Technology and the Future of Work
Aggregate Employment Effects of Digitization*

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Abstract

There is a controversial public debate on the socio-economic consequences of the accelerating digitization, but only little scientific evidence on the contemporary consequences of cutting-edge digital technologies for aggregate employment. In this paper, we develop a theoretical framework that captures the key macroeconomic adjustment mechanisms to digitization. We conduct a survey among German firms concerning their current digitization measures, link it to the social security records of the firms and their employees, and empirically estimate our model using this data. Based on a decomposition that we directly derive from our model, we estimate the aggregate effects of digitization, as well as the contributions of different adjustment mechanisms, on employment, unemployment and wages. Our preliminary results suggest that cutting-edge digital technologies have little effect on aggregate employment, but lead to large movements of workers between occupations and industries.

Keywords: technology, machines, automation, jobs, capital-labor substitution

JEL: E24, J23, J24, O33

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1 Introduction

Although the discussion on labor market consequences of automation technologies and the induced automation anxiety are not new (Mokyr et al., 2015; Autor, 2015), recent advances in the fields of robotics and artificial intelligence have revived the debate once more. For producing firms, such technologies ("4.0 technologies") include production facilities up to Smart Factories, Cyber-Physical Systems and Internet of Things. For service providers, innovations have brought forward analytic tools for Big Data, Cloud Computing systems, internet platforms, shop systems or online marketplaces. All these advances have raised the question of whether machines and algorithms will at some point make human labor obsolete (Brynjolfsson and McAfee, 2011). The debate has been fuelled by a recent series of "future of work" studies according to which about half of the workforce faces a high risk of automation in coming decades (Frey and Osborne, 2017). Although other studies have put forward reasons to believe that these studies may be overstating the risk of automation (Arntz et al., 2017), there does not yet seem to exist a clear view on how modern technologies impact employment.

Existing empirical evidence on the industry level suggests that industrial robots had no detrimental effect on aggregate employment in developed countries (Graetz and Michaels, 2015). Studies on the firm-level suggest no employment losses in firms specialized in routine tasks (Cortes and Salvatori, 2015). Further evidence on the level of US local labor markets suggest that labor markets specialized in routine tasks did not experience employment declines (Autor et al., 2015) or even experienced a positive impact on labor demand as for the case of European regions (Gregory et al., 2016). A somewhat different result has recently been put forward for the US suggesting that regions using more robots experienced a negative effect on employment (Acemoglu and Restrepo, 2017). A recent study by Dauth et al. (2017) finds negative employment effects of robots in the German manufacturing sector, which are off-set by induced positive employment effects in the service sector. In line with this, Acemoglu and Restrepo (2017) highlight that the employment effects of robots apparently differ strongly from those of other types of technology as, e.g. computerization.

A major shortcoming of existing empirical assessments is that they use either indirect measures of technology such as the degree of routinization of work tasks (Routine Replacing Technological Change, RRTC) or specific technologies such as industrial robots. In case of routinization measures, studies rely on the assumption that all jobs involving routine (non-routine) tasks actually become automated (are safe from automation), which might not be realistic, especially in an era of technologies that increasingly enter domains previously preserved for human labor. Using robot data provides a more direct approach in measuring technological adaption, although the results are restricted to producing firms and neglect the important role of service providers which use algorithms and data rather than robots. Besides, up to the authors knowledge, none of the studies looks at the impact of “4.0 technologies” on employment, although they are attributed to fundamental changes on the labor market compared to former technologies. Finally, the underlying mechanisms through which technology affects employment are only partly understood. Most studies focus on job destruction channels such as capital-labour substitution and neglect beneficial channels of technology including positive product demand effects or capital-labour complementarities. The aim of this study is to fill these research gaps by making at least three major contributions.

First, to better understand the underlying mechanisms of technology impacting jobs, we set up a labor demand model that is able to explain technology adaption. The model links technology to occupational labor demand directly and explains the main job creation and job destruction channels arising from technology including substitution and product demand effects. Substitution effects arise as machines substitute (or complement) for certain work tasks. Product demand effects arise as machines allow firms to operate more cost efficient, leading to lower product prices and, hence, higher sales and labor demand. The model provides testable predictions for total labor demand as well as its subsequent transmission channels. The effects thereby depend on the substitution elasticity between job tasks as well as the elasticity of substitution between goods bundles across industries. In addition, we also model wage and labor supply respones to a changing labour demand in order to capture all relevant mechanisms through which technological change affects employment.

Second, we conduct a representative “IAB-ZEW Labour Market 4.0” firm survey among 2032 producing firms and service providers in Germany. Within the survey, we ask firms about their technology investments between 2011 and 2016. Among others, we gathered technology use data for producers (production equipment) and service providers (electronic office and communication equipment) and distinguish between different degrees of automation in order to identify technologies of the “Industry 4.0” (fourth industrial revolution). We then link the survey data to employment biographies from social security records (BeH) of all workers employed in the surveyed firms. We thus establish a unique linked employer-employee panel data set among German firms in a recent period of rapid technology improvements which allows us to (1) draw a first and detailed representative picture on the extent and change in modern automation technologies and to (2) relate these changes to changes in the level and structure of employment at the firm-level.

Third, based on the theoretical framework, we assess the impact of modern technology on total employment as well as the contributions of the key transmission channels via a decomposition by estimating the key parameters of the theoretical model: (1) task-specific labor demand as a function of technology investment yields the elasticity of substitution between job tasks and allows conclusions on whether modern technologies substitute (or complement) for certain tasks/occupations; (2) product demand as a function of technology investments yields the elasticity of substitution between goods bundles across industries which tells us to what extent firm's product demand profits from technology through lower product prices; (3) wages in a particular occupation-industry-cell as a function of the cell-specific employment rate; (4) labor supply shifts across industry-occupation cells in response to employment rates and wages. In the demand-side estimates, the unique linked employer-employee panel data set allows holding constant a rich set of firm characteristics and controlling for endogenous changes in capital, wages and revenues within an instrumental variables (IV) approach. For the supply-side estimations, we use rich administrative employment records and apply fixed effects and IV approaches to take account of potential endogeneities.

Our preliminary results suggest that the net effects of these technologies is actually positive, but small. We find that firms' technology investments have raised aggregate employment by, on average, 0.17% per year in Germany, which is less than half of the average yearly employment growth rate (0.41%). Contrary to existing results for the effects of robots, this is driven by positive labor demand effects. On net, complementarity dominates worker-machine substitution. In addition, we find net positive technology-induced product demand effects. While the net effects remain small, we do find huge reallocations of workers between industries and occupations. Technologies have mostly substituted for routine manual and cognitive workers while raising employment in interactive, abstract and non-routine manual jobs. Moreover, the technologies have accelerated structural change towards service industries, although those manufacturing sectors that produce the new technologies diverge from this picture and experience technology-induced employment growth.

The rest of our paper is structured as follows. Section 2 introduces a theoretical framework that captures key adjustment channels of the economy to technology investments. Based on the model, we derive a decomposition that allows us to study the contributions of several macroeconomic mechanisms to the aggregate employment effects of technological change. Section 3 describes our data sources. In Section 4, we present the empirical implementation of our theoretical framework. Based on our estimated model, we estimate the aggregate employment effects of technological change, as well as the contributions of the several macroeconomic mechanisms using our decomposition in Section 5. Section 6 concludes.

2 Theoretical Framework

We model industries $i = 1, ..., I$ located in country r which sell their products to the destinations $r' = 1, ..., R'$ (including the home country r). The firms are endowed with several types of technological capital. We study the role of the composition of firms' technological capital for firms' demand for different types of labor, the product demand responses to the changing cost and prices, the wage responses as well as the labor supply responses. We derive a decomposition from our framework which allows us to estimate the effect of technological change on aggregate employment, unemployment and wages while distinguishing several adjustment mechanisms.

2.1 Labor Demand

The representative firm in industry i combines tasks-sets (occupations) $T_j, j = 1, ..., J$ to produce output Y_i with a CES technology, $Y_i = \left[\sum_{j=1}^{J} (\beta_j T_{ij})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$, where $0 < \eta < 1$. $\eta < 1$ ensures that firms cannot elastically substitute between tasks, so that price-changes in a task do not lead to disproportionally large changes in task inputs. The optimum task composition is

$$T_{ij} = Y_f \beta_j^{\eta-1} \left(\frac{c_j^T}{c_i}\right)^{-\eta}. \tag{1}$$

Marginal costs c_i are a CES aggregate of task-specific marginal costs c_{ij}^T,

$$c_i = \left[\sum_{j=1}^{J} \left(\frac{c_{ij}^T}{\beta_j}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{2}$$

To produce one unit of task T_{ij}, firms require A_{ij} units of occupation-specific labor N_{ij}

$$N_{ij} = T_{ij} A_{ij} \tag{3}$$

A_{ij} is thus the input-coefficient for labor. It depends on the endowment of the firms with the k types of technological capital C_k and the relation of these capital types to workers' productivity α_{kj}, $A_{ij} = \prod_{k=1}^{K} C_{ik}^{-\alpha_{kj}}$. Assume, for example, that C_{ik} is a technology that substitutes for j-type workers. In this case, $\alpha_{kj} > 0$, so that A_{ij} declines in the size of technological capital C_{ik}. The technology reduces the number of workers required to produce that task, hence it substitutes for these workers. Vice versa, technology k' and workers j' are complements if $\alpha_{k'j'} < 0$. This substitution or complementarity applies to any given level of task output T_{ij}. However, note that the technological endowment further affects the marginal costs of the tasks, thus inducing changing task compositions of firms.

