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# Do New Technological Innovations Lead to Labor Market Polarization? Analyzing Productivity Growth in Advanced Economies

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**Abstract**

This paper analyzes cross-country firm-level data from 11 European countries and the USA between 1995-2017 to uncover the effect of technological innovations on increasing labor market polarization within industries in advanced economies. It contributes to the existing literature by making an extension on the theoretical framework of Acemoglu & Restrepo (2018) and by making use of a proxy of Total Factor Productivity (TFP) to represent new technologies. Findings would suggest that technological innovations do contribute to increased polarization in the selected time-period. The share of high-skilled workers increases, presumably due to the replacement effect. This occurs at the expense of middle-skilled workers who are more likely to be replaced by automated technologies, caused by the displacement effect. Low-skilled workers do not experience significant changes. Nevertheless, the findings are different for specific countries and industries and require consideration of other explanatory variables such as offshoring and import competition from China.

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# 1. Introduction

Robots taking over jobs, Artificial Intelligence (AI) making laborers redundant and blockchain technologies replacing tasks commonly performed by people are all examples of potential threats to our labor market and the future of work. Many developed countries are experiencing a growth in the number of new technologies penetrating their markets. Such technologies potentially replace human labor in which capital is subsequently substituting labor as a production factor (Acemoglu & Restrepo 2018). However, there are multiple, direct and indirect possibly countervailing channels that can play a role in determining the eventual final demand effect of human labor. Despite the fact that certain jobs might disappear, the so-called *displacement effect*, new jobs might arise, referring to *the replacement effect* (Acemoglu & Restrepo, 2018). This provides for new opportunities to some workers. Jobs are expected to be affected differently by new technologies, depending on their respective tasks. A job that consists of routine tasks is more susceptible to be replaced by automated technologies. Subsequently, an accountant is more likely to lose his or her job due to replacement by a computer compared to a psychiatrist. Therefore, there might be prevailing differences between the effect of technological innovations on low, middle and high-skilled jobs (Goos, Manning & Salomons, 2014).

During the past two decades labor market dynamics in advanced countries have developed towards a U-shaped pattern (Breemersch, Damijan & Konings, 2017). This indicates that employment growth is mainly prevalent at high-skilled jobs and low-skilled jobs, at the expense of the middle-skilled jobs. In general, it is believed that middle-skilled workers are overrepresented in jobs performing routine-based tasks. The introduction of new technologies potentially replaced routinised middle-skilled jobs, leading to increased polarization (Dao, Das, Koczan & Lian 2017). On the other hand, this effect may not be as clear-cut. Middle-skilled workers potentially have benefited from newly introduced tasks and high-skilled workers, such as financial planners, face replacement by automated technologies as well (Michaels, Natraj, Van Reenen, 2014).

This paper will attempt to disentangle and provide insights into the effects of technological innovations on labor market polarization in advanced economies during the past decades. It will build on the economic framework of Acemoglu & Restrepo (2018) to do so. However, their study only examined the effect of technological innovations on high and low-skilled labor groups. This paper aims to make an extension on their framework by including the middle-skilled group. Based on the economic framework this study hypothesizes that technological innovations cause increased labor market polarization. The effect on the share of high-skilled workers is expected to be positive. New tasks will create more opportunities for this group. Middle-skilled workers on the other hand are expected to experience a decline in their share due to displacement of their jobs. Low-skilled workers are not expected to be affected by technological innovations, since they are presumed to engage predominantly in non-routine tasks.

Most often technological innovations are measured by analyzing the Research & Development (R&D) expenditures or the ICT usage of firms (Piva & Vivarelli, 2018). Such variables have the ability to proxy the amount of new technologies adopted in companies. However, technological innovations have the ability to enhance overall productivity within a firm. Solow (1957) established a framework in which it is believed that Total Factor Productivity (TFP) growth is a residual solely attributable to innovation and technological improvements. The change in growth is not explicable by other input factors (Solow, 1957). Recently, academic literature started to build on these assumptions. For example, Acemoglu & Restrepo (2018) argue that automation creates a positive productivity effect, which dominates over potential other counteracting forces. Furthermore, Autor & Salomons (2018) make use of TFP to analyze the effect of automation on labor-share displacement.

Inspired by previous academic literature, this paper will therefore make use of TFP as a proxy for recent technological innovations. TFP increases either the efficiency of the factors of labor and capital or reallocates tasks from one production factor to the other. Rather than focusing on a specific type of technological innovations, such as robotics, TFP has the advantage to measure the overall effect of technological innovations on the labor market. In addition, it provides a consistent measurement of technological innovations in different sectors over time (Autor & Salomons, 2018). This paper is the first, as far as known, to make use of TFP in order to measure the effect of technological innovations on labor market polarization in advanced economies during the past decades. It will do so by analyzing cross-country firm-level data of advanced economies between 1995 and 2017, using the most recent release of the EU Klems dataset of 2019. This period was chosen because of the recent upsurge in new technologies and due to a lack of existing research during this recent time period. Laborers will be appointed to the high, medium or low-skilled labor group based on their prior education. The outcome variable subsequently consists of the wage bill share – comprising of wage per hour and hours worked – of laborers of the different educational groups, which is a commonly used indicator of skill demand. First-differencing will be used as the identification strategy to account for potential unobserved time-invariant variables. Additionally, the regression analysis will include country and year fixed effects, as well as an interaction term of business cycle indicators obtained from the OECD. Distributed lags are included to account for the potential cyclicality of trends. In addition, other explanatory variables that potentially lead to polarization, such as offshoring, will be considered and controlled for. Since the use of TFP as a proxy for technological innovations may be disputable due to its dependence on assumptions, this study will perform a robustness test and adopt a frequently used proxy for technological innovations. Namely, R&D expenditures of a firm.

Studying the effect of the introduction of new innovative technologies on the labor market in advanced countries is of particular relevance. To be able to prepare for future developments it is important for advanced and developing countries to gain a thorough understanding of the change in labor dynamics caused by the continuous introduction of new technologies. Carefully crafted policies are required to prevent increase of wage inequalities (Benzell, Kotlikoff, Lagarda & Sachs, 2018).

Overall the findings of this paper weakly support the expectations based on the theoretical framework. The share of high-skilled wage bill has significantly grown due to an increase of TFP of a firm in advanced countries in the time period 1995-2017, while the middle-skilled wage bill share significantly decreased. Results for the low-skilled wage bill share are ambiguous and inconclusive. Nevertheless, results appear not to be robust and mixed while applying different tests and samples of the dataset, possibly implying a need for further research.

This paper is structured as follows. Chapter 2 will elaborate on prior literature related to this topic. Chapter 3 will establish the economic framework in which the effect of new technologies on labor market polarization is hypothesized. Subsequently, chapter 4 and 5 will describe the data and methodology used in this paper. Chapter 6 will represent the results of the analysis, including numerous robustness tests. In addition, chapter 7 will continue with the discussion and conclusion of the findings. Lastly, chapter 8 and 9 shortly discuss the limitations and future recommendations of this study.

## 2. Literature overview

The purpose of this chapter is to elaborate upon the existing academic literature on the topic of new technologies and the labor market. The market polarization hypothesis and the supporting empirical evidence is shortly discussed. Subsequently other factors leading to market polarization will be considered.

### 2.1. Market polarization hypothesis

Throughout the past decades much attention has been paid to the study of skills and technological change. A common understanding is that Skill-Biased Technical Change (SBTC) is associated with labor share displacement and increasing wage inequality. Tinbergen's (1974) approach assumes that technological innovations are factor-augmenting. They increase the productivity of skilled workers more compared to the productivity of unskilled workers. Simple tasks performed by unskilled workers are more likely to be replaced by new technologies. Therefore, there might be a displacement of occupations that have routine-based tasks. Goldin & Katz (2008) continued to expand on this framework. Labor-using tasks are replaced with capital due to recent technological innovations. Acemoglu & Restrepo (2018) however argue that besides a displacement effect of new technologies, which entails capital substituting the labor share, there also is a replacement effect prevalent. New tasks and jobs arise due to the introduced technologies, which potentially reinstate the labor share.

