well, although it cannot fully account for all observed changes: Results are presented in Online Appendix A.5.3.

The results reported in this section highlight four main findings. First, we provide the first estimate in the literature of the overall effect of RRTC on the number of jobs, finding that the net employment effects of routine-replacing technologies are positive as RRTC improves regions' terms of trade. This implies there is no support for the scenario of overall routinization that leads to a net displacement of humans from the labor market. Of course, this does not rule out that there could be individual (automation) technologies that produce net aggregate disemployment effects, such as those found for industrial robots in the United States (Acemoglu and Restrepo 2017), nor the displacement of individual workers from their jobs (Bessen et al. 2019). Furthermore, our results suggest that technological progress is a key driver of job growth: While the estimated employment increases of 14.63 million jobs over 1999–2010 across Europe reflects a lower bound, it is large compared to the total employment growth of 23 million jobs observed across these countries over the period considered (see Online Appendix Figure A.1).

The second important finding is that all three channels are quantitatively relevant: There are substantial labor-saving effects at the task level, leading to decreases in labor demand and employment for a given level of output, 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 labor-saving effects. This highlights the importance of considering the interactions between labor and product markets and their role for regions' terms of trade when thinking about the employment effects of technological change, as also pointed out by Autor (2015) and Acemoglu and Restrepo (2018a,c).³³ 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:

weight; and from an alternative model specification regressing actual employment changes on predicted employment changes while controlling for regions' initial employment size.

33. 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.

Even within the tradable sector, there is no decline in employment as a result of RRTC, consistent with Autor, Dorn, and Hanson's (2015) findings for the United States.³⁴ However, there is more job growth in non-tradables, industries that 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 reallocating toward non-tradables (see also Online Appendix Figure A.1 Online).

The fourth result is that localized spillover effects to industries that are not directly affected by technological progress play a quantitatively important role for understanding the total labor demand and employment effects of RRTC.³⁵ 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 Table 6 imply that each job generated in the local tradable industry as a result of RRTC results in an additional employment effect of $8.73/(15.34-9.44) = 1.48$ jobs in the local non-tradable industry. This employment multiplier is similar to the one found by Moretti (2010), who concludes that for each additional job in the tradable industry in a given US 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 US 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.

The next two subsections extend our baseline model and empirical results by considering the role of firm profits in local demand, and of elastic capital-labor substitution.

4.2. *Assessing the Role of Elastic Capital-Labor Substitution*

We have so far examined the employment effects of RRTC through its effects on regions' terms of trade: That is, negative net employment effects arise only if regions' increase in sales as a response to declining costs and prices is insufficient to compensate for the decline in demand for labor per unit of output. We now consider the role of an additional mechanism through which routine task replacement potentially leads to

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

35. Note that the size—though not the sign—of this spillover may be different if the substitution between tradable and non-tradable goods in consumption is not unity, as our baseline model assumes. In Online Appendix A.5.1, we relax this assumption and instead use a range of elasticities from the literature, allowing for both inelastic and elastic substitution between tradables and non-tradables in consumption. While we find that inelastic substitution between tradables and non-tradables lowers the net employment effects through a smaller spillover, this does not alter our overall conclusion of net positive employment effects.

labor displacement: elastic substitution of capital for labor within tasks (“substitution effect”).

This mechanism is not captured by our baseline model since it assumes a unit elasticity of substitution between capital and labor ($\eta = 1$). Elastic substitution implies labor shares could decline within tasks and regions as a result of RRTC. Furthermore, even absent labor share changes, reallocation of activity across occupations and regions with heterogeneous labor shares could further reduce labor demand, if such reallocation is toward more capital-intensive activities.