Task-specific marginal costs are

$$c_{ij}^{T} = w_{ij} \prod_{k=1}^{K} C_{ik}^{-\alpha_{kj}} \tag{4}$$

We approximate firm marginal costs with a Cobb-Douglas price index

$$c_i \approx \prod_{j=1}^{J} c_j^{T\kappa_{j|i}} \tag{5}$$

where $\kappa_{j|i}$ is the cost share of task j in the representative firm of industry i.

Occupation-specific labor demand is

$$N_{ij} = Y_f A_{ij} \left(\frac{c_{ij}^{T}}{c_i} \right)^{-\eta} \beta_j^{\eta-1} \tag{6}$$

Using the definitions of marginal costs and taking logs provides our labor demand equation

$$\begin{aligned} \ln N_{ij} = & \ln Y_i - \eta \left(\ln w_j - \sum_{j'=1}^{J'} \kappa_{j'|i} \ln w_{j'} \right) + (\eta - 1) \sum_{k=1}^{K} \alpha_{jk} \ln C_{ik} \\ & + (\eta - 1) \ln \beta_j - \eta \sum_{j'=1}^{J'} \sum_{k=1}^{K} \kappa_{j'|i} \alpha_{j'k} \ln C_{ik} \end{aligned} \tag{7}$$

The elements in the first row of the equation are straight forward: real sales, relative occupational wages and capital composition. The first element of the second row is an occupation-fixed effect, the second element of the second row is constant across occupations and can thus be controlled for using a time trend or time dummies.

Our model provides a flexible approach of routine replacing technological change: Instead of pre-defining the relationship between different occupations and capital, we directly estimate it to let the data define which tasks/occupations are complements or substitutes to computerized capital. This approach can be interpreted as a generalization of the approaches by Autor et al. (2003), Goos et al. (2014) and Gregory et al. (2016) (see Appendix A for more details).

2.2 Transmission Channels of Technological Change on Labor Demand

We rewrite the labor demand equation (7) to study the different channels through which technology choices affect labor demand:

$$\ln N_{ij} = \underbrace{\ln Y_i}_{(A)} - \eta \left(\ln w_j - \sum_{j'=1}^{J'} \kappa_{j'|i} \ln w_{j'} \right) - \underbrace{\sum_{k=1}^{K} \alpha_{jk} \ln C_{ik}}_{(B)}$$
$$+ \underbrace{\eta \left(\sum_{k=1}^{K} \alpha_{jk} \ln C_{ik} - \sum_{j'=1}^{J'} \sum_{k=1}^{K} \kappa_{j'|i} \alpha_{j'k} \ln C_{ik} \right)}_{(C)} + (\eta - 1) \ln \beta_j \tag{8}$$

Assume that technology k is a substitute for j workers, $\alpha_{jk} > 0$. (The opposite holds true if the two are complements, $\alpha_{jk} < 0$.) A rise of the technological capital C_{ik} then has three effects on demand for labor N_{ij}: Firstly, the technology directly reduces A_{ij}, the number of workers required to produce the tasks T_{fj}, and labor demand N_{ij} declines (B). Secondly, as the number of workers required to produce tasks T_{ij} declines, the marginal costs of producing task that task (c_{ij}^T) decline and it becomes profitable for the firm to use more of these tasks. This partly compensates the negative effect on labor demand if $0 < \eta < 1$ (C). Thirdly, as the task-specific marginal costs decline, also overall marginal costs of the representative firm c_i decline and the firm reduces its prices, which leads to an increase of production Y_i. This raises labor demand (A).

2.3 Investments

We assume that the composition of firms' technological capital is the result of optimal firm behavior. We observe firms' actual capital choices in our data and assume that these are optimal to infer on the underlying capital price changes. Assume that firms minimize the costs of obtaining their technological capital stock while taking into account that any change in capital endowments affects the optimal labor composition from above. We take into account the latter constraint via the marginal costs that are the result of the optimum labor choice:

$$\min \sum_{k=1}^{K} p_k C_k \text{ s.t. } c_i = \left(\sum_{j=1}^{J} \left(\frac{c_{ij}^T}{\beta_j} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}} = \left(\sum_{j=1}^{J} \left(\frac{\prod_{k=1}^{K} C_k^{-\alpha_{jk}} w_j}{\beta_j} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{9}$$

We take the ratio of the first order condition of the optimatimization problem between two types of capital and plug the result into the definition of total costs TC to get:

$$\frac{p_{k'} C_{k'}}{TC} = \frac{\sum_{j=1}^{J} \alpha_{jk'}}{\sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_{jk}} \tag{10}$$

The cost shares of the capital types correspond to the average productivity of the capital types across all occupations, relative to all capital types. From this we can derive that the price elasticity of demand for technological capital type k is -1:

$$\begin{aligned}
\frac{\partial \ln C_{ik}}{\partial \ln p_k} =& -1 + \frac{\partial \ln \sum_{k'=1}^{K'} p_{k'} C_{ik'}}{\partial \ln p_k} \\
=& 1 - + s_k^{TC} \frac{\partial \ln C_{ik}}{\partial \ln p_k} + s_k^{TC} \\
& \text{where } s_c^{TC} = \frac{p_k C_{ik}}{TC} \\
\frac{\partial \ln C_{ik}}{\partial \ln p_k} =& -1
\end{aligned} \tag{11}$$

Hence, there is an inverse relationship between changes in optimal capital choices and changes in capital prices, $\Delta \ln p_k \approx -\Delta \ln C_{ik}$.

2.4 Product Demand

Consumers in country r' consume the aggregate final good $Y_{r'}^D$, which is a CES aggregate of the varieties from the producer countries $r = 1, 2, ..., R$, $Y_{r'}^D = \left[\sum_{r=1}^{R} \left(\beta_r Y_{r'r}^D \right)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}$. Exports from home country r to any country r' thus are

$$Y_{r'r}^D = \left(\frac{\tau_{rr'} p_r}{P_{r'}} \right)^{-\epsilon} I_{r'} \beta_r^{\epsilon-1} \tag{12}$$

where $P_{r'}$ is the CES price index in location r', $P_{r'} = \left(\sum_{r=1}^{R} \left(\tau_{rr'} p_r \right)^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}$ and p_r is the domestic producer price index. The home country r produces a CES aggregate of industry i goods, $Y_{r'r}^D = \left[\sum_{i=1}^{I} \left(\beta_{ir'} Y_{ir'r}^D \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$. Exports from home country r and industry i to any destination r' thus are

$$Y^D_{ir'r} = \left(\frac{p_{ir}}{p_r}\right)^{-\sigma} Y^D_{r'r}\beta^{\sigma-1}_{ir'} \tag{13}$$

where p_r is a CES price index of the industry producer prices, $p_r = \left(\sum_{i=1}^{I} (p_{ir})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. Industry output is a CES aggregate of the firms' outputs in that industry, $Y^D_{ir'r} = \left[\sum_{f=1}^{F} \left(Y^D_{ir'rf}\right)^{\frac{\sigma_i-1}{\sigma_i}}\right]^{\frac{\sigma_i}{\sigma_i-1}}$. Firms' sales to destination r' thus are

$$Y^D_{ir'rf} = \left(\frac{p_{irf}}{p_{ir}}\right)^{-\sigma_i} Y^D_{ir'r} \tag{14}$$

Aggregate demand for final goods produced by home country r and industry i across all destination markets r' thus is:

$$Y^D_{ir} = \sum_{r'=1}^{R'} \left(\frac{p_{ir}}{p_r}\right)^{-\sigma} \left(\frac{\tau_{rr'}p_r}{P_{r'}}\right)^{-\epsilon} I_{r'}\beta^{\epsilon-1}_{r}\beta^{\sigma-1}_{ir'} \tag{15}$$

2.5 Capital Sector

A competitive sector produces the capital stock under real marginal resource costs r_k using only the national output from sectors i with technology

$$C_{i'k} = \frac{1}{r_k} Y^{C_k}_{i'} = \frac{1}{r_k}\left[\sum_{i=1}^{I} \left(\beta^{C_k}_{i} Y^{C_k}_{i'i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{16}$$

where $C_{i'k}$ is the stock of technological capital type k used by industry i', $Y^{C_k}_{i'}$ are the aggregate inputs used for producing capital type k for industry i' and $Y^{C_k}_{i'i}$ are the inputs produced by industry i for producing capital type k to be used in industry i'. The capital sector optimally chooses the composition of the inputs so that

$$Y^{C_k}_{i'i} = \left(\frac{p_{ir}}{p_r}\right)^{-\sigma} {\beta^{C_k}_{i}}^{\sigma-1} Y^{C_k}_{i'} \tag{17}$$

$$p_r = \left(\sum_{i=1}^{I} p^{1-\sigma}_{ir}\right)^{\frac{1}{1-\sigma}} \tag{18}$$

Competition in the capital sector implies that capital prices correspond to marginal costs, $p_k = p_r r_k$. Total sales of capital type k to sector i' are $p_k C_{i'k} = p_r Y^{C_k}_{i'}$ and the associated real resource costs are $Y^{C_k}_{i'} = r_k C_{i'k}$.