Labor economists have predicted different effects of innovations on the composition of the labor market. On the one hand there is a considerable share of supporters of the diffusion hypothesis. They assume that unskilled workers, or in this respect low-skilled workers, are hit hardest by the introduction of new technologies, since their tasks are easily replaceable. The implementation of new technologies has a factor augmenting nature and therefore complements high-skilled workers (Acemoglu & Autor, 2011).

On the other hand, there is the market polarization hypothesis, which expects that rather than low-skilled workers, middle-skilled workers will endure a drop in their labor share due to new technologies (Spiezia, Polder & Presidente, 2016). This paper limits itself to consider only the market polarization hypothesis, since findings of this hypothesis upon this point have been mixed and therefore require further research.

In general, middle-skilled workers are overrepresented in jobs performing routine-based tasks, for example being a bank clerk. High-skilled occupations such as consultants or physicians instead are more likely to perform non-routine tasks (Dao, Das, Koczan & Lian 2017). Traditionally, high-skilled occupations specialize in more complex tasks and are therefore supposedly safeguarded against automation and possibly even perform new tasks associated with technological innovations. Their jobs overall require more analytical or social skills, which are less likely to be displaced (Acemoglu & Restrepo, 2018). Although part of low-skilled occupations is routine-based, they are also frequently employed in occupations performing non-routine tasks such as a cleaning-lady, a hairdresser or a cab driver. Subsequently, due to the nature of the performed tasks, middle-skilled jobs are more susceptible to be replaced by automated and innovative technologies compared to high and low-skilled workers, potentially explaining increased polarization (Dao, Das, Koczan & Lian 2017). Nevertheless, recent technologies such as AI cause risk of replacement of high-skilled tasks as well. For example, consider accounting, financial planning or even surgery. Automation of high-skilled jobs is on the rise, which can be considered to be a counterargument to the market polarization hypothesis (Michaels, Natraj & Van Reenen, 2014).

### 2.2. Empirical evidence on the effect of new technologies on labor market polarization

Evidence of the market polarization hypothesis in the academic literature show different results. The study of Gregory, Salomons & Zierahn (2019) for example identify both labor-replacing and labor-augmenting forces. Results of their study show that between 1999-2010 across 27 European countries there indeed has been strong labor displacing effects. However, the countervailing forces of new jobs that were created through increased product demand outweigh these displacing effects. In addition, Michaels, Natraj & Van Reenen (2018) for example find a positive link between ICT usage and labor market polarization in the European Union between 1980 to 2004. In their study they argue middle-skilled workers tend to have more cognitive routine tasks while performing their jobs. Less-skilled workers are more prevalent in non-routine manual tasks and are therefore less affected by technological innovations. Furthermore, Dao, Das, Koczan & Lian (2017) conclude, based on evidence from 34 advanced economies between 1991-2014 that labor share decline driven by technology and global integration was particularly sharp for middle-skilled workers, resulting in job polarization. Sectors that are initially more specialized in routine-intensive activities experienced a larger decline in the labor share.

On the other hand, Handel (2012) finds no compositional changes in either the Unites States of America (USA) or the European Union (EU) between 1997 and 2009. Using the O*NET database he argues that the frequency of routinized tasks in general have declined during this period. Moreover, Spiezia, Polder & Presidente (2016) estimated the impact of ICT usage on labor demand from 1990-2012 in selected OECD countries. This study found permanent effects on labor demand by industry. In the short run ICT usage leads to increased polarization. However, in the long run these effects will disappear.

The above-mentioned studies show mixed results of empirical evidence. However, Autor & Salomons (2017) argue several countervailing channels are at play that help determine the eventual effect of automation on the labor market. Namely; the own-industry output effects, cross-industry input output effects, between-industry effects, and final demand effects. They analyze these effects by making use of TFP as a proxy and make use of the EU Klems dataset release of 2007. Subsequently, by taking the sum of five distributed lags, they look into the different direct and indirect effects on labor market dynamics.

### 2.3. Factors causing labor market polarization: automation, off-shoring and import low-wage countries

Other studies suggest that there are different factors that should be taken into account while analyzing the effect of technological innovations. Goos, Manning & Salomons (2014) discuss the notion of Routine Biased Technological Change (RBTC) in which is focused on how easily tasks can be routinized in different occupations. Their study analyzes the pervasiveness of job polarization in Europe between 1997 and 2010. They introduce offshoring as another important factor influencing labor market polarization. This argument suggests that routinised tasks, mainly prevalent in middle-skilled jobs, are being off-shored to low-wage countries. Their study however does not vary over time, which is a disadvantage of their identification analysis (Goos, Manning & Salomons, 2014). Another study confirming the importance of offshoring is the study of Oldenski (2014). Observing the USA labor market they find that an increase in off-shoring leads to an increase in the wage gap between middle, high and low-skilled workers.

A different development that is often associated with increased labor market polarization is import competition from China. Bloom, Draca & Van Reenen (2011) find that increased import competition is associated with a fall of the share of unskilled workers. However, they also conclude that import competition leads to more innovation in these sectors, representing the complicated relation between the two. The report of the OECD of 2017 defined the impact of off-shoring, technology and import competition from China to have the largest impact on polarization in the European Union. Their results show that within-industry changes are mainly caused by technological advances, while between-industry change is mainly attributed to the widespread deindustrialization of Europe. Furthermore, they suggest that automation replacing labor is mainly prevalent in the manufacturing industry (Breemersch, Damijan & Konings, 2017).

## 2.4. Specific channels of technological innovations

The previously discussed papers all make use of proxies for technological innovations similar to the expenditures on R&D of a firm, the largest R&D investors, or ICT usage of a firm. This paper distinguishes itself by making use of TFP. A shortcoming of making use of TFP is that it incorporates productivity growth arising from all production factors. Therefore, you cannot identify the effect of specific technological innovations such as artificial intelligence or robotics. Solely the overall effect of the introduction of new technologies can be identified (Autor & Salomons, 2018).

Nevertheless, there are multiple other papers that look into these specific channels. This is most often done by analyzing the impact of robotics on the labor market. Acemoglu & Restrepo (2018; 2020a) for example make use of the dataset of the International Federation of Robotics to identify the effects of robots on the USA labor market. By making use of an Instrumental Variable (IV) strategy they find large and negative effects of robots on employment and wages in different commuting zones in the USA. In addition, Chiaccho, Petropoulos & Pichler (2018) apply similar data to the European labor market. They identify a significant displacement effect present, particularly for workers in the middle-skilled group. On the other hand, there are studies that find weakly positive effects on the labor market. Dauth Findeisen, Südekum & Wößner (2017) look into the German labor market and do not find evidence that robots destroy jobs between 1990 and 2014. Furthermore Graetz & Michaels (2018) find that investment in industrial robots did not reduce total employment, but potentially did affect the composition of the labor market. They identify negative effects for both the middle-skilled and low-skilled workers caused by these investments between 1993-2007 while observing 17 countries.

This study will not make any inferences on the effects of specific new technologies such as robotics but will refer to other literature to elaborate on this.

### 2.5. Summary literature overview

Overall, the results of the previously discussed studies are mixed. Although part of the existing academic literature is able to confirm the influence of new technologies such as robotics on labor market polarization, other research papers have shown that potential countervailing channels take part in the eventual effect. Furthermore, literature has identified other important factors causing labor market polarization, off-shoring being the most important in within-industry analysis. The next section will elaborate upon the economic and theoretical foundation underlying the effect of new technologies on labor market dynamics.

# 3. Theoretical framework

The task-based framework used in this paper is based on findings from Acemoglu & Restrepo (2018; 2019) and the conceptual framework of Autor & Salomons (2018). In turn these frameworks built on Zeira (1998), Autor, Levy, Murnane (2003) and Acemoglu & Autor (2011). This framework is chosen since it is the most relevant and recent framework referred to in the study of technological change and skills. First the effect of new technologies on the labor share in general is established. Subsequently, heterogeneity is introduced by differentiating between high, medium and low-skilled workers. I do this by making a small extension on the established framework.