We now relax our baseline assumption of a unit capital-labor substitution elasticity in task production, and the implied constant labor shares. Specifically, we change the production technology at the task level from CD to CES, using $\eta^K > 0$ as the elasticity of substitution between capital and labor at the task level. This implies that labor shares become region- and task-specific. In particular, the production technology for tasks now is

$$T_{ij} = \left(\dot{L}^{\frac{\eta^K-1}{\eta^K}} + K^{\frac{\eta^K-1}{\eta^K}} \right)^{\frac{\eta^K}{\eta^K-1}}. \quad (18)$$

We then use a log-linear approximation of marginal costs, $\ln c_{ij} = \kappa_{ij} \ln \dot{w}_{ij} + (1 - \kappa_{ij}) \ln r_j$, where κ_{ij} is the initial labor share. Using this definition of the task production function and following the same steps as above, we obtain an alternative decomposition for net employment effects of RRTC³⁶:

$$\begin{aligned} \Delta N = & \sum_j \sum_i (1 - \kappa) \rho \dot{s}_{j|i}^R d_j^R \frac{\varepsilon}{\varepsilon + \eta^K (1 - \kappa_{ij}) + \sigma \kappa_{ij}} \\ & \times \left[\eta^K - \sigma + (1 - \sigma) \frac{\tilde{N}_i}{\dot{N}_i} \frac{\varepsilon + \eta^K}{\varepsilon + 1} \right]. \end{aligned} \quad (19)$$

This net employment effect of RRTC may be smaller compared to our baseline decomposition if (a) there is elastic substitution between capital and labor at the task level ($\eta^K > 1$) or (b) if there is reallocation across occupations that differ in their labor shares κ_{ij} .

To implement this equation, we need a value for one additional parameter, the elasticity of substitution between capital and labor η^K . To obtain this, we calibrate η^K such that our adjusted model reproduces the overall decline in the labor share in our data (see Figure 4(a) for corresponding evidence). In particular, the change in regional

36. We impose the additional simplifying assumption that labor income remains proportional to sales due to the lack of data on region-occupation specific wages. Note that no such assumption is required in our baseline and that this assumption only matters for the size of the spillover effect. It does not qualitatively affect our findings since even without any spillovers, the net employment effect remains positive in this extended decomposition.

labor shares in our model is³⁷

$$\begin{aligned}\Delta\kappa_{it} = & (\eta^K - 1) \sum_{j=1}^J d_j^R \rho (1 - \kappa_{ijt}) \dot{s}_{j|it}^T \kappa_{ijt} \\ & + (1 - \eta) \sum_{j=1}^J d_j^R \rho (1 - \kappa_{ijt}) \dot{s}_{j|it}^T (\kappa_{ijt} - \kappa_{it}).\end{aligned}\quad (20)$$

This equation highlights that changes in regional labor shares $\Delta\kappa_{it}$ occur due to substitution between capital and labor within occupations (first element in equation (20)) and due to substitution between occupations that differ in their labor shares (second element in equation (20)). Relying on our parameter estimates for η and ρ and using data on labor shares, we obtain one value for the elasticity of substitution between capital and labor, η^K , for each region i and year t , which solves this equation.³⁸ On average across regions and years, this calibrated elasticity of substitution between capital and labor at the task level is 1.12 with a standard deviation of 0.49: Figure 3(a) shows the distribution of calibrated values. Hence, on average, the elasticity of substitution between capital and labor exceeds unity, which explains the decline in the labor share in our data. We choose the average calibrated value of η^K , which implies that we, on average, reproduce the declining labor share observed in E.U. regions.