2.6 Aggregate Demand and Income

Aggregate demand for products produced by industry i and sold across all countries r' for final demand, or domestically as input in capital production for sectors i', is

$$Y_{ir} = \left(\frac{p_{ir}}{p_r}\right)^{-\sigma} \left[\underbrace{\sum_{r'=1}^{R'} \beta_{ir'}^{\sigma-1} \left(\frac{\tau_{r'r} p_r}{P_{r'}}\right)^{-\epsilon} I_{r'} \beta_r^{\epsilon-1}}_{MR_{ir}^D} + \underbrace{\sum_{i'=1}^{I'} \sum_{k=1}^{K} \beta_i^{C_k \sigma-1} r_k C_{i'k}}_{MP_{ir}^C} \right] \tag{19}$$

Real income in country r is equal to real sales, lowered by the real resource costs for producing the capital

$$I_r = \sum_{i=1}^{I} \sum_{r'=1}^{R'} Y_{ir'r}^D + \sum_{i=1}^{I} \sum_{i'=1}^{I'} \sum_{k=1}^{K} Y_{i'i}^{C_k} - \sum_{i=1}^{I} \sum_{k=1}^{K} r_k C_{ik} \tag{20}$$

Income corresponds to real sales for final demand across all markets, real sales of the output to be used as input for capital production, lowered by the real resource cost of producing that capital. Note that the real resource cost of producing the capital consists solely of the inputs in capital production. Hence, summing across all industries and capital types, the latter two terms sum to zero. Real income thus is $I_r = \sum_{i=1}^{I} \left(\frac{p_{ir}}{p_r}\right)^{-\sigma} MP_{ir}^D$

2.7 Labor Market Frictions

We rely on the wage-bargaining model of Blanchflower et al. (1996) to model wage responses and apply it to each segment ij of our labor market individually, i.e. each industry-occupation has its own union which bargains for segment-specific wages. In their model, the Nash-equilibrium of unions bargaining with employers for wages with union bargaining power ϕ is

$$\max \phi \log \left[(u(\ln w) - u(\ln \bar{w})) \frac{N_{ij}}{L_{ij}} \right] + (1-\phi) \log \pi \tag{21}$$

If no agreement between the trade union and the employers is achieved, workers earn the outside wage $\bar{w}$ whereas firms' outside profits are zero. Profits in case of an agreement are π_{ij}, wages in case of an agreement are w_{ij} and the objective function of the trade union is $u(w_{ij})$. Following Blanchflower et al. (1996), the agreed-upon wages are:

$$\ln w_{ij} = \ln \bar{w} + \frac{\phi}{1-\phi} \pi \frac{N_{ij}}{L_{ij}} \tag{22}$$

That is, wages depend on outside wages $\ln \bar{w}$ (e.g. unemployment benefits) and the employment rate $\frac{N_{ij}}{L_{ij}}$, where N_{ij} is employment and L_{ij} is the number of people searching for employment in segment ij. We can approximately rewrite this equation as a Wage Curve

$$\ln w_{ij} = \beta_0 + \beta_1 \ln \bar{w} - \beta_2 \frac{\bar{u}}{1-\bar{u}} \ln u_{ij} \tag{23}$$

where $u_{ij} = 1 - N_{ij}/L_{ij}$ is the unemployment rate, $\bar{u}$ is the steady state unemployment rate and β_0 is a constant which depends on the steady state values of the unemployment rate.

2.8 Labor Supply

Assume that each worker $n = 1, 2, ..., N$ supplies ν_{ijn} efficiency units of labor in segment ij. Workers receive utility from wages and expected employment chances,

$$\log U = \gamma_1 \ln \frac{N_{ij}}{L_{ij}} + \gamma_2 \ln w_{ij} \nu_{ijn} \tag{24}$$

If $\gamma_1 = \gamma_2$, workers focus on expected earnings, only. The probability of worker n to choose labor market segment ij over another labor market segment then is

$$\Pr\left(\gamma_1 \ln \frac{N_{ij}}{L_{ij}} + \gamma_2 \ln w_{ij} + \gamma_2 \nu_{ijn} > \gamma_1 \ln \frac{N_{i'j'}}{L_{i'j'}} + \gamma_2 \ln w_{i'j'} + \gamma_2 \nu_{i'j'n}\right) \tag{25}$$

Assuming that $\ln \nu_{ijn}$ follows a type 1 extreme value distribution, we can estimate this as a multinomial choice model based on McFadden (1973, 1981). Following Berry (1994), we can further interpret this probability as the share $s_{ij} = L_{ij}/\bar{L}$ of workers who choose a specific labor market segment:

$$\begin{aligned} \ln s_{ij} - \ln s_{i'j'} =& \gamma_1 \ln \frac{N_{ij}}{L_{ij}} + \gamma_2 \ln w_{ij} - \gamma_1 \ln \frac{N_{i'j'}}{L_{i'j'}} - \gamma_2 \ln w_{i'j'} + \gamma_2 \ln(\nu_{ij} - \nu_{i'j'}) && (26) \\ \ln L_{ij} =& \gamma_1 \ln \frac{N_{ij}}{L_{ij}} + \gamma_2 \ln w_{ij} - \gamma_1 \ln \frac{N_{i'j'}}{L_{i'j'}} - \gamma_2 \ln w_{i'j'} + \ln L_{i'j'} \\ & + \gamma_2 \ln(\nu_{ij} - \nu_{i'j'}) && (27) \end{aligned}$$

We use the average of the labor market as the reference sector $i'j'$ and estimate:

$$\ln\frac{L_{ij}}{\bar{L}} = \gamma_1\left(\ln\frac{N_{ij}}{L_{ij}} - \ln\overline{N/L}\right) + \gamma_2(\ln w_{ij} - \ln\bar{w}) + \gamma_2(\ln\nu_{ij} - \ln\bar{\nu}) + \epsilon_{ij} \tag{28}$$

where $\overline{N/L}$ is the average employment rate in all other segments and $\bar{w}$ are average wages in all other segments.

2.9 Decomposition

From our model, we can derive a decomposition of technology-induced aggregate employment changes (see Appendix B for details):

$$\Delta N = \mathbf{n}\underbrace{\left(\mathbf{I} - \frac{1}{1+\eta\beta_2}\mathbf{B}\right)^{-1}}_{(5)}\underbrace{\mathbf{X}}_{(1)-(3)}\left(1 - \underbrace{\frac{\eta\beta_2}{1+\eta\beta_2}}_{(4)}\right)\mathbf{c} \tag{29}$$

Matrix $\mathbf{X}$ contains the additive labor demand effects (1)-(3) to be explained below, (4) reflects the wage response to those labor demand effects, and (5) reflects the labor supply response. We expect that a positive labor demand shock leads to rising wage, which reduce the positive employment effects. Moreover, we expect that a positive labor demand shock leads to increasing (decreasing) labor supply in that segment (all other segments), which raises (reduces) employment in that segment (all other segments).

$\mathbf{n}$ is an ij column-vector of initial employment L_{ij}, $\mathbf{X}$ is an $ij \times i^*k$ matrix that represents the labor demand shocks, $\mathbf{B}$ is an $ij \times ij$ matrix which represents the labor supply responses, and $\mathbf{c}$ is an i^*k row-vector of changes in capital endowments. i and j represent the industries and occupations that are exposed to the shock, i^* represents the investing industry and k represents the capital type that industry i^* invests into.

More specifically, the matrix $\mathbf{X}$ consists of the elements:

$$X_{ij,i^*k} = \underbrace{-\alpha_{jk}}_{(1)} + \underbrace{\eta\left(\alpha_{jk} - \sum_{j'=1}^{J'}\alpha_{j'k}\right)}_{(2)} + \underbrace{a_i\sum_{j'=1}^{J'}\kappa_{j'|i^*\alpha_{j'k}}}_{(3)} \;\; \forall\; i = i^* \tag{30}$$

$$X_{ij,i^*k} = \underbrace{b_{ii^*}\sum_{j'=1}^{J'}\kappa_{j'|i^*}\alpha_{j'k}}_{(3)} \;\; \forall\; i \neq i^* \tag{31}$$

$$\tag{32}$$

where a_i and b_{ii^*} contain the product demand responses. Element (1) represents direct capital-labor substitution, (2) represents substitution between tasks, and (3) represent product demand effects that are induced by the capital investments.