## 3.1. Framework new technologies and labor share

The simple intuition behind the introduction of a new technology with fixed capital is the production function $F = (L, K, \theta)$ in which $\theta$ represents the new technology. $\frac{\partial F}{\partial \theta} > 0$ indicating that a new technology will increase the eventual output, naturally if $\frac{\partial^2 F}{\partial L \partial \theta} < 0$ as a consequence the marginal product of labor will fall. This model however is much too simplistic since it does not take into account the possibility that marginal product of labor may increase (Caselli & Manning, 2019). The framework of Acemoglu & Restrepo (2018) does not solely look into the labor-share displacing effect of new technologies, but also considers the introduction of new tasks in which labor has a comparative advantage. It starts in a static model in which capital is fixed and technology is exogenous. Due to automated technologies previous tasks performed by labor input are substituted with capital. Subsequently the framework is extended to a dynamic economy. Two main restrictions are implemented. First, there is productivity growth due to the introduction of new tasks, and second, automation and the creation of new tasks occur at equal rates. Following these conditions, Acemoglu & Restrepo (2018) consider the uniqueness and stability of a balanced growth path.

Consider the following Cobb-douglas (unit elasticity) production function which consist of a combination of services of a unit measure of tasks with limit of integration of $x \in [N-1, N]$;

(1) $$Y = \int_{N-1}^{N} \ln y(x) dx$$

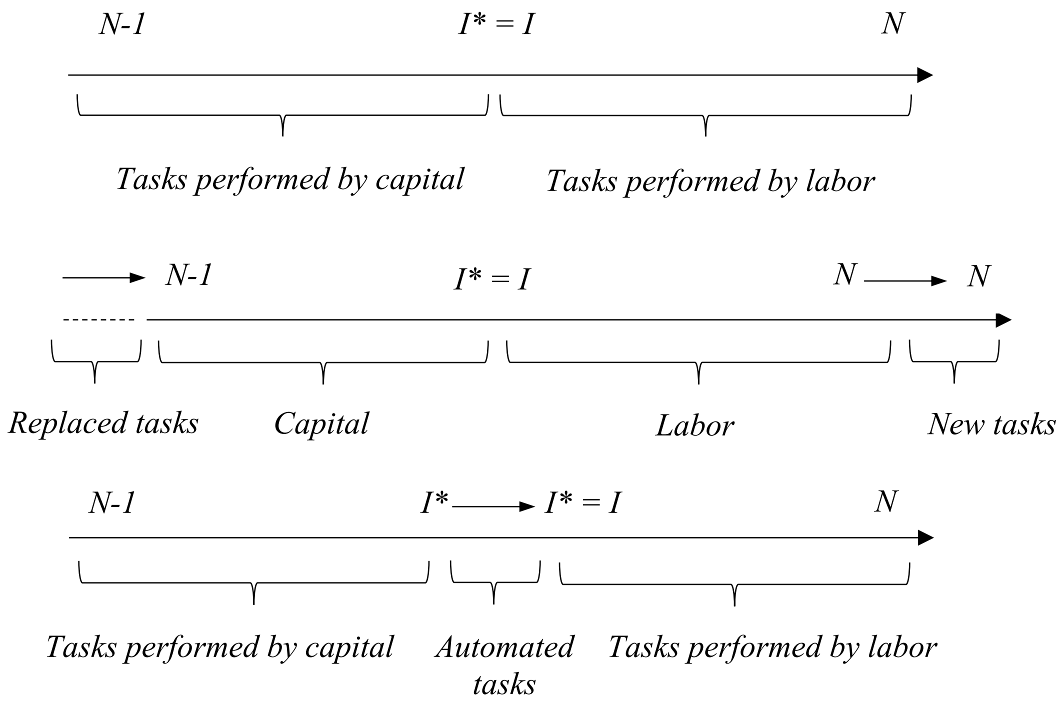
In which $Y$ denotes the aggregate output and $y(x)$ is the output of input $x$. It is assumed that all tasks involved can be performed by labor, $l(x)$. Later on, heterogeneity will be introduced in labor $l(x)$ between the different skill levels. Machines, $m(x)$ are able to perform a task whenever it becomes technologically automated, implying labor and capital are perfect substitutes. At a certain point, due to the introduction of new technologies, a share of $x \in [N-1, I]$ tasks will therefore be technologically automated. Although labor and capital are substitutes, their productivity level and associated costs may still differ while performing certain tasks (Autor & Salomons, 2018). Subsequently services of task $x$ are equal to:

$$(2) \qquad \left\{ y(x) = \begin{array}{ll} a_L y_L(x) l(x) + a_m y_m(x) m(x) & if\ x\ \in [N-1, I] \\ a_L y_L(x) l(x) & if\ x\ \in [I, N] \end{array} \right.$$

$a_l$ and $a_m$ are efficiency terms, which can alter the productivity of the production factors labor and capital. Furthermore, $y_l(x)$ and $y_m(x)$ are efficiency terms that are unique to the included tasks. An important assumption here is that $\frac{y_l(x)}{y_m(x)}$ is increasing in $x$. This implies that labor has a comparative advantage in higher-indexed tasks (Autor & Salomons, 2018). Threshold $I$ is "the frontier of automation possibilities" (Autor & Salomons, 2018, pg. 9). It can be extended by means of the introduction of new technologies such as robotics, artificial intelligence, big data, block-chain technologies and 3d-printing. Consider the introduction of robots, which will cause a shift of $I$, leading to tasks previously performed by labor, now being replaced by machines.

Factor prices are denoted as $W$, wage rate and $R$, rental rate of capital. Given a range of tasks $[N-1, N]$, automation technology $I \in (N-1, N]$, static equilibrium is reached with factor prices, $W$ and $R$, and threshold tasks $I^*$.
The following figure is a representation of both the replacement effect due to the creation of new tasks (middle panel) and the displacement effect of jobs that are displaced due to the introduction of automated technologies (bottom panel) (Acemoglu & Restrepo, 2018). All tasks $i < I^*$ are produced with capital and tasks $I > I^*$ are produced with labor.

**Figure 1. Replacement and Displacement effect.**




*Notes:* Source figure: Acemoglu & Restrepo, 2018.

Following the rationale of Autor & Salomons (2018) there are several forms of technological changes that should be considered. Namely: (1) factor-augmenting technical changes, (2) extensive margin (labor-displacing) technical changes, corresponding to a rise in *I* (3) intensive margin capital- or labor augmenting technical changes and (4) task creating technical changes. Labor market equilibrium, assuming cost-minimizing firms, results in the following equation combining both the replacement and displacement effect (derivations in Appendix 11.1. retrieved from Autor & Salomons 2018).

$$(3) \qquad d\ \ln W = \left[\ln\left(\frac{R}{a_m y_m(N-1)}\right) - \ln\left(\frac{W}{a_l y_l(N)}\right)\right] d\mathrm{N} + \left[\ln\left(\frac{W}{a_l y_l(I)}\right) - \ln\left(\frac{R}{a_m y_m(I)}\right)\right] dI + \left[\frac{1}{N-I}\right](d\mathrm{N} - d\mathrm{I})$$

In which the first bracketed term represents the rise in productivity resulting from the creation of new tasks, which will always be positive (replacement effect), the second bracketed term represents the gain in labor's share of income ($W$) as tasks will be reallocated towards workers. The third and fourth bracketed terms represent the rising productivity. Since capital is more cost-effective due to the introduction of a new technology, automation will subsequently raise output. Last, the fifth bracketed term represents the displacement effect which is negative (positive in this formula since we are considering the net effect) in which tasks are reallocated from labor to capital (Autor & Salomons 2018).

All derivations of the theoretical model explained above imply a shift in TFP. This is achieved by reallocating tasks from capital to labor or the other way around. Furthermore, this is induced by increasing the productivity of one of the factors. Therefore, making use of TFP as a proxy for technological innovations should allow for just estimation of new technologies.