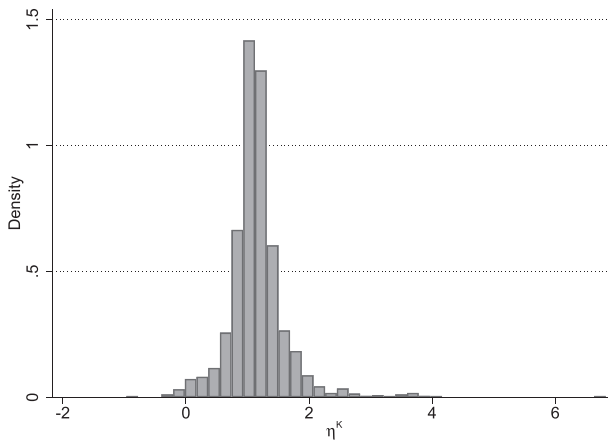
To gauge the effect of elastic substitution between capital and labor, we use both the average of the calibrated substitution elasticities ($\eta^K = 1.12$) and the calibrated 95th percentile value ($\eta^K = 1.87$) in the decomposition equation (19). Figure 3(b) reports the results, also comparing this to our baseline decomposition where the elasticity is assumed to be unity. Note that the overall effects in the baseline decomposition are smaller because we can implement this analysis only for those countries for which sufficient information on labor shares is available.

As expected, the net employment effect declines when using an elasticity of substitution between capital and labor larger than 1 ($\eta^K > 1$) compared to the case where $\eta^K = 1$ but holding constant the sample of regions. Using higher estimates of η^K further reduces the effects. However, we still find a net positive employment effect even when using the 95th percentile estimate of η^K .³⁹ Hence, adjusting our model such that it reproduces the overall decline in the labor share in the European Union through elastic substitution between capital and labor and reallocation between occupations

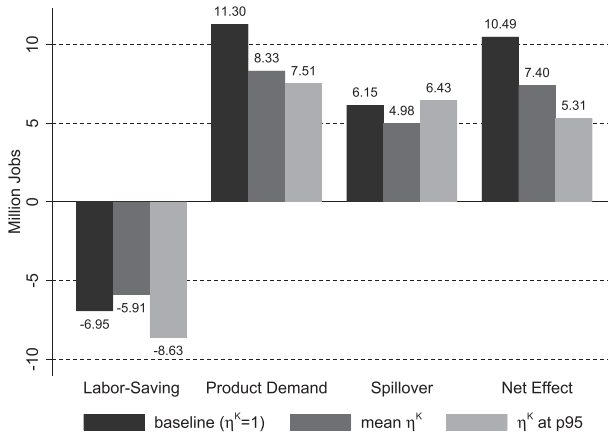
37. We obtain this result by deriving changes in regional labor shares as $\Delta\kappa_i = \kappa_i \sum_{j=1}^J \frac{\partial \ln \kappa_i}{\partial \ln r_j} \rho d_j$.

38. To implement this, we need region-specific labor shares. Labor shares are only available by country, industry, and year. We map country-industry-year labor shares to the occupational level using occupation-industry employment data and assume that occupational labor shares are the same across regions within countries. Regional labor shares then differ due to differences in occupational employment shares across regions. We define the labor share as labor compensation divided by the sum of labor compensation and consumption of fixed capital.

39. Note from equation (19) that for positive employment effects to arise, one of the conditions is that σ exceeds η^K . A bootstrapped test for the distribution of σ estimates shows σ exceeds the calibrated mean value of η^K in 91% of sample draws.



(a) Distribution of calibrated capital-labor substitution elasticities



(b) Predicted European employment change, 1999–2010

FIGURE 3. Assessing the role of elastic capital-labor substitution. Figure (a) shows the distribution of the elasticity of substitution between capital and labor, calibrated from actual changes in labor shares assuming that all labor share changes are due to elastic substitution between capital and labor within occupations. Figure (b) shows predicted employment change in Europe (20 countries) between 1999 and 2010 in millions of jobs. The baseline assumes a unit elasticity of substitution between capital and labor within occupations, $\eta^K = 1.00$. The second set of bars uses the mean calibrated elasticity of substitution between capital and labor, $\eta^K = 1.12$. The third set of bars uses the 95th percentile of this calibrated elasticity, $\eta^K = 1.87$.

with heterogeneous labor shares does not substantively change our conclusions.⁴⁰ The net employment effect declines in size, but clearly remains positive.