We further use $\mathbf{B} = \eta\beta_2\hat{\mathbf{S}}^{\mathbf{L}} + \beta_2\mathbf{A} - \beta_2\mathbf{A}\hat{\mathbf{S}}^{\mathbf{L}}$, where $\hat{\mathbf{S}}^{\mathbf{L}}$ reflects wage effects induced by workers movements between segments (see Appendix B for details) and matrix $\mathbf{A}$ consists of the elements

$$A_{ij,i'j'} = (\eta - a_{ir})\kappa_{j'|i} \;\forall\; i = i' \tag{33}$$

$$A_{ij,i'j'} = (\eta - b_{ii'})\kappa_{j'|i'} \;\forall\; i \neq i' \tag{34}$$

Note that we can compute the decomposition for each segment ij separately by transposing the vector of initial employment $\mathbf{n}$.

Based on equation (29), we can decompose the aggregate change in employment ΔN into the labor demand effects ΔN^{demand}, the wage response effect ΔN^{wage}, and the labor supply effect ΔN^{supply} with

$$\Delta N^{demand} = \mathbf{nXc} \tag{35}$$

$$\Delta N^{wage} = \mathbf{n}\left(\mathbf{I} - \frac{\beta_2}{1+\eta\beta_2}\mathbf{A}\right)^{-1}\mathbf{X}\left(1 - \frac{\eta\beta_2}{1+\eta\beta_2}\right)\mathbf{c} - \Delta N^{demand} \tag{36}$$

$$\Delta N^{supply} = \mathbf{n}\left(\mathbf{I} - \frac{1}{1+\eta\beta_2}\mathbf{B}\right)^{-1}\mathbf{X}\left(1 - \frac{\eta\beta_2}{1+\eta\beta_2}\right)\mathbf{c} - \Delta N^{wage} - \Delta N^{demand} \tag{37}$$

As our model is based on constant aggregate labor supply, we can easily produce a decomposition of changes in the unemployment rate based on the labor demand decomposition:

$$\Delta U = -\frac{\Delta N}{L} \tag{38}$$

Moreover, we can derive an analogous decomposition of average wage changes

$$\Delta\bar{w} = \left[(1+\beta_2)\mathbf{s^w} - \mathbf{s^N} - \beta_2\mathbf{s^w}\hat{\mathbf{S}}^{\mathbf{L}}\right]\left(\mathbf{I} - \frac{1}{1+\eta\beta_2}\mathbf{B}\right)^{-1}\mathbf{X}\left(1 - \frac{\eta\beta_2}{1+\eta\beta_2}\right)\mathbf{c} \tag{39}$$

where $\mathbf{s^N}$ is an ij vector of the initial employment share of the segments and $\mathbf{s^w}$ is an ij vector of wage-income shares of the segments.

3 Data

3.1 IAB-ZEW Labour Market 4.0 Database

Our main data source is the IAB-ZEW Labour Market 4.0 database, a linked employer-employee database. It combines a firm-survey with social-security records of the firms and their workers. We construct the data from two main sources including (1) "IAB-ZEW Labour Market 4.0" firm survey and (2) employment biographies from social security records (BeH). The data sources are described in detail below.

Firm survey. In order to gather unique information on modern technology investments, we conducted a representative "IAB-ZEW Labour Market 4.0" firm survey among 2032 firms between March-May 2016. Firms were randomly chosen from a pool of all German firms with at least 1 employee subject to social security contributions. The firm survey was stratified by firm size (4 categories), industrial sector (5 categories) and region (East/West Germany). For each cell, we conducted about 50 CATI-based interviews with mostly production managers or the firms' management. The response rate was 21 percent, although the reasons for non-participation were not associated with technology usage for X percent of the non-participating firms. The interviews lasted, on average, 30 minutes and covered questions around (1) the relevance of "new" digital technologies (including 4.0 technologies) (2) the degree of automation of work equipment (3) changes in firm labor demand regarding skills, tasks and competencies as well as (4) background characteristics including sales and profits. The information was gathered for the presence, past (before 5 years) and future (in 5 years).

The firm survey is the main data source for our technology (capital) measures. For this, we asked production managers to assess the shares of their overall production and electronic office and communication (O&C) equipment by degree of automation (compare Table 1). Note that X% of the firms use only production equipment, whereas Z% use both. We conduct regressions in two versions. In a first version, we distinguish between production and O&C equipment. In a second version, we create an aggregated technology measure, where capital is defined as production equipment for producers and O&C equipment for service providers. For firms that use both, we calculate the average capital stock of firm i at time t as follows: $k_{i,s,t} = \delta k_{i,s,t}^{O\&C} + (1+\delta) k_{i,s,t}^{prod}$, where s represents the capital type $s = 1, 2, 3$ and where $\delta_j = 0.7$ for service providers and $\delta_j = 0.3$ for producers. Capital type shares add up to 100%, that is

Table 1: Work equipment by automation degree

Production equipment (p)	Electronic office and communication equipment (d)
1. manually controlled (k_1^{prod}) e.g. drilling machine, motor vehicles or X-ray machine → humans are largely involved in work process	**1. not IT-supported** ($k_1^{O\&C}$) e.g. telephones, fax and copy machines → humans are largely involved in work process
2. indirectly controlled (k_2^{prod}) e.g. CnC machines, industrial robots or process engineering systems → humans are only indirectly involved in work process	**2. IT-supported** ($k_2^{O\&C}$) e.g. computers, terminals, electronic checkout systems or CAD-systems → humans are only indirectly involved in work process
3. self-controlled (k_3^{prod}) e.g. production facilities up to Smart Factories, Cyber-Physical Systems and Internet of Things → work processes are largely performed automatically	**3. IT-integrated** ($k_3^{O\&C}$) e.g. analytic tools for Big Data, Cloud Computing systems, internet platforms such as Amazon, shop systems or Online-Markets → work processes are largely performed automatically

$k_{i,s=1,t} + k_{i,s=2,t} + k_{i,s=3,t} = 100$. For each capital type, we then calculate the log capital type share change as follows: $\Delta k_{i,s} = \ln(k_{i,s,t} + 1) - \ln(k_{i,s,t-5} + 1)$, where t=2016.

From the firm survey we further construct 5-year changes between 2011-2016 in log purchased goods and services (in Euros), revenues (in Euros) as well as value added defined as revenues minus purchased goods and services.

Employment histories (BeH) The survey data was linked to employment biographies from social security records (BeH) of all workers employed in the surveyed firms between 2011-2015. The data includes, among others, information on the employment status, earnings, occupation and industry of workers. In total, we observe 282,130 employees in any of the years between 2011-2015. We restrict the data to employment spells overlapping june 30th of a year, which leaves us with 950.795 worker-year observations. Based on the data, we calculate log changes between 2011 and 2015 in the number of firm-level workers, the number of firm-level workers by task domain, average log firm daily wages, average log firm occupation daily wages as well as average log daily industry wages (2-digit WZ08).[1] As employment biographies for the year 2016 are not yet available, we multiply our four-year changes with 5/4. If no data is available for $w_{ij,t-4}$ we take $w_{i,t-3}$ and multiply $\Delta \ln w_{ij}$ by (5/3) and so forth for t=2, t=1.

The task domain is defined based on a German expert data base BERUFENET of the Federal Employment Agency including detailed information on work tasks by 5-digit occupation Dengler and Matthes (2015). For each occupation, we calculate the share of tasks falling into the following task domains: (1) analytic non-routine (2) interactive non-routine (3) cognitive routine (4) manual routine (5) manual non-routine. We then calculate 5-year changes in the number of employed

[1] Wage imputation...

workers as follows: $\Delta \ln N_{ij} = \Big(\ln(\sum_{k=1}^{K} \delta_{ijkt} N_{ijkt} + 1) - \ln(\sum_{k=1}^{K} \delta_{ijkt-4} N_{ijk,t-4} + 1)\Big) * (5/4)$, where δ_{ij} is individual k's share of task j at work and t=2015. We calculate wages in a similar manner.

3.2 SIAB

As our second main data source, we use the Sample of Integrated Labor Market Biographies (SIAB 7514) from the IAB. This is a sample of the social security records for the time period 1975 to 2014 for Germany. This data provides more information on employment, wages and worker mobility than the "IAB-ZEW Labour Market 4.0" Database.

The first main indicator which we derive from this data is employment at the occupation- and industry level N_{ijt} for each year t. We differentiate between $i = 1, \ldots, 13$ sectors and $j = 1, \ldots, 5$ occupations. For the occupations, we classify each occupation according to the main task out of five task domains as provided by Dengler and Matthes (2015). For merging the information from Dengler and Matthes (2015), we use the KldB2010 on the 3-digit level as the occupational classification. However, we have to deal with a relevant structural break in 2011/2012 because employment spells ending after the 30th of Nov 2011 are classified according to KldB 2010 while employment spells ending before that date are classified according to KldB 1988. Although the KldB2010 time series has been extended before 2012 based on some recoding, there are much more missings in the KldB2010 in 2011 (and to a lesser extent in 2012) than in any other year due to the introduction of the new classification scheme (Ganzer et al., 2017, p. 9). We reduce these missings by backward and forward extrapolation if people stayed in the same firm, i.e. the firm counter remains unchanged for two consecutive employment spells. Similarly, we fill in related missing for the part-time status of the worker. We analogously apply backward and forward extrapolation, but extrapolate information only if in addition to staying in the same firm, the daily gross wage changed less than 10% (up or down) between two consecutive observations.