### 3.2. Introducing heterogeneity in skills levels

Now consider extending this model to include heterogeneity in skills level and inequality in wages between high, medium and low-skilled workers. As hypothesized in previous literature new automated technologies may increase polarization (Spiezia, Polder & Presidente, 2016; Dao, Das, Koczan & Lian, 2017; Breemersch, Damijan, Konings, 2017). The model of Acemoglu & Restrepo (2018) only considers differentiation between low and high-skilled workers. However, I extend this model to include middle-skilled workers.

Since middle-skilled occupations perform routinised, or lower-indexed tasks, they are most susceptible to automation and therefore replacement by capital. Their share diminishes due to the displacement effect with the introduction of new technologies. Lower-indexed tasks are tasks that require the use of routine motor skills and routine cognitive skills (Goos, Manning, Salomons, 2014). On the other hand, both the high-skilled and low-skilled workers perform high-indexed tasks, which are less likely to be replaced by automation. High-skilled workers mainly perform the new and complex tasks introduced by the replacement effect (Acemoglu & Restrepo, 2018). They therefore have a comparative advantage in this respect. Low-skilled workers do not benefit from the replacement effect. However, they are unharmed by automation since they perform non-routine, high-indexed tasks. It is assumed that their share will therefore remain unchanged with the introduction of new technologies.

Together, the effects on high, medium and low-skilled workers are expected to result in increased polarization in the short run. Nonetheless, new tasks will standardize over time, which will benefit the middle-skilled workers. Following this logic, it is expected that there will be a reduction again in the polarization level and the effects will fade away in the long run.

The different types of workers have different productivity levels. Middle-skilled workers $\gamma_M(i,t)$ have a time-varying productivity with task *i,* and time *t.* High-skilled workers have productivity $\gamma_H(i)$ and low-skilled workers $\gamma_L(i)$ have a constant productivity, unaffected by the introduction of new tasks. Productivity gains are expected to be exponential, since it is anticipated that new technologies result in new tasks that contribute to constant growth. This paper makes use of the productivity functions proposed by Acemoglu & Restrepo (2018) to represent the high and medium-skilled workers and subsequently adds a constant productivity term for the low-skilled worker. The productivity levels are given by:

(4) $\gamma_H(i) = e^{A_{Hi}}$

(5) $\gamma_M(i,t) = e^{\xi A_{Hi}} \tau(t - T(i))$

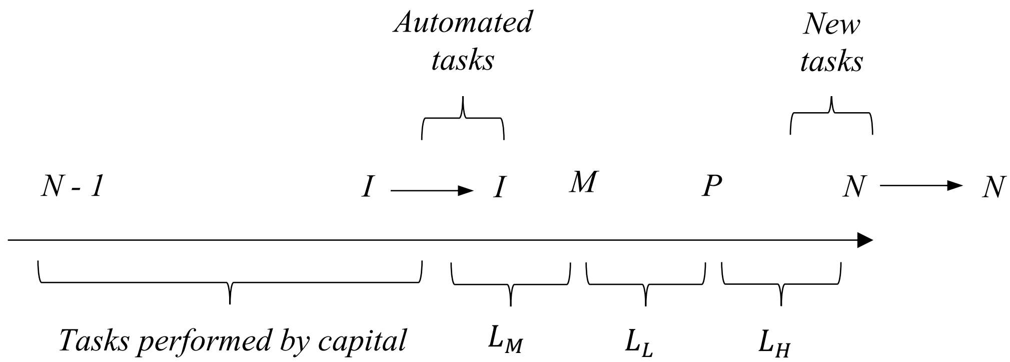
(6) $\gamma_L(i) = c$

In which $A > 0, \tau$ is increasing with $\lim_{x \to \infty} \tau(x) = 1$ , $\xi \in (0,1]$ and *T (i)* denotes the time when task *i* was introduced (Acemoglu & Restrepo 2018; Acemoglu, Gancia & Zilibotti, 2010).
The increasing number of $\tau$ implies that the productivity of middle-skilled workers increases whenever a task is performed for a longer time period. Therefore, such a task becomes standardized in the long run.

Due to this standardization, the ratio $\frac{\gamma_H(i)}{\gamma_M(i,t)}$ is increasing with $i$. This indicates that high-skilled workers will have a comparative advantage with high-indexed tasks given that $\xi \in (0,1]$ . Tasks that are high-indexed have had limited time to become standardized. In addition, $\frac{\gamma_L(i)}{\gamma_M(i,t)}$ is increasing. $\gamma_L(i)$ remains constant since low-skilled workers' productivity will not be influenced by the introduction of a new tasks, meanwhile $\gamma_M(i)$ diminishes with the introduction of a new task due to the displacement effect. The parameter $\xi$ determines whether a task is fully standardized since $\tau(x)$ is limited to 1. Whenever $\xi$ equals to 1 a task is fully standardized. Middle-skilled workers will experience a productivity converging to 1. New tasks will become standardized and middle-skilled workers will also be able to perform these new tasks. This rationale also implies that in the long run middle-skilled workers may perform new tasks due to improved schooling, on-the-job learning or the standardization of such new tasks. Nevertheless, whenever $\xi < 1$ the productivity of middle-skilled workers will converge to 0 as more tasks are introduced that are advanced and less standardized.

Based on the comparative advantage that accompanies high-skilled jobs and the constant, unaffected productivity of low-skilled workers, there are two threshold tasks fixed at M and P. For simplicity it is assumed that supply of high-skilled labor is fixed at $L_H$ , middle-skilled labor fixed at $L_M$ and low-skilled fixed at $L_L$. Difference in skills levels is best illustrated by means of the following figure:

**Figure 2. Skills level, replacement effect and displacement effect.**




*Notes:* Source figure: Author's interpretation, based on Acemoglu & Restrepo, 2018.

### 3.3. Summary theoretical framework & hypotheses

Figure 2 displays the extension this study makes on the theoretical framework of Acemoglu & Restrepo (2018) by including middle-skilled workers. Based on this extension it is hypothesized that the creation of new tasks, the replacement effect, will only benefit high-skilled workers $L_H$ since they have a comparative advantage in this respect. Furthermore, the displacement effect only affects middle-skilled workers $L_M$, as their tasks are more likely to become automated. The low-skilled workers $L_L$ are unaffected since they mainly perform high-indexed tasks. Therefore, in the short run the wage gap and polarization indeed will increase with the introduction of new technologies. The intensity of this effect is determined by the parameter $\xi$. Since high-indexed tasks will also become standardized in the long run, it is expected that the share of middle-skilled workers eventually will recover. One should however keep in mind this theoretical framework is a simplified version of reality.

# 4. Data

This section will elaborate upon the data and variables used. Furthermore, trends observed in the data will be analyzed and a shift-share analysis will be discussed herby legitimizing why this study restricts itself to observe within-industry changes.

## 4.1. EU Klems release of 2019

This study makes use of the statistical dataset of the EU Klems 2019 release to provide firm-level data on TPF and labor segments in Europe. The EU Klems release of 2019 comprises of 28 European countries, USA and Japan over the period 1995-2017 and encompasses data on growth accounts, national accounts, capital and labor for a total of 40 industries (NACE Revision 2). Growth accounts, including TFP, are available for EU11 countries (Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Netherlands, Sweden, and UK) as well as the USA from 1995-2017. USA is included since it is often at the frontier of implementing technological innovations and is therefore a good predictor of the future of other nations (Michaels, Natraj, Van Reenen, 2014). Additionally, for EU20 (Czech Republic, Estonia, Hungary, Lithuania, Luxembourg, Latvia, Romania, Slovenia, Slovak Republic) data on growth accounts from 2008-2016 is available. The TFP variable used in this paper is the index of TFP growth, in which 2010=100.

The National Accounts database is used to deliver data on labor related data, such as number of employees and hours worked. The data does not suffice to make inferences regarding wage polarization. Therefore, this paper only looks at employment polarization. The division between high, medium and low-skilled employees is retrieved from the level of education for 2008-2017 in the EU Klems release of 2019. Education-level breakdown are (1) university graduates, (2) high school graduates and (3) no formal qualifications for the EU (EU Klems, 2019). Based on the education level the wage bill share groups are created.