40. We show in Online Appendix A.5.5 that much of the lower employment growth compared to our baseline model is due to the substitution of capital for labor. However, while studying capital-labor substitution without the reallocation between occupations with heterogeneous labor shares leads

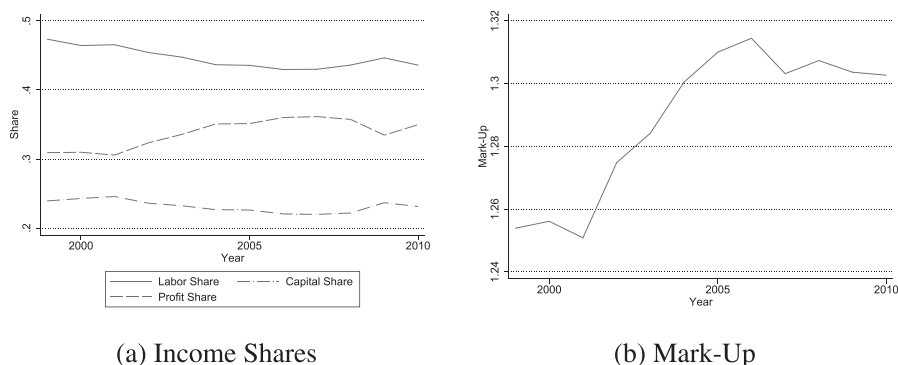


FIGURE 4. Trends in income shares and mark-ups in the tradable sector. European regions, 1999–2010, tradable sector. The labor share is defined as labor compensation divided by income, where income is the sum of labor compensation and consumption of fixed capital. The capital share is the consumption of fixed capital divided by income. The profit share is the net operating surplus divided by income. Mark-ups are defined as prices divided by marginal costs, where marginal costs are defined as $[(\text{nominal income} - \text{nominal net operating surplus}) / \text{real income}]$.

In sum, there is a negative substitution effect: The employment effect of RRTC would have been higher without capital-labor substitution. However, RRTC improves regions' terms of trade sufficiently to ensure overall positive net employment effects even when we allow for elastic substitution between capital and labor.

4.3. The Role of Rising Firm Profits and Mark-ups

Our baseline decomposition abstracts from firm profits feeding back into local demand. As discussed, this may lead to an underestimation of the net employment effect of RRTC, especially if mark-ups are rising, as a recent literature has documented. Consistent with this literature, the left-hand panel of Figure 4 shows a declining labor share and increasing profit share for European regions over time based on our data. The right-hand panel further shows mark-ups have increased. The mark-ups calculated from our data are close to Hall (2018), who finds an increase in the average mark-up from around 1.2 in 2000 to around 1.3 in 2010 for the United States. De Loecker and Eeckhout (2020) report an increase of the mark-up in the European Union from 1.01 in 1980 to 1.63 in 2016. The smaller changes in income shares and mark-ups in our data are not surprising, given that we focus on a shorter time horizon.

To incorporate the role of firm profits, we can compare our baseline lower-bound estimates to an upper bound that assumes the other extreme, namely that all additional firm profits accrue locally. Spillovers to the non-tradable sector are larger when mark-ups rise, implying larger net employment effects compared to our baseline where no

to similar net effects, it exaggerates both the labor-saving and product demand effects. This is because production reallocates toward more labor-intensive occupations, dampening the labor-saving effect, which also attenuates the cost-decline and thereby the product demand effect.

TABLE 8. Relationship between prices and marginal costs.

	Dependent variable: yearly changes in log prices ($\Delta \ln \hat{p}_i$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Yearly changes in log marginal costs ($\Delta \ln c_i$)	0.679*** (0.058)	0.649*** (0.060)	0.639*** (0.059)	0.547*** (0.070)	0.640*** (0.060)	0.630*** (0.059)
Intercept		X	X	X	X	X
Industry dummies		X			X	
Year dummies			X			
Country dummies				X	X	
Country×industry dummies						X
N	979	979	979	979	979	979

Notes: European regions, 1999–2010 annual differences. Standard errors clustered by country reported in parentheses. *** $p < 0.01$.

firm profits feed back into the local economy. This comparison informs on the role of firm profits in driving employment effects from technological change.