Our second main indicator from this data are wages. The data provides reliable information on daily gross wages. However, wages are reported only up to the social security contribution limit. We therefore follow Card et al. (2013) and Dustmann et al. (2009) by applying Tobit regressions to impute wages above this limit.[2] Moreover, we only have gross daily wages, hence always mixing a wage component and an hours of work component. Hence, in order to eliminate

[2]We would like to thank Johann Eppelsheimer and Wolfgang Dauth for providing us their code for the wage imputation.

the hours component and the corresponding bias for the estimation of some structural equations (such as the wage curve, see 4.3), we also calculate cell-specific wage levels for full-time workers only.

Our third main indicators is unemployment (or non-employment). While the social security records provide very reliable information on employment and wages, they used to report unemployment only if workers register as unemployed and receive unemployment benefits or unemployment assistance. Hence, there exist spells where workers are neither employed, nor reported as unemployed in the data despite being unemployed and seeking employment. Since 2007[3], however, the data includes additional spell information whenever people are registered at the employment agency as seeking employment (ASU information). For the estimation of the labour supply function, we hence rely on this information and apply a narrow definition of non-employment (nNE) following implementation A of Kruppe et al. (2007). We define a period of unemployment as each uninterrupted unemployment period as shown in the ASU information (unemployed and looking for job). Minor jobs as well as internships parallel to ASU are being ignored and still count as unemployment period, while all other forms of employment parallel to ASU dominate ASU. In a more refined concept (concept 2/3), Kruppe et al. (2007) also ignore employment spells if working hours is less than 15 hours/week, but working time information for the relevant years is imprecise and has many missings in 2011. Hence, we exclude all ASU spells with parallel employment spells from socially insured employment irrespective of working hours.

Based on this unemployment definition, we construct cell-specific labor supply as the sum of employees and unemployed in each cell ij (industry-occupation). The key problem is that we do not know where unemployed workers seek employment. To cope with this, we apply two different approaches. In the first approach, we use the occupation and industry of the previous job of each unemployed to define their occupational and sectoral affiliation during unemployment. In the second approach, labor supply in cell ij is employment in that cell plus a weighted sum of unemployed in all other cells. The weights correspond to the observed job mobility of workers between cells, so that the resulting number reflects the number of unemployed workers who likely seek employment in cell ij given their previous occupational and sectoral affiliation. In order to ensure a sufficiently large sample, we calculate worker mobility by exploiting all job transitions irrespective of whether its job-to-job or job-unemployment-job transition. Moreover, we pool job transitions from two years and also pool some ij-cells in order to ensure statistically

[3]The informatoin was also available between 1999 and 2003/4.

reliable transition probabilities. Hence, unemployed job seekers with a certain cell-affiliation are redistributed to other cells according to a (time varying) transition probability. Applying these weights yields a weighted labor supply (wL).

3.3 Auxiliary Data

In addition to this, we use several auxiliary data sets:

World Input-Output Database (WIOD): We use the 2013 revision[4] of the WIOD (Timmer et al., 2015) to get international trade flows at the industry level between Germany and 39 other countries, marginal costs (wages per value added) at the country and industry level, and local income in the destination countries. Moreover, we derive several shares from the data that are required for constructing other variables and for the decomposition: Shares of exporter-specific imports in importers' price index, shares of industries in the countries' price index, share of final demand in total sales by industry, share of intermediates demand in total sales by industry, share of importer country in the total sales of the exporter country, and share of industries in total income. We convert all values to Euros and deflate them to 1995 Euros using the exchange rate and deflators available in the WIOD.

EU KLEMS: We use the EU KLEMS September 2017 release to get industry-specific depretiation rates as well as industry-specific capital stock information.

4 Empirical Implementation

4.1 Labor Demand

Below, we present our preliminary estimates of our labor demand equation from Section 2.1. *Currently, we are preparing the data from our firm survey to implement the labor demand equation. As this process is not finalized, we instead present a preliminary analysis which relies on the classical Routine-Task-Intensity approach following Gregory et al. (2016). We will update this section and apply our labor demand specification from Section 2.1 once the data preparation has been finalized.*

[4] The socio-economic accounts of the WIOD currently are only available for the 2013 revision, they will become available for the 2016 revision not before December 2017. We will update the database once they are available.

Our preliminary labor demand equation is

$$\ln N_{ijt} = \beta_1 \ln Y_{it} + \beta_2 \ln p_{it} + \beta_3 \ln w_{ijt} + \beta_4 t + \beta_5 \mathrm{RTI}_{ij} \times t + \beta_i + \beta_j + \epsilon_{ijt} \tag{40}$$

where N_{ijt} is employment in industry i and occupation j in year t, Y_{it} is value added, w_{ijt} are wages, p_{it} are industry-level marginal costs, and RTI is the routine task intensity of occupation-industry ij. Following Gregory et al. (2016), we thus approximate occupation-industry specific capital price changes using the initial routine intensity of the cells. The idea of this approach is that cells which more strongly rely on routine tasks, have larger potentials for automation via algorithms and thus profit more from declining prices for processing power.

Estimation results are presented in Table 2. The first column is an OLS-estimation of Equation (40) including industry and occupation dummies and a time trend. The second column is as column (1), but uses an IV approach that takes account of potential endogeneity of value added and marginal costs. Our IV for industry-level marginal costs are average industry marginal costs of selected other countries. This IV captures common technology-driven trends in industry costs. We use two alternative sets of countries for this IV.[5] Our IV for industry-level value added is the industry-specific capital stock as reported in the 2013 revision of the WIOD. Since the corresponding capital data is available only until 2007 so far, the IV estimations are restricted to a period of 1999 to 2007 whereas the OLS estimations capture the period from 1999 until 2011.[6]

The third column is a Fixed Effects Panel estimation of Equation (40), and the last column an instrumented version of column (3) where the instruments are chosen as discussed above. In all specifications, RTI has a negative effect on employment, as expected: The more routine an occupation-industry cell, the lower the overall employment growth, since these cells face stronger declines in capital prices so that they face stronger substitution of labor by capital. The coefficient is -0.005 in our preferred specification (column 3), which suggests that labor demand growth is lower by 0.5 percentage points in occupation-industry cells which have a routine intensity that is higher by one standard deviation. Our coefficient on value added is close to unity, as predicted by our theory. The coefficient on marginal costs corresponds to the elasticity of substitution between tasks, η, and is 0.82 in our preferred specification (column 3). This is close to comparable estimates by Gregory et al. (2016) and Goos et al. (2014). Moreover,

[5] Our first set of countries comprises India, Indonesia, Mexico and Brasil; our second set of countries comprises Australia, Canada, Japan and Korea.

[6] We will update this as soon as the 2016 revision of the WIOD data becomes available. Moreover, once we estimate labor demand based on the firm survey, we will focus on the more recent period from 2011 onwards.

Table 2: Labor Demand Results

VARIABLES	(1) ols_RTI2_P3 ln_N_ij	(2) iv_cs_RTI2_P3 ln_N_ij	(3) FE_RTI2_P3 ln_N_ij	(4) IV3_RTI2_P3 ln_N_ij
std_RTI2_t	-0.0472***	-0.0585***	-0.00515*	-0.000822
	(-2.690)	(-2.624)	(-1.949)	(-0.0990)
	0.00910	0.00868	0.0557	0.921
ln_VA	0.785***	0.969***	0.828***	0.657*
	(4.085)	(3.543)	(8.020)	(1.672)
	0.000125	0.000396	0	0.0945
ln_P3_ir	0.761**	1.148**	0.816***	4.239
	(2.528)	(1.992)	(4.843)	(0.892)
	0.0139	0.0464	8.47e-06	0.372
ln_wft_ij	-0.670	-0.672	-0.909***	-0.497
	(-1.525)	(-1.493)	(-2.973)	(-0.516)
	0.132	0.135	0.00415	0.606
Constant	8.856***	9.617***	10.46***	25.17
	(4.619)	(3.123)	(7.352)	(1.246)
	1.92e-05	0.00179	4.47e-10	0.213
Observations	1,105	845	1,105	845
R-squared	0.590	0.591	0.476	0.978
N	1105	845	1105	845
Sector Dummies	✓	✓		
Occupation Dummies	✓	✓		
Number of Cells			65	65

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the coefficient on wages is negative, as expected: higher wage costs imply lower labor demand.

4.2 Product Demand

We separate the product demand equation from Section 2.4 into two parts, one at the country-country-trade-flow level and one at the country-country-industry-trade-flow level to correctly estimate the two parameters of interest: ϵ, the elasticity of substitution between countries' goods bundles in consumption is estimated at the first level whereas σ, the elasticity of substitution between industries within those goods flows is estimated at the second level.