Wage bill consists of the labor compensation of employees given the current prices and hours worked by employees. Data for 1995-2005 on wage bill by skill group is retrieved from the EU Klems dataset of 2007. The years 2006 and 2007 are estimated by taking the mean of 2005 and 2008 and replacing these values, since no data is available for these years using the exact same classification as EU Klems data. This is a common way of imputing missing values, however it does potentially lead to underestimated standard deviations (Gelman & Hill, 2006). By replacing these missing values there also is the possibility of measurement error present in the dataset, which should be taken into account while interpreting the results (Wooldridge, 2016). The analysis will therefore be repeated while dropping 2006 & 2007.

The USA makes use of different educational assignments compared to the EU. These groups are assigned to the high, medium and low-skilled group. Unfortunately, this classification is not available at the industry-level but only at country-level by year, again potentially leading to measurement error (Table 1).

**Table 1. Education levels division high, middle and low skilled groups.**

| *Countries* | *High Skilled Group* | *Middle Skilled Group* | *Low Skilled Group* |
|---|---|---|---|
| EU | Education: University Graduates (by industry) | Education: High School Graduates (by industry) | Education: No Formal Qualifications (by industry) |
| USA | Education: A college degree education group or more than a college degree education group (by country) | Education: A high school diploma (or GED) education group, or some college education group (by country) | Education: Less than a high school diploma education group (by country) |

*Notes*: this paper makes use of the classification presented and used in the EU Klems Release of 2019 report.

Often in other academic research on this topic, the routines of occupations are tested to ensure that middle-skilled occupations indeed perform more routinized tasks compared to high- and low-skilled occupations. This is done by monitoring the involvement of, for example, eye-hand-foot coordination, finger dexterity and set limits, tolerances, and standards. The most frequently used indicator for this is the Routine Task Intensity (RTI) index. These findings show that occupations that are either high-skilled (such as physicians, teachers and lawyers), or low-skilled (such as cleaners and frameworkers) typically have low routine cognitive and manual tasks. On the other hand, middle-skilled occupations score above average on routine tasks. Based on findings from previous literature this paper makes the assumption that the middle-skilled wage bill share group is more easily routinized due to their performed tasks in their occupations. I will therefore not repeat this analysis (Autor & Dorn, 2013; Goos, Manning & Salomons, 2014; Michaels, Natraj & Van Reenen, 2014).

### 4.2. Firm-level data

This study makes use of firm-level data. An advantage of using firm-level data is that it leads to improved identification strategies. Nevertheless, a pitfall is to make inferences based on the relative effect of TFP growth on for example employment and referring to this as an effect on the aggregate level. Autor & Salomons (2018) looked into three micro-macro linkages to overcome this pitfall. By observing indirect effects of input-output linkages in both the customer and supplier industry, the first link was created. Second, aggregate economic growth is connected to labor demand by sector. Third, it is recognized that value added share of an industry may cause a shift in the total labor share of value-added creating composition effects. This study refers back to these linkages as proof that making use of firm-level data improves the identification possibilities of the appropriate channels. Exploiting these linkages is supported by earlier studies of Acemoglu, Autor, Dorn, Hanson & Brendan (2016), Pierce & Schott (2016) and Acemoglu, Akcigit, & Kerr (2016).

### 4.3. Observed trends in data

The 40 different identified industries in the dataset are appointed to five main sectors. Namely, (1) *mining & quarrying, agriculture, forestry and fishing (*A & B), (2) *manufacturing & construction (*C, D, E, F), (3) *low-tech services* (G, H, I, L), (4) *high-tech services* (J, K, M-N), and lastly, (5) *education & health* (P & Q). Due to a lack of observations and accuracy of the measurement, the private household sector, public administration and defense (O), arts and entertainment (R-S), activities of households as employers (T) as well as extraterritorial organizations and bodies (U) are omitted from the dataset. Table 2 displays the trends of the main variables of this paper averaged over the time period 1995-2017 by industry. Wage bill shares are weighted by country share in employment and TFP and Value Added (VA) are weighted by country shares of VA. These weights will continuously be used throughout this paper, which can be found in Appendix 11.2.

**Table 2.1 Descriptive Statistics by Industry, 1995-2017, average across years**

| | *Average across years* | | | | |
|---|---|---|---|---|---|
| *Code & Industry* | *High Skilled Wage Bill Share* | *Medium Skilled Wage Bill Share* | *Low Skilled Wage Bill Share* | *Log VA* | *Log TFP* |
| (4) Agriculture, forestry and fishing | 19,91 | 60,32 | 19,76 | 10,86 | 4,59 |
| (5) Mining and quarrying | 25,14 | 63,31 | 11,54 | 10,39 | 4,69 |
| (6) Total manufacturing | 23,98 | 64,11 | 11,89 | 13,32 | 4,54 |
| (20) Electricity, gas, steam and air conditioning supply | 30,69 | 63,49 | 5,90 | 11,19 | 4,63 |
| (21) Water supply; sewerage; waste management and remediation activities | 22,56 | 63,88 | 13,55 | 9,87 | 4,64 |
| (22) Construction | 19,86 | 65,95 | 14,65 | 12,18 | 4,66 |
| (23) Wholesale trade and retail trade: repair of motor vehicles and motorcycles | 21,96 | 65,95 | 12,08 | 13,06 | 4,57 |
| (27) Transportation & storage | 20,39 | 67,53 | 12,06 | 12,05 | 4,63 |
| (33) Accommodation and food service activities | 19,00 | 65,68 | 15,30 | 11,49 | 4,67 |
| (34) Information and communication | 37,58 | 55,86 | 6,55 | 12,29 | 4,51 |
| (38) Financial and insurance activities | 35,89 | 61,20 | 2,91 | 12,36 | 4,54 |
| (39) Real estate activities | 33,72 | 59,92 | 6,33 | 12,99 | 4,63 |
| (40) Professional, scientific, technical, administrative and support service activities | 44,76 | 48,744 | 6,49 | 12,87 | 4,68 |
| (43) Education | 57,97 | 39,73 | 2,28 | 11,54 | 4,63 |
| (44) Health and social work | 36,52 | 59,26 | 4,21 | 12,59 | 4,63 |
| (46) Arts, entertainment and recreation | 42,76 | 51,05 | 6,17 | 10,73 | 4,64 |
| (47) Other service activities | 42,76 | 51,05 | 6,17 | 11,29 | 4,66 |

*Notes*: Source: EU Klems Database release of 2019 & 2007. Authors' calculations.
a. Averaged by industry and weighted by employment or VA country shares
b. Changes are annualized log changes *100

**Table 2.2 Descriptive Statistics by Industry, 1995-2017, annualized changes**

| | *Annualized changes 1995-2017* | | | | |
|---|---|---|---|---|---|
| *Code & Industry* | $\Delta$ *Log High Skilled Wage Bill Share* | $\Delta$ *Log Medium Skilled Wage Bill Share* | $\Delta$ *Log Low Skilled Wage Bill Share* | $\Delta$ *Log VA* | $\Delta$ *Log TFP* |
| (4) Agriculture, forestry and fishing | 10,24 | -0,25 | -1,32 | 1,45 | 1,40 |
| (5) Mining and quarrying | 7,17 | -1,09 | 0,25 | 2,97 | -0,39 |
| (6) Total manufacturing | 8,02 | -1,14 | 0,43 | 2,18 | 1,61 |
| (20) Electricity, gas, steam and air conditioning supply | 9,11 | -1,99 | -3,35 | 2,66 | -0,71 |
| (21) Water supply; sewerage; waste management and remediation activities | 5,65 | -1,52 | 3,18 | 4,60 | 0,17 |
| (22) Construction | 8,90 | -0,47 | -0,46 | 3,36 | -0,54 |
| (23) Wholesale trade and retail trade: repair of motor vehicles and motorcycles | 5,34 | -0,58 | 0,47 | 3,36 | 1,08 |
| (27) Transportation & storage | 6,97 | -1,01 | 2,98 | 3,44 | 0,12 |
| (33) Accommodation and food service activities | 7,86 | -0,29 | 1,84 | 4,52 | -0,82 |
| (34) Information and communication | 10,33 | -3,43 | -6,99 | 4,96 | 2,37 |
| (38) Financial and insurance activities | 5,92 | -2,64 | -1,27 | 3,79 | 1,24 |
| (39) Real estate activities | 2,48 | -0,74 | -1,83 | 4,08 | -0,04 |
| (40) Professional, scientific, technical, administrative and support service activities | 1,20 | -0,85 | -3,31 | 4.97 | -1,05 |
| (43) Education | 2,42 | -3,71 | -2,04 | 4,52 | -0,67 |
| (44) Health and social work | 5,01 | -1,77 | -0,18 | 4,67 | -0,67 |
| (46) Arts, entertainment and recreation | 1,35 | -0,87 | -3,31 | 4,62 | -0,31 |
| (47) Other service activities | 1,35 | -0,87 | -3,31 | 3,13 | -0,90 |