To illustrate the relationship between our lower and upper bound estimates, recall that we regress local tradable output on local tradable marginal costs to estimate the price elasticity of product demand as $\sigma = \partial \ln \hat{Y}_i / \partial \ln c_i$, because prices and marginal costs are proportional when mark-ups are constant. If mark-ups rise, the price elasticity instead becomes $\partial \ln \hat{Y}_i / \partial \ln \hat{p}_i = \sigma / \theta$, where $\theta = \partial \ln \hat{p}_i / \partial \ln c_i < 1$ is the rate at which firms pass on changes in marginal costs to prices. The calculation of the upper bound estimate requires an estimate of this elasticity of marginal costs to prices: We obtain it by regressing changes in log prices on changes in log marginal costs.⁴¹

Table 8 shows estimates for this relationship in tradable industries, estimated at the country-industry level due to the lack of adequate price data for European regions. We find that $\theta = 0.68$, implying that about 68% of changes in marginal costs are passed on to consumers via changes in prices. This is robust to adding industry dummies, country dummies, year dummies, or interactions thereof. Since $\theta < 1$, firms pass on only part of the decline in marginal costs to prices such that mark-ups and profit shares increase, consistent with the patterns shown in Figure 4.

We use this θ estimate to construct the upper-bound and counterfactual decompositions using equations (10) and (11), respectively: Results are shown in Figure 5. The first set of bars are the baseline results, assuming no firm profits feed back into the local economy. The second set of bars includes rising firm profits for the demand for local non-tradables, assuming all profits are spent locally. This illustrates that if the RRTC-induced increase of firms' profits is spent locally, the positive employment effects of RRTC are around 30% ($= (19.10 - 14.63) / 14.63$) larger since this increases the spillover effect to the local non-tradable sector. We denote this

41. This implies that we use observed changes in mark-ups from the data: We do not attempt to endogenously explain changes in mark-ups since the empirical implementation would require firm-level data.

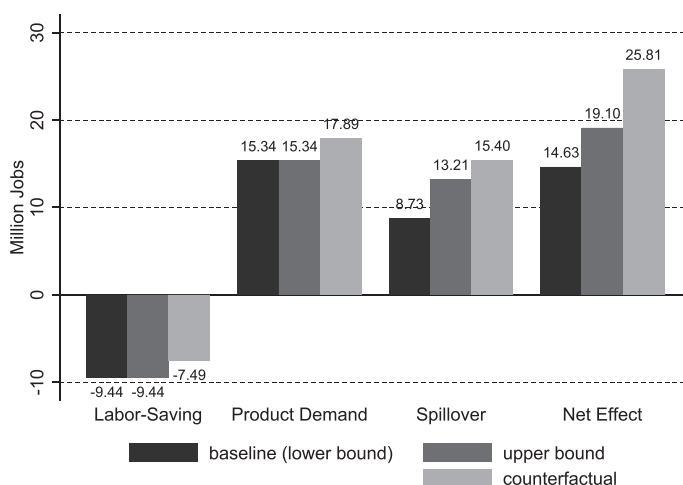


FIGURE 5. Predicted European employment change. Predicted employment change in Europe (27 countries) between 1999 and 2010 in millions of jobs. The baseline (lower bound) assumes no firm profits feed back into the local economy. The upper bound assumes that all firm profits are spent locally. The counterfactual simulation assumes no increase in firm mark-ups and thus larger price declines.

as our upper-bound estimate. Depending on how much of the rise in firms' profits has been spent locally in Europe, RRTC has raised net employment in the European Union between 14.63 and 19.10 million jobs from 1999 to 2010.