For the country-country-trade-flow level, we estimate

$$\ln Y_{r'r} = -\epsilon \ln \frac{p_r}{P_{r'}} - \epsilon \ln \tau_{r'r} + \ln I_r + (\epsilon - 1) \ln \beta_r \tag{41}$$

where $Y_{r'r}$ are the sales of country r (Germany, only) to country r' (all 40 countries including

Table 3: Product Demand Equation - Results (1)

Variable		FE	FE IV	Pooled	Pooled IV
$I_{r't}$	coef.	1.035	1.119	0.875	0.965
	t	60.700	44.360	10.180	7.920
	p	0.000	0.000	0.000	0.000
$\ln \frac{p_{rt}}{P_{r't}}$	coef.	-0.034	-0.204	0.008	-0.209
	t	-3.110	-6.100	0.320	-1.680
	p	0.002	0.000	0.753	0.093
N		680	680	680	680
R^2		0.862		0.990	0.985
Dummies/FE		r', t	r', t	r', t	r', t

Germany), p_r are marginal costs, $P_{r'}$ is the consumer price, and $I_{r'}$ is local income. A main threat to identification of ϵ is the potential endogeneity of relative prices (marginal costs). We apply an instrumental variable approach and rely on a Bartik-type IV. Specifically, we use world marginal costs at the industry level and reweight it using national industry shares in 1995 as a measure for p_r and we proceed analogously for $P_{r'}$. We then calculate the log ratio of the two and use it as an IV for $\ln \frac{p_r}{P_{r'}}$. This IV is based on the idea that there exist world-wide shocks to industry-specific marginal costs due to general technological developments, so that we can use changes in other countries' industry-specific cost structures as an IV for changes in Germany's cost structures.

Using these data, we estimate

$$\ln Y_{r'rt} = -\beta_1 \ln I_{r't} + \beta_2 \ln \frac{p_{rt}}{P_{r't}} + \beta_{r'} + \beta_t + \varepsilon \tag{42}$$

for the time period 1995-2011 for the 13 SIAB-sectors using data for Germany and 39 trading partners r' of Germany. *This serves as a preliminary implementation until the updated socio-economic accounts of the WIOD's 2016 revision with more recent data is available.*

We implement the model as a Fixed Effects Panel Model and as a Pooled Panel Model, both with and without IVs. Preliminary results are shown in Table 3. The results for β_2 are close to 0.2 both IV approaches, whereas β_1 is close to 1, as predicted by the theory. This implies that the elasticity of substitution between countries' goods bundles is $\epsilon \approx 0.2$.

For the second part, we estimate the shares of industries in Germany's trade flows

$$\ln \frac{Y_{ir'r}}{Y_{r'r}} = -\sigma \ln \frac{p_{ir}}{p_r} + (\sigma - 1) \ln \beta_{ir'} \tag{43}$$

Table 4: Product Demand Equation - Results (2)

Variable		FE	FE IV	Pooled	Pooled IV
$\ln \frac{p_{irt}}{p_{rt}}$	coef.	0.064	-0.352	0.054	-0.469
	t	1.520	-1.690	0.630	-1.080
	p	0.128	0.091	0.533	0.281
N		20338	17946	20338	17946
R^2		0.024		0.738	0.737
Dummies/FE		$r' \times i$, t	$r' \times i$, t	r', i, t	r', i, t

where $Y_{ir'r}$ are the sales of industry i and Country r (Germany, only) to country r' (all 40 countries including Germany), pir are marginal costs (wages per value added) in industry i and country r, and the remaining variables are as before. To cope with the endogeneity of $\ln \frac{p_{ir}}{p_r}$ we apply an instrumental variable strategy, using a Bartik-type IV. specifically, we use relative industry-to-national marginal costs in other countries as an IV for relative industry-to-national marginal costs in Germany.[7] To empirically implement the equation, we estimate

$$\ln \frac{Y_{ir'r}}{Y_{r'r}} = \beta_1 \ln \frac{p_{ir}}{p_r} + \beta_{r'} + \beta_i + \beta_t + \varepsilon \tag{44}$$

We implement the model as a Fixed Effects Panel Model and as a Pooled Panel Model, both with and without IVs. Preliminary results are shown in Table 4. The results imply an between-industry elasticity of substitution between $\sigma = 0.35$ in the FE IV Model and $\sigma = 0.47$ in the Pooled IV Model and thus are similar to comparable estimates by Goos et al. (2014) who find an elasticity of substitution between industries of $\sigma = 0.42$ at the European level.

4.3 Wage Curve

We empirically implement our labor market frictions from Section 2.7 as a wage curve-type estimation:

$$\ln w_{ijt} = \beta_1 + \beta_2 \ln \frac{N_{ijt}}{L_{ijt}} + \epsilon_{ijt} \tag{45}$$

where w_{ijt} is the median wage in sector i and occupation j in year t, N_{ijt} is the number of workers, and L_{ijt} is labor supply in that occupation-industry and year. Labor supply is defined as described in section 3.2 as the number of workers in each occupation-industry plus the number of unemployed U_{ijt} in that cell. The number of unemployed in each cell results from those workers

[7] We use two different sets of countries, firstly we use Indonesia, India, Mexico and Basil; secondly, we use Australia, Canada, Japan and Korea.

who were previously employed in that cell but who are unemployed in the respective year.[8]

In addition, we rearrange the labor market frictions equation to estimate a classical wage curve:

$$\ln w_{ijt} = \alpha_1 + \alpha_2 \ln \frac{U_{ijt}}{L_{ijt}} + \epsilon_{ijt} \tag{46}$$

One can show that the relationship between β_2 and α_2 is

$$\beta_2 = -\frac{1-\bar{u}}{\bar{u}}\alpha_2 \tag{47}$$

where $\bar{u}$ is the steady state unemployment rate.

The preliminary results of these estimations are reported in Table 5. The first column reports an OLS-implementation of Equation (45) with occupation, industry, and year dummies. The second column reports results of the same model including a set of control variables in order to control for cell-specific differences in worker characteristics. In column (3), we re-estimate the model from the first column as an Instrumental Variable model. We do so to take into account the potential endogeneity of the employment rate. Our IVs are the employment rate, lagged by two, three and four years. Column (4) is an IV implementation of the model from the second column, relying on the same IV. Column (5) implements equation (46) as an IV model, using the 2-years lagged unemployment rate in the cell and applying the same control variables as in column (4).

The estimate of β_2 is quite stable across the equations, although it is generally smaller when applying control variables. We prefer the specification including control variables, as these control for differences between workers. Note that there are only little differences between the model with and without IVs. Our preferred specification in column (4) reports an estimate of $\hat{\beta}_2 = 1.655$. This is consistent with the corresponding estimate of the classical wage curve (column 5) if the steady state unemployment rate is 12%. The estimate of the unemployment elasticity of wages from the classical wage equation (column 5) are somewhat larger that the usual estimate of -0.1. However, this is very plausible for our case of occupation-industry specific employment, where workers have lower chances of finding employment elsewhere, so that their wages should indeed respond more strongly to the unemployment rate compared to the classical estimation at the regional level.

[8] We do not use the weighted labor supply for the estimation of the wage responses since wL already captures responses to wage changes and employment changes which should thus be highly endogenous.

Table 5: Wage Curve Results

	(1)	(2)	(3)	(4)	(5)
	Pooled	Pooled	Pooled IV	Pooled IV	Pooled IV
VARIABLES	ln_wft_ij	ln_wft_ij	ln_wft_ij	ln_wft_ij	ln_wft_ij
ln_N_L	2.271***	1.437***	2.217***	1.655***	
	(5.078)	(3.886)	(4.459)	(4.660)	
	3.53e-06	0.000244	8.24e-06	3.16e-06	
ln_U_L					-0.230***
					(-3.968)
					7.25e-05
Constant	4.924***	5.952***	4.949***	6.171***	5.033***
	(57.45)	(21.82)	(64.35)	(17.92)	(10.41)
	0	0	0	0	0
Observations	325	325	195	195	195
R-squared	0.800	0.942	0.789	0.947	0.945
N	325	325	195	195	195
Year Dummies	✓	✓	✓	✓	✓
Sector Dummies	✓	✓	✓	✓	✓
Occupation Dummies	✓	✓	✓	✓	✓
Add. controls		✓		✓	✓

Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Additional controls comprise the cell-specific shares of females, foreigners, young workers, old workers, low-educated workers, high-educated workers and part-time workers, as well as average tenure.

4.4 Labor Supply

We empirically implement our labor supply equation from Section 2.8 as:

$$\ln wL_{ijt} = \gamma_1 \ln \left(\frac{N_{ijt}}{L_{ijt}} / \frac{\bar{N}}{\bar{L}} \right) + \gamma_2 \ln \frac{w_{ijt}}{\bar{w}} + \varphi_{ij} + \tau_t + \epsilon_{ijt} \tag{48}$$

where wL_{ijt} is the weighted labor supply as described in section 3.2. It represents a measure of how many workers seek employment in cell ij at time t according to the probability to experience a transition between all cells as observed for job movers in the previous two years. Labor supply is assumed to respond to differences across cells in the employment rate. Hence, $\frac{N_{ijt}}{L_{ijt}}$ is the employment rate in cell ij and $\frac{\bar{N}}{\bar{L}}$ is the average employment rate across all cells. Note that on the RHS we do not use the weighted labor supply, wL, but but the labour supply resulting from the sum of employed and unemployed workers when unemployed are classified according to their previous sectoral and occupational affiliation (L). This better reflects the employment chances in a particular cell that may induce labor supply shifts across cells. w_{ijt} are cell-specific wages and $\bar{w}$ is the average wage rate. φ_{ij} are cell-specific fixed effects and τ_t are year dummies.