*Notes*: Source: EU Klems Database release of 2019 & 2007. Authors' calculations.

a. Averaged by industry and weighted by employment or VA country shares

b. Changes are annualized log changes *100

As one can observe, overall the middle-skilled group is the largest group in most industries while adopting the EU Klems classification by education. Nevertheless, naturally, in industries such as education and professional, scientific, technical, administrative and support service activities the high-skilled group is most prevalent, indicating employees with college or university degrees are employed more frequently in these industries. Furthermore, one can examine a positive annualized change in the case of the high-skilled group, while both the middle and low-skilled groups experience a decline in their respective wage bill shares. These trends may be explained by automation replacing routinised jobs, an argument following the rationale of this study. Nevertheless, other trends should also be considered, such as offshoring of jobs or a change in the demographics of a country. These trends will be accounted for during the analysis.

Over the time period 1995-2017 VA shows a positive annual growth, while TFP growth is somewhat ambiguous in its direction, dependent on the industry. The information and communication sector for example experienced considerable growth, while accommodation and food service activities annually declined. Considering the assumption of this paper that TFP is caused by technological innovations, it is reasonable to believe that for example the ICT industry experienced TFP growth.

Table 3 summarizes the main trends of the countries included in the analysis. Belgium and the USA have a relatively high share of high-skilled wage bill share, while Austria, Italy and Sweden have the highest middle-skilled group share. Since every country makes use of their own classification scheme these shares should however not be compared with one another. Again, the annualized change of the high-skilled wage bill share is positive, while medium and low-skilled groups experience a predominantly negative change. Overall, all countries experience a positive annual VA and TFP growth. Values are weighted by the industry share of employment or value added to ensure that the real economy is accurately represented.

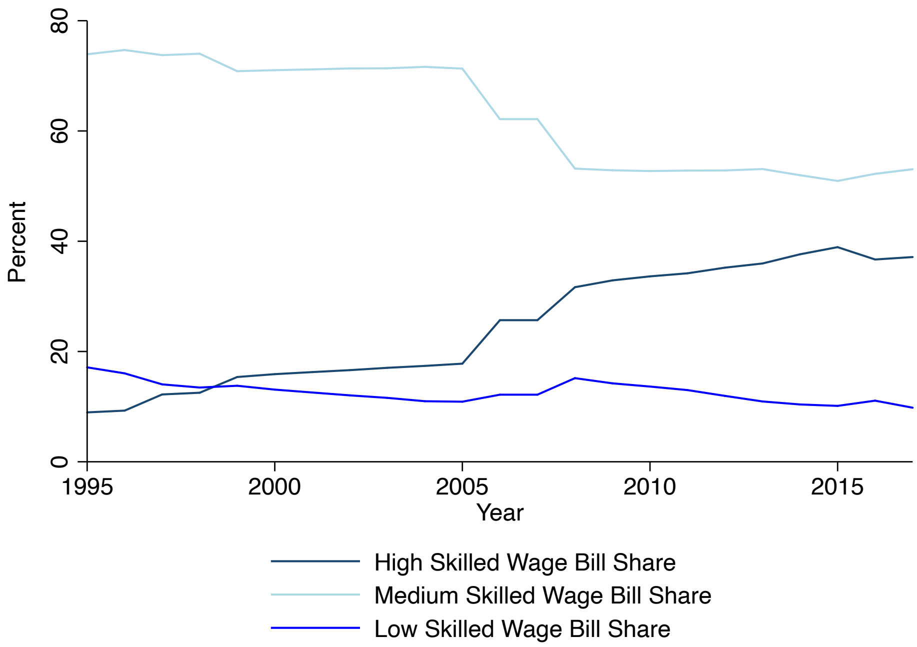
**Table 3. Descriptive Statistics by Country, 1995-2017**

| | *Average of total economy across years* | | | | | *Annualized changes of total economy from 1995-2017* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Country* | *High Skilled Wage Bill Share* | *Medium Skilled Wage Bill Share* | *Low Skilled Wage Bill Share* | *Log VA* | *Log TFP* | *Δ Log High Skilled Wage Bill Share* | *Δ Log Medium Skilled Wage Bill Share* | *Δ Log Low Skilled Wage Bill Share* | *Δ Log VA* | *Δ Log TFP* |
| Austria | 10,82 | 83,87 | 5,30 | 9,40 | 4,59 | 10,26 | -0,21 | -6,23 | 3,36 | 0,51 |
| Belgium | 46,2 | 38,97 | 14,81 | 9,61 | 4,60 | 3,48 | -0,69 | -6,50 | 3,13 | 0,53 |
| Denmark | 15,28 | 69,9 | 14,72 | 11,13 | 4,60 | 14,75 | -1,39 | -3,88 | 3,43 | 0,48 |
| Spain | 30,28 | 19,59 | 50,12 | 10,54 | 4,59 | 9,84 | 1,12 | -4,53 | 4,09 | 0,56 |
| Finland | 37,24 | 52,22 | 10,51 | 8,91 | 4,59 | 1,13 | 0,23 | -8,37 | 3,52 | 0,53 |
| France | 27,33 | 63,10 | 9,56 | 11,29 | 4,60 | 10,51 | -2,75 | -3,66 | 2,71 | 0,43 |
| Germany | 24,94 | 62,12 | 12,94 | 11,68 | 4,59 | 9,65 | -0,66 | -8,02 | 2,57 | 0,51 |
| Italy | 9,91 | 75,53 | 14,55 | 11,09 | 4,59 | 10,67 | -2,12 | 30,87 | 2,35 | 0,63 |
| Netherlands | 17,57 | 71,16 | 11,26 | 10,13 | 4,60 | 13,68 | -2,57 | 12,09 | 3,59 | 0,47 |
| Sweden | 18,61 | 74,95 | 6,44 | 10,88 | 4,59 | 8,79 | -1,63 | -5,20 | 4,04 | 0,57 |
| United Kingdom | 21,98 | 62,28 | 15,7 | 11,02 | 4,69 | 6,48 | -1,64 | -2,13 | 3,90 | 0,41 |
| United States | 42,14 | 54,18 | 15,74 | 13,45 | 4,61 | 1,76 | -1,17 | -2,91 | 3,94 | 0,55 |
| Mean | 24,25 | 62,07 | 13,68 | 12,31 | 4,60 | 8,49 | -1,08 | -0,88 | 3,60 | 0,54 |

*Notes*: Source: EU Klems Database release of 2019 & 2007. Authors' calculations.
a. Averaged by country, weighted by time-averaged industry shares of employment or VA.
b. Changes are annualized log changes *100.
c. TFP is other country, same industry growth.
d. Reported mean weighted by average shares of industry and country.

Figure 3 shows the trends of the high, medium and low-skilled wage bill shares of the time period 1995-2017. Middle-skilled wage bill shows a clear decline, while the high-skilled wage bill share group has considerably grown throughout this period. The low-skilled wage bill share group declined somewhat, however did not experience much development compared to the other two groups.