Lastly, the third set of bars in Figure 5 shows a simulation of what would have happened had firms not raised their mark-ups, such that price declines had instead matched those in marginal costs. The counterfactual net employment effect is 25.81 million jobs compared to 19.10 million jobs in our upper bound estimate, which highlights that rising mark-ups prevent more positive employment effects of RRTC. This is a relevant finding, as mark-ups are on the rise in many Western economies, and more broadly contributes to a recent literature that discusses the relationship between technological change, rising mark-ups, and declining labor shares. All in all, results in this section show that the labor market effects of technological change depend on the allocation of the gains from these innovations, consistent with a recent theoretical literature (Benzell et al. 2016; Sachs, Benzell, and LaGarda 2015).

5. Conclusion

There are long-standing public concerns about technological change destroying jobs, invoking images of labor racing against the machine. These concerns are echoed in a recent crop of theoretical models that allow technology to be labor-replacing, showing conditions under which labor-displacement occurs in aggregate as a result of technological change. However, empirical evidence on such aggregate effects is scarce, as most existing studies have focused on the relative effects of technological

progress across worker skill levels and job types or on very specific technologies such as industrial robots. Furthermore, the body of empirical evidence considering absolute 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 key job-destroying and job-creating channels of technological change and quantifying their empirical relevance for the overall employment impact. Our approach complements work focusing on specific technologies such as industrial robots by studying routine-replacing technologies as a whole: Unlike robotics, these technologies have already permeated many jobs and sectors.

We find that routine-replacing technologies have substantially increased employment in Europe over the period 1999–2010, suggesting that recent technological change has created more jobs than it has destroyed. 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 more than 9 million jobs as a result of machines replacing workers in performing routine tasks. RRTC reduces the number of workers who are needed per unit of output. Besides these labor-saving effects, labor demand is reduced further by the substitution of capital for labor. However, our study also shows that these job losses are more than outweighed by the job-creating effects of RRTC. These countervailing effects result from lower product prices, which improve regions' terms of trade, raising their tradable output and employment, as well as from growing local incomes and positive demand spillovers to the non-tradable sector. 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.

A final key finding is that positive aggregate employment effects depend not only on countervailing effects operating through product demand, but also on the allocation of the gains from technological progress. In particular, we find more positive employment effects from RRTC when profits accrue locally compared to when they do not flow back into the economy. Furthermore, we show that employment would have grown substantially more had firm mark-ups not increased. These results highlight that the distribution of gains from technological progress matters for its job-creating potential. It also stresses the importance of debates about who owns the technological capital (Freeman 2015), and of studying the impact of recent technological change on labor's share in national income (Autor et al. 2018; Autor and Salomons 2018; Karabarbounis and Neiman 2014).

References

- Acemoglu, D. and David Autor (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4, edited by O. Ashenfelter and D. Card. Elsevier, pp. 1043–1171.