Table 6 reports the preliminary results. We implement the equation as a pooled OLS model (columns 1 and 2) and as a fixed effects model (columns 3 and 4). Columns 2 contains dummies for occupations and industries, column 4 contains time trends for occupations and industries. Both, columns 3 and 4 contain occupation-industry fixed effects. The coefficients are generally smaller in the FE models compared to the OLS models. We prefer the FE models, as these correspond most closely to our model. The results highlight that both the employment rate as well as wages positively affect cell-specific labor supply, as expected. However, the effect of wages is insignificant. Our preferred specification is column 3. The coefficient on the employment rates highligts that an increase of the employment rate by 1% raises cell-specific labor supply by roughly 1.2%.

5 Preliminary results

In this section, we use the parameter estimates from Section 4 to implement our employment decomposition (Equation 29). We first implement the decomposition individually for each labor market segment (occupation-industry), before performing the aggregate decomposition.

Figure 1 shows the four effects as well as the overall effect for two selected labor market

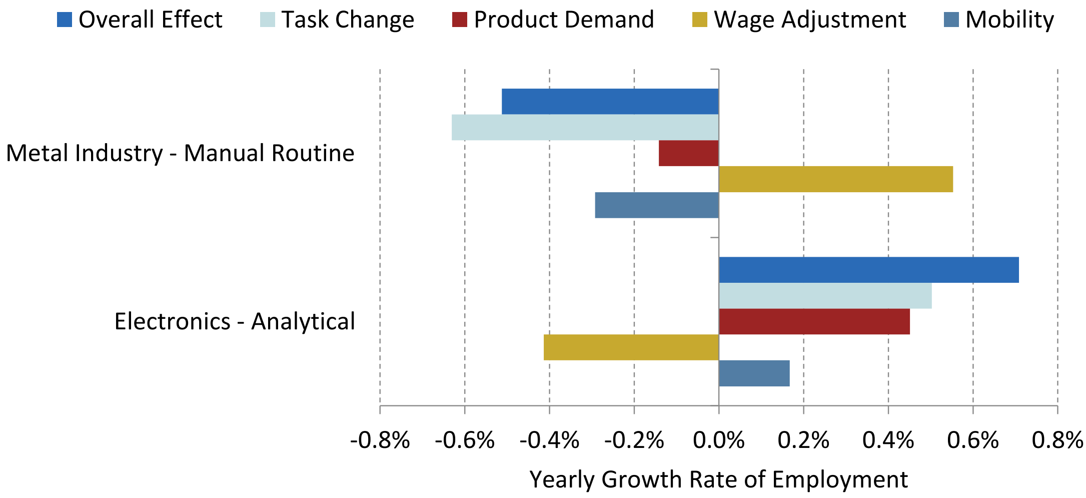
Table 6: Labor Supply Results

VARIABLES	(1) Pooled ln_wL_ij	(2) Pooled ln_wL_ij	(3) FE ln_wL_ij	(4) FE ln_wL_ij
ln_N_L_rel	2.127	3.249	1.224**	2.100***
	(0.466)	(1.187)	(2.141)	(3.784)
	0.643	0.240	0.0361	0.000342
ln_wft_rel	-0.733	-0.686	0.584	0.734
	(-0.701)	(-0.892)	(1.026)	(1.480)
	0.486	0.376	0.309	0.144
Constant	-6.136***	-7.677***	-3.736***	-3.923***
	(-2.996)	(-2.735)	(-4.466)	(-5.931)
	0.00388	0.00807	3.31e-05	1.33e-07
Observations	325	325	325	325
R-squared	0.490	0.819	0.571	0.717
N	325	325	325	325
Add. controls	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Sector Dummies		✓		
Occupation Dummies		✓		
Occ.-specific time trend				✓
Sector-specific time trend				✓
Number of cell			65	65

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: Additional controls comprise the cell-specific shares of females, foreigners, young workers, old workers, low-educated workers, high-educated workers and part-time workers, as well as average tenure.

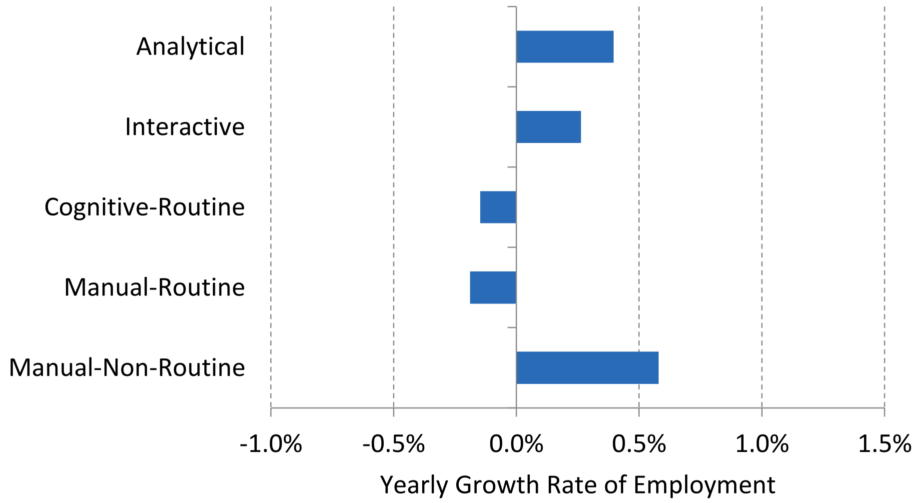
Figure 1: Decomposition: Effects for Selected Segments



segments, manual routine occupations in the metal industry and analytical occupations in the electronics industry. The effects are measured in terms of the yearly growth rate of employment. As expected, the Task Change effect is negative for manual routine jobs and positive for analytical jobs, i.e. new technologies substitute for manual routine labor and reduce labor demand for these jobs, while the opposite holds true for analytical labor. Moreover, we find a negative product demand effect for the first labor market segment, whereas the effect is positive for the latter. This suggests that the metal industry could not profit from declining costs and prices via demand increases, as the technological change has led to a restructuring of capital endowments towards digital tools. This is at the expense of classical technologies, produced by the metal industry, and favors digital tools, produced by the electronics industry.

The first two effects represent the pure labor demand effect. The third effect – the wage adjustments – has the opposite sign. Any increase in labor demand leads to rising employment and declining unemployment, which triggers rising wages, which partly compensates for the increase in employment, and vice versa for declining labor demand. This highlights that employment effects would have been larger if wages didn't rise. However, workers mobility counteracts these adjustment processes, as highlighted by the fourth effect: As workers leave the declining and move to the growing labor market segments, the wage decline in the declining and the wage increase in the growing labor market segment is decelerated, which favors negative employment effects for the former and positive employment effects for the latter segment. Overall, we find that the sign of the overall effect is determined by the sign of the labor demand effects, although

Figure 2: Decomposition by Occupations



the wage adjustments limit the aggregate employment effects.

Figure 2 provides the overall effect by our five occupations. As expected, Cognitive- and Manual-Routine occupations decline, whereas Analytical, Interactive, and Manual-Non-Routine Occupations grow. Quite interestingly, the growth rate of Manual-Non-Routine occupations exceeds the growth rates of Analytical and Interactive Occupations. This might be due to the structural change towards service industries, which is triggered by the technological change: As evident from Figure 3, most manufacturing sectors loose employment due to technological change, whereas most service sectors grow. The only exception among the manufacturing sectors is the Electronics and Automotive Industry. This is the industry that produces the new technologies which other firms apply. Among the service industries, the Transport and Communication sector experiences the largest growth induced by the technological change – this also is the industry that is involved in producing and maintaining the new technologies.