**Figure 3. Percentage Changes High, Medium and Low Skilled Wage Bill Shares 1995-2017**



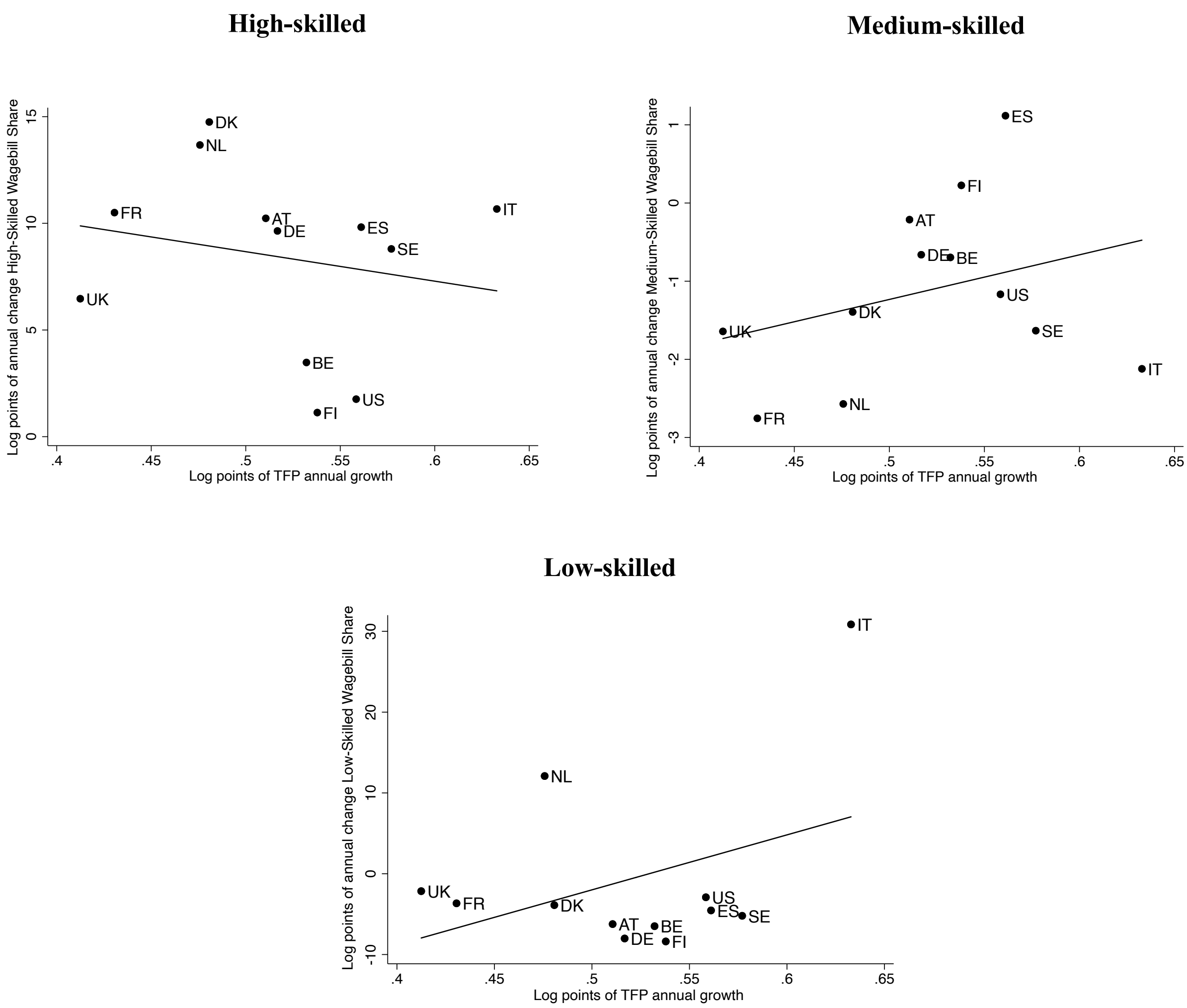

*Notes*: Source: EU Klems Database Release of 2019 & 2007. Authors' calculations.
Weighted by industry and country share of employment.

Lastly, figure 4 shows a weighted cross-country scatterplot of the main observed variables of this study. The trends are not as expected. The high-skilled share shows a slightly downward sloping trend, implying that an increase in TFP would result in a lower increase of the high-skilled share. Moreover, both middle and low-skilled shares show a counterintuitive upward sloping trend.

Unweighted scatterplots can be observed in Appendix 11.6. These figures do display the trends as one would expect based on the hypotheses. Namely, an upward sloping trend for the high-skilled workers and a downward sloping trend for low-skilled workers. Differences between the trends of weighted and unweighted data may be explained by leading industries in countries. Observing the respective weights of overall industries (appendix 11.3.) it becomes clear that on average the following industries make up the largest share: manufacturing (14,5%) wholesale trade and retail trade (15,3%) real estate activities (11,5%) professional, scientific, administrative & support service activities (12,6%) and health and social work (12,4%). Although manufacturing is an industry in which one would expect new technologies to replace jobs, this does not apply to the other large industries such as wholesale trade, real estate activities or professional and scientific activities (Dao, Das, Koczan & Lian, 2017). Therefore, the application of weights to industries might explain the observed unexpected trends. While conducting the analysis in the next chapter this paper will therefore take this into account.

Furthermore, based on the figures Italy seems to be an outlier in the data, particularly in the case of low-skilled wage bill share. Other trends, besides automation of middle-skilled jobs, that could explain these numbers are large numbers of off-shoring of middle-skilled jobs or a growing mismatch of skills on the Italian labor market (Hoftijzer & Gortazar, 2018). However, another likely possibility is an issue with the data being used. Italy made use of a different classification system of education levels between 1995-2005 and 2008-2017, causing a sudden surge in the growth share of the low-skilled wage share. This therefore implies the possibility of measurement error being present. As a robustness test Italy will be removed from the dataset later on.

**Figure 4. Weighted Cross-Country Variation of Annualized High, Medium and Low Skilled Wage Bill Share Change and TFP growth, 1995-2017**




*Notes*: Source EU Klems Release of 2019, author's calculations. Weighted by country specific time-averaged industry-shares.

### 4.4. Shift-share analysis

A change in labor share of different skills levels may be explained by two effects. Namely a within-industry effect and a between-industry effect (Breemersch, Damijan & Konings, 2017). Comparing between-industry and within-industry trends is most often done by analyzing a shift-share table (Molnar & Chalaux, 2015 & Autor & Salomons, 2018). In order to legitimize why this paper only focuses on within-industry changes a shift-share analysis is performed on the 12 countries in the dataset. The aim is to identify the trend on increased polarization and decomposing it in both within- and between-industries components.

Based on the shift-share analysis of Autor & Salomons (2018), let $L_{c,t}^{T} = \Sigma\omega_{i,c,t}l_{,i,c,t,}^{T}$ equal the aggregate log share of total labor. This consists of the sum of the shares of high, medium and low skilled labor. In which $\omega_{i,c,t}$ corresponds to industry $i$'s share in value added in that respective year and country. Furthermore, let $\Delta L_{c,\tau}^{T}$ denote the change in country $c$ in a time interval of five years (Autor & Salomons, 2018). The years 2016 and 2017 were omitted from the dataset in order to observe the trends over the time period of 1995-2015 of five-year intervals. Finally, let $\bar{l}_{i,c,t,}^{T} = \frac{l_{i,c,t1}^{T} - l_{i,c,t0}^{T}}{2}$ and $\bar{\omega}_{i,c,t} = \frac{\omega_{i,c,t1} - \omega_{i,c,t0}}{2}$ in which 1 signifies for example 2000 and 0 signifies 1995 in that case. This allows for the following shift-share analysis of the total labor share

$$(7)\ \Delta\bar{L}_{c,\tau}^{T} = \sum_{i} \bar{\omega}_{i,c,\tau}\Delta l_{i,c,\tau}^{T} + \sum_{i} \bar{l}_{i,c,\tau}^{T}\,\Delta\omega_{i,c,\tau}$$

In which the first term represents the contribution of within industry-changes of the total composition of skills. The second term represents the changes between industries, in which some workers may have shifted towards other industries. Total labor share is labor compensation divided by the total value added (Autor & Salomons, 2018).