- Acemoglu, Daron and Pascual Restrepo (2017). "Robots and Jobs: Evidence from US Labor Markets." NBER Working Paper No. 23285. <http://www.nber.org/papers/w23285>.
- Acemoglu, Daron and Pascual Restrepo (2018a). "Artificial Intelligence, Automation and Work." In *The Economics of Artificial Intelligence*, edited by Ajay K. Agrawal, Joshua Gans, and Avi Goldfarb. University of Chicago Press.
- Acemoglu, Daron and Pascual Restrepo (2018b). "Modeling Automation." *American Economic Review: Papers and Proceedings*, 108, 48–53.
- Acemoglu, Daron and Pascual Restrepo (2018c). "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment." *American Economic Review*, 108(6), 1488–1542.
- Appelbaum, Eileen and Ronald Schettkat (1999). "Are Prices Unimportant? The Changing Structure of the Industrialized Economies." *Journal of Post Keynesian Economics*, 21, 387–398.
- Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2017). "Revisiting the Risk of Automation." *Economics Letters*, 159, 157–160.
- Autor, D. and D. Dorn (2009). "Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States." IZA Discussion Paper No. 4290.
- Autor, David (2013). "The 'Task Approach' to Labor Markets: An Overview." *Journal for Labour Market Research*, 46, 185–199.
- Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen (2018). "Concentrating on the Fall of the Labor Share." *American Economic Review*, 107(5), 180–185.
- Autor, David and Anna Salomons (2018). "Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share." *Brookings Papers on Economic Activity*, 1, 1–87.
- Autor, David H. (2015). "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives*, 29(3), 3–30.
- Autor, David H. and David Dorn (2013). "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." *American Economic Review*, 103(5), 1553–1597.
- Autor, David H., David Dorn, and Gordon H. Hanson (2013). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6), 2121–68.
- Autor, David H., David Dorn, and Gordon H. Hanson (2015). "Untangling Trade and Technology: Evidence from Local Labour Markets." *The Economic Journal*, 125, 621–646.
- Autor, David H., Frank Levy, and Richard J. Murnane (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics*, 118, 1279–1333.
- Bartik, Timothy J. (1991). "Boon or Boondoggle? The Debate over State and Local Economic Development Policies." In *Who Benefits from State and Local Economic Development Policies*, edited by Timothy J. Bartik. W.E. Upjohn Institute for Employment Research, Kalamazoo, MI, pp. 1–16.
- Baumol, William J. (1967). "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *The American Economic Review*, 57(3), 415–426.
- Benzell, Seth G., Laurence J. Kotlikoff, Guillermo LaGarda, and Jeffrey D. Sachs (2016). "Robots Are Us: Some Economics of Human Replacement." NBER Working Paper No. 20941.
- Bessen, James, Maarten Goos, Anna Salomons, and Wiljan Van den Berge (2019). "Automatic Reaction—What Happens to Workers at Firms that Automate?" Working paper, CPB Netherlands Bureau for Economic Policy Analysis.
- Blien, Uwe and Helge Sanner (2014). "Technological Progress and Employment." *Economics Bulletin*, 34, 245–251.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2019). "Quasi-Experimental Shift-Share Research Designs." NBER, Working Paper No. 24997.
- Bowles, Jeremy (2014). "The Computerization of European Jobs." Working paper, The Bruegel Institute.
- Byrne, David and Carol Corrado (2017). "ICT Services and Their Prices: What Do They Tell Us about Productivity and Technology?" *International Productivity Monitor*, 33, 150–181.

- Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro (2019). "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica*, 87, 741–835.
- Card, David and Thomas Lemieux (2001). "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *The Quarterly Journal of Economics*, 116, 705–746.
- Caselli, Francesco and Alan Manning (2018). "Robot Arithmetic: New Technology and Wages." *American Economic Review: Insights*, 1(1), 1–12.
- Cashin, Paul and C. John McDermott (2003). "Intertemporal Substitution and Terms-of-Trade Shocks." *Review of International Economics*, 11, 604–618.
- Chetty, Raj, Adam Guren, Manoli Day, and Andrea Weber (2011). "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins." *American Economic Review*, 101(3), 471–475.
- Chiacchio, Francesco, Georgios Petropoulos, and David Pichler (2018). "The Impact of Industrial Robots on EU Employment and Wages: A Local Labour Market Approach." Working Paper No. 25186, The Bruegel Institute.
- Chih, Foued and Michel Normandin (2013). "External and Budget Deficits in Some Developing Countries." *Journal of International Money and Finance*, 32, 77–98.
- Cingano, Federico and Fabiano Schivardi (2004). "Identifying the Sources of Local Productivity Growth." *Journal of the European Economic Association*, 2, 720–742.
- Combes, Pierre-Philippe, Thierry Magnac, and Jean-Marc Robin (2004). "The Dynamics of Local Employment in France." *Journal of Urban Economics*, 56, 217–243.
- Cortes, G.M. and A. Salvatori (2015). "Task Specialization within Establishments and the Decline of Routine Employment." Working paper, University of Manchester.
- Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum, and Nicole Wößner (2017). "German Robots—The Impact of Industrial Robots on Workers." Working paper, Institute for Employment Research, Nuremberg, Germany.
- Dauth, Wolfgang, Sebastian Findeisen, and Jens Südekum (2014). "The Rise of the East and the Far East: German Labor Markets and Trade Integration." *Journal of the European Economic Association*, 12, 1643–1675.
- De Loecker, Jan and Jan Eeckhout (2020). "Global Market Power." NBER Working Paper No. 24768.
- De Loecker, Jan, Jan Eeckhout, and Gabriel Unger (2020). "The Rise of Market Power and the Macroeconomic Implications." *Quarterly Journal of Economics*, 135, 561–644.
- Freeman, R. (2015). "Who Owns the Robots Rules the World." *IZA World of Labor*, 5, 1–10.
- Frey, Carl Benedict and Michael Osborne (2017). "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, 114, 254–280.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8), 2586–2624.
- Goos, Maarten, Jozef Konings, and Marieke Vandeweyer (2015). "Employment Growth in Europe: The Roles of Innovation, Local Job Multipliers and Institutions." TKI Discussion Paper No. 15-10, Utrecht University School of Economics.
- Goos, Maarten and Alan Manning (2007). "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistics*, 89, 118–133.
- Goos, Maarten, Alan Manning, and Anna Salomons (2014). "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review*, 104(8), 2509–2526.
- Graetz, Georg and Guy Michaels (2018). "Robots at Work." *Review of Economics and Statistics*, 100, 753–768.
- Hall, Robert E. (2018). "New Evidence on the Markup of Prices over Marginal Costs and the Role of Mega-Firms in the US Economy." NBER Working Paper No. 24574.
- Harrison, Rupert, Jordi Jaumandreu, Jacques Mairesse, and Bettina Peters (2014). "Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries." *International Journal of Industrial Organization*, 35, 29–43.
- Imbs, Jean and Isabelle Mejean (2010). "Trade Elasticities: A Final Report for the European Commission." Working paper, Directorate General Economic and Monetary Affairs (DG ECFIN), European Commission.

- Jensen, J. Bradford and Lori G. Kletzer (2006). "Tradable Services: Understanding the Scope and Impact of Services Offshoring." In *Offshoring White-Collar Work, Issues and Implications*, edited by L. Brainard and S. M. Collins. Brookings Institution Press.
- Jensen, J. Bradford and Lori G. Kletzer (2010). "Measuring Tradable Services and the Task Content of Offshorable Services Jobs." In *Labor in the New Economy*, edited by Katharine G. Abraham, James R. Spletzer, and Michael Harper. NBER, pp. 309–335, <http://ideas.repec.org/h/nbr/nberch/10826.html>.
- Karabarbounis, Loukas and Brent Neiman (2014). "The Global Decline of the Labor Share." *The Quarterly Journal of Economics*, 129, 61–103.
- Katz, Lawrence F. and Kevin M. Murphy (1992). "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *The Quarterly Journal of Economics*, 107, 35–78.
- Krugman, Paul (1991). *Geography and Trade*. MIT Press.
- Moretti, E. (2010). "Local Multipliers." *American Economic Review*, 100(2), 373–77.
- Moretti, E. (2011). "Local Labor Markets." In *Handbook of Labor Economics*, Vol. 4, edited by O. Ashenfelter and D. Card. Elsevier, pp. 1237–1313.
- Moretti, Enrico and Per Thulin (2013). "Local Multipliers and Human Capital in the United States and Sweden." *Industrial and Corporate Change*, 22, 339–362.
- Neisser, Hans P. (1942). "Permanent Technological Unemployment: Demand for Commodities Is Not Demand for Labor." *American Economic Review*, 32(1), 50–71.
- Nordhaus, William D. (2015). "Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth." NBER Working Paper No. 21547.
- Sachs, Jeffrey D., Seth G. Benzell, and Guillermo LaGarda (2015). "Robots: Curse or Blessing? A Basic Framework." NBER Working Paper No. 21091.

Supplementary data

Supplementary data are available at [JEEA](#) online.