While the movements at the occupation and industry level are quite large, the aggregate effects at the national level are much smaller, as highlighted by Figure 4. The overall effect is positive, albeit small. Quite interstingly, the sign of the overall effect is determined by the two labor demand effects, which both are positive. That is, contrary to common fears, technological change has raised labor demand, whereas the effects on actual employment are smaller due to the sluggish labor supply adjustments. Even the Task Change effect, which captures capital-labor substitution and complementarity, is positive, suggesting that on aggregate, capital complements labor. Nevertheless, as we have seen before, this affects workers very heterogeneously depending

Figure 3: Decomposition by Sectors

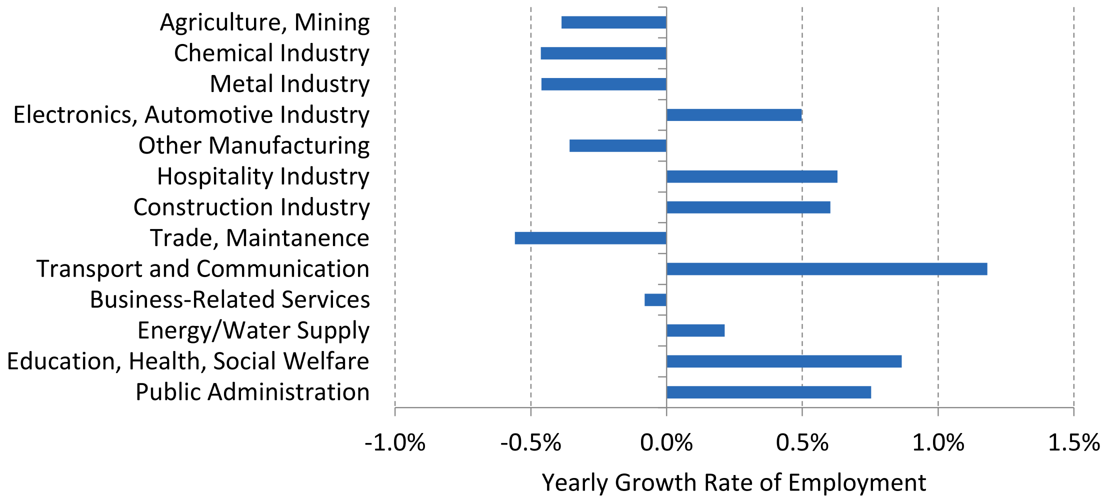
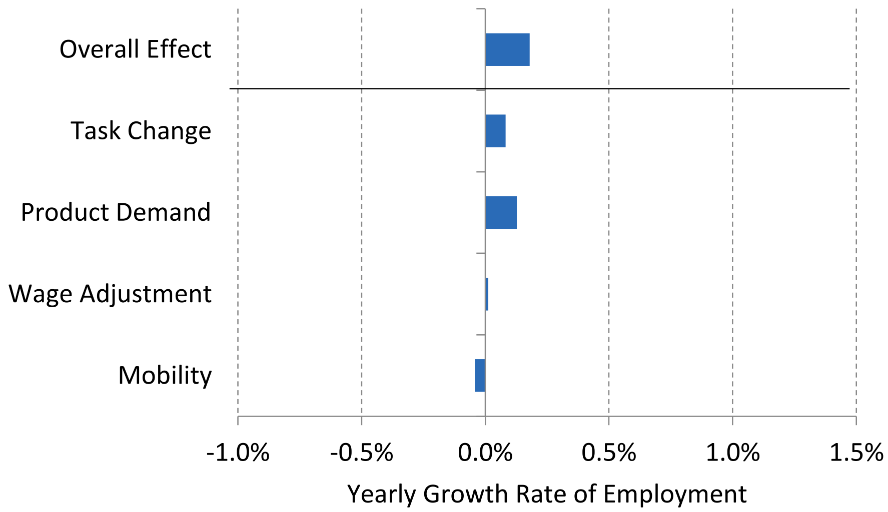


Figure 4: Decomposition: Effects



on their occupation and sector.

We therefore conclude that technological change has had overall positive effects on employment, although the effect is quite small. This was, however, accompanied by hughe structural changes between sectors and occupations. Moreover, technological change has not only substituted for workers, but also complemented workers and the latter effect actually dominated. The labor demand effects have been decelerated by sluggish labor supply adjustments.

6 Conclusions

New digital and interconnected technologies provide ever-increasing opportunities for automating tasks that previously only humans could do. There is a controversial public debate on the likely consequences for employment, unemployment and wages. There is also growing scientific evidence on the labor market consequences of these technologies. However, most studies focus only on the structural effects of these technologies, such as changing task or occupational structures and are silent on the aggregate employment effects which are at the core of the public debate. Other papers focus on aggregate employment effects, but restrict their focus to only robots. While the focus robots as a specific technology helps identifying their effects, this likely restricts the focus to new technologies that substitute for workers while leaving out many potential other new technologies that complement workers. Such studies thus provide only an incomplete picture of the overall effects of the new digital and interconnected technologies ("Industry 4.0") on the labor market.

In this paper, we study the aggregate employment, unemployment and wage effects of cutting-edge digital and interconnected technologies on the German labor market and decompose the contributions of the underlying macroeconomic adjustment processes. We make three major contributions. Firstly, we develop a theoretical framework that captures the key adjustment mechanisms: (1) machine-labor substitution and complementarity, (2) product demand responses, (3) wage responses and (4) labor supply responses via worker mobility. Secondly, we conduct a representative survey among German firms to retrieve direct measures of the adoption of cutting-edge digital and interconnected technologies at the firm level. We link the survey information to the social security records of the firms to create a unique linked employer-employee dataset to study the labor market consequences of "Industry 4.0" in Germany. Thirdly, we empirically estimate the model and implement a decomposition that we directly derive from our model in order to estimate the overall effect of firms' investments in these technologies on employment, unemployment and wages, as well as to disentangle the contributions of the several macroeconomic adjustment mechanisms.

Our preliminary results suggest that the net employment effect of these technologies is actually positive, but small. We find that the firms' technology investments have raised aggregate employment by on average 0.17% per year in Germany, which is less than half of the average yearly employment growth rate (0.41%). Contrary to existing results for the effects of robots, this is driven by positive labor demand effects. On net, complementarity dominates worker-machine substitution. In addition, we find net positive technology-induced product demand effects. These small net positive labor demand effects have been decelerated by limited worker mobility. While the net effects remain small, we do find huge reallocations of workers between industries and occupations. Technologies have mostly substituted for routine manual and cognitive workers while raising employment in interactive, abstract and non-routine manual jobs. Moreover, the technologies have accelerated structural change towards service industries, although those manufacturing sectors that produce the new technologies diverge from this picture and experience technology-induced employment growth.

Our preliminary results highlight – in contrast to common fears in the public debate – that new technologies have not been a threat to aggregate employment. To the contrary, they have even raised aggregate employment, although the effect was rather small. Nevertheless, these technologies have induced a huge restructuring of occupations and industries, forcing workers to adjust their careers. The likely challenge for the future thus is not how many jobs, but which jobs we will have and whether workers will be able to fill these jobs while maintaining a fair share of the gains from technological change.

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A Relation to other Models of RRTC

To understand the key differences of this model to other models of RRTC, let us fist summarize the main features of other key models. The Autor et al. (2003) (ALM, hereafter) model has the following features:

- Routine labor L_R and computer capital C are always perfect substitutes.
- Non-routine labor L_N and computer capital C are always (!) p-substitutes, i.e. a price decline in capital induces firms to substitute non-routine labor for routine capital for any given level of output Q.
- Non-routine labor L_N and computer capital C are gross-complements if the price elasticity of demand exceeds unity ($\sigma > 1$). That is, if capital prices decline, firms grow fast enough to overcompensate the initial substitution of non-routine labor for capital only if $\sigma > 1$.

The production technology of Goos et al. (2014) (GMS, hereafter) – or of Gregory et al. (2016) (GSZ, hereafter) – is an approximate generalization[9] of the ALM framework with comparable features:

- Occupation-specific labor N_j and occupation-specific capital C_j are substitutes with a unit elasticity.
- Occupation-specific labor N_j and capital $C_{j'}$ from other occupations are always (!) p-substitutes, i.e. a price decline for capital $C_{j'}$ induces firms to substitute workers N_j for capital $C_{j'}$ for any given level of output Y.
- Occupation-specific labor N_j and capital $C_{j'}$ from other occupations are gross-complements if the price elasticity of demand exceeds the elasticity of substitution between tasks ($\sigma > \eta$). That is, if capital prices decline, firms grow fast enough to overcompensate the initial substitution of non-routine labor for capital only if $\sigma > \eta$.

The present framework is more flexible. Firstly, the technological capital of the firms is used by all workers. Secondly, each type of technological capital has its own relationship to occupation-specific labor, indicated by α_{jk}. This enables us to model different types of capital

[9]Technically, it is not an exact generalization, as the task production function in ALM involves perfect substitution between capital and labor, whereas the elasticity of substitution between capital and labor at the task level is unity in GMS and GSZ.

and labor as being either complements or substitutes. It is fundamentally different to the ALM, GMS and GSZ frameworks, where capital and labor are always p-substitutes and where any complementarity is solely via firm size (via a scale effect). The key advantage of this approach thus is that we can estimate the relationship between capital types and labor types, rather than imposing the assumptions that routine capital replaces routine workers. The downside of this is that we have to estimate the relationship for all combinations of worker and capital types, which requires good data.

The present framework can be interpreted as an approximate generalization of the GMS and GSZ framework. It can reproduce the features of GMS, GSZ and ALM as a special case. The framework would be an exact generalization of the GMS and GSZ framework, if the task production function was $T_{ij} = N_{ij}^{\alpha_N}/A_{ij}$. Under this assumption, the GSZ model is a special case of this framework with $\alpha_N = \kappa$, $\alpha_{jj} = (1-\kappa)\ \forall\ j \in J$ and $\alpha_{jj'} = 0\ \forall\ j \neq j'$ (where we have replaced the index k with j, as capital types and job types correspond to each other in the GSZ framework).

B Decomposition

... to be added