**Table 4. Shift-Share Analysis between and within industry Total Labor Share**

| | | *Weighted* | | | *Unweighted* | |
|---|---|---|---|---|---|---|
| *Year* | *Total* | *Between* | *Within* | *Total* | *Between* | *Within* |
| 1995-2000 | -0,16 | -0,02 | -0,14 | -0,16 | -0,02 | -0,14 |
| | | (0,45) | (0,55) | | (0,10) | (0,89) |
| 2000-2005 | -0,66 | -0,29 | -0,37 | -0,66 | -0,29 | 0,37 |
| | | (0,28) | (0,72) | | (0,44) | (0,56) |
| 2005-2010 | 0,27 | -0,07 | 0,34 | 0,27 | -0,07 | 0,34 |
| | | (0,25) | (0,72) | | (-0,26) | (1,27) |
| 2010-2015 | -0,13 | 0,05 | -0,19 | -0,13 | -0,04 | -0,19 |
| | | (0,87) | (0,10) | | (-0,35) | (1,39) |

*Notes:* Source: EU Klems release of 2019. Values are annualized log changes *100 of every five years. Labor shares are weighted by averaged country weights of value added or are unweighted.

As the shift share analysis in table 4 shows, most changes are caused by within-industry changes, both unweighted and weighted by the country share of value added. The values in parentheses show the share of change that is caused by either within or between industry changes. As one can observe, in almost all cases within shares are larger. Take as an example changes from 1995-2000 in total labor share, in which 55% of the decrease is explained by within industry change and 45% by between industry changes. Estimates of the individual high, medium and low labor-shares could not be retrieved since the data does not provide the shares of value added by skill category. Nevertheless, appendix 11.7. shows that within-industry changes of the skills levels divided by total VA is larger for almost all changes, confirming the results of table 4. Together these results therefore suffice to conclude that this study will limit itself by studying solely within-industry changes, rather than between-industry changes. Although between-industry changes are interesting to analyze, it falls outside the scope of this paper. It is therefore suggested to be included in further research.

## 5. Methodology

This section will elaborate upon the adopted methodology of this study, including the main specifications used.

### 5.1. Identification strategy

To be able to identify the effect of TFP growth on the labor market composition in Europe this study makes use of a first-differencing estimation of the balanced panel dataset. The advantage of using first differencing is that the Omitted Variable Bias (OVB) is addressed. Variables that are currently unobserved and time-invariant, but that do have an effect on the outcome variable will be removed from the measured effect (Wooldridge, 2016). Examples of such variables in this study may be the institutions or culture of a specific country. By making use of first-differencing these explanatory variables are accounted for. Additionally, measurement error will be smoothed out while making use of first differencing.

Several issues associated with the estimation of the effect of TFP on labor market polarization have to be dealt with. A first issue that arises with making use of TPF, is the correlation of TPF growth and shifts in its labor share. The EUKlems calculation of TFP growth subtracts the log change in labor growth and capital growth from the value added. As a consequence, labor change and other factors such as wage bill, which is the outcome variable of this research, enters the right hand of the equation while estimating the changes in wage bill shares on TFP growth. This mechanical correlation causes a simultaneity issue. To account for this issue Autor & Salomons (2018) make use of other country, but same industry mean of TFP as a predictor of same country, same industry TFP growth. They construct TFP growth for each industry-country pair by year by estimating the mean of all other countries TFP growth, except for the own industry-country TFP growth. This has the advantage of removing the simultaneity issue. Furthermore, it exploits movements in the technology frontier that frequently occur in industrialized countries. It therefore helps to remove this trend as an exogenous variable. Because of these advantages this study adopts the same method. Nevertheless, the disadvantages of decreasing the amount of variation potentially leading to measurement error ought to be acknowledged as well. Outputs presented in appendix 11.9. change somewhat while repeating the analysis using same country, same industry TFP growth. This may be caused by before-mentioned simultaneity issue. In the remainder of this paper, while mentioning to TFP the own industry, other country TFP growth is referred to.

Another issue with measuring technological innovations is the fact that innovations are not implemented instantaneously into a firm. It requires time for innovations to be adopted and the steady state to be reached. Therefore, a timing issue arises when using TPF. Making use of a lag-structure may help to solve this issue. Based on previous literature (Autor & Salomons 2018; Ramey, 2016; Francis, Owyang, Roush & Dicecio, 2014) it takes a maximum of four to five years for the steady state to be reached. Therefore, the regression estimates in this study will include five distributed lags.

In addition, several fixed control variables are added to the regression. Fixed effects are used, rather than random effects. Fixed effects allow for unobserved heterogeneity and therefore permit unobserved variables to be correlated to the explanatory variables in the regression. A Hausman test could not be performed since the analysis makes use of clustered standard errors. However, in general, fixed effects are used while analyzing countries (Wooldridge, 2016). Firstly, TFP is expected to be confounded by business cycle trends, which may affect the wage bill shares. To address this issue, this study follows the lead of Autor & Salomons (2018) and includes data from the OECD regarding peak and trough indicators. Data by country is retrieved and included in the estimation, interacted with country dummy variables. Moreover, country and industry specific linear trends of the timeframe of this dataset may affect the outcome variable. Therefore, these are included as control variables. Furthermore, sector groups are included to account for industry-specific trends. By making use of a first-difference estimator at the country-industry-time level, country and industry effects are expected to be accounted for. Lastly, by including a country-time interaction term, trends in countries have the ability to change and not have an effect on the outcome variable.

Another important factor to take in mind is the explanatory variable; offshoring. This may be an important predictor of changes in wage bill shares within industries. As shown by prior academic literature routine jobs are hypothesized to be off-shored to lower-wage countries (Breemersch, Damijan & Konings, 2017; Goos, Manning & Salomons 2014). This therefore may be an important factor causing polarization of the labor market by displacing middle-skilled jobs. It is not accounted for by making use of first-differencing due to its time varying properties. Therefore, the analysis is executed on a subsample of tradable sectors. Based on Gregory, Salomons & Zierahn (2019) this paper assumes the following sectors to be tradable or non-tradable (Table 5). The distinction is based on the spatial concentration of industries, hereby showing the tradability of the outputs of a certain industry.

**Table 5. Tradable industries, NACE division 2.1.**

| *Nace Division 2.1* | *Industry* | *Classification* |
|---|---|---|
| B | Mining and quarrying | Tradable |
| C | Total Manufacturing | Tradable |
| D | Electricity, gas, steam and air conditioning supply | Tradable |
| F | Construction | Non-tradable |
| G | Wholesale and retail trade: repair of motor vehicles and motorcycles | Non-tradable |
| I | Accommodation and food service activities | Non-tradable |
| H | Transportation and storage | Tradable |
| K | Financial and Insurance activities | Tradable |
| L | Real Estate Activities | Tradable |
| O | Public Administration, Defence, Education, Human Health and Social Work Activities | Non-tradable |
| P | Education | Non-tradable |
| Q | Health and Social Work | Non-tradable |
| S | Other Service Activities | Non-tradable |
| T | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use | Non-tradable |

*Notes*: Original classification Gregory, Salomons & Zierahn (2019) makes use of NACE division 1.1. This study transformed this into NACE Division 2.1 using the classification scheme in Appendix 11.5. Due to a lack of observations industry O and S are omitted from the EU Klems release of 2019 dataset.

By performing the analysis on a subsample of the traded industries it is possible to examine whether labor market polarization is caused by TFP, or in other words, technological innovations rather than offshoring of jobs. Although Breemersch, Damijan & Konings (2017) consider imports from China to be another confounding variable, this paper does not take this account since these effects mainly appear in the between-industry analysis. Based on the previously performed shift-share analysis this paper is restricted to within-industry analysis.

First, the analysis will be executed using unweighted data. Second, the analysis is repeated while making use of time-averaged weights of employment shares by industry and country between 1995-2017 to ensure economies are reflected accurately. Standard errors are clustered at the country-industry pair level to allow for serial correlation and heteroskedasticity.

### 5.2. Main specifications

Based on the above-mentioned regression analysis the main specifications of this study are:

$$(1)\ \Delta lnSHARE^{H}{}_{i,c,t} = \beta_0 + \sum_{k=0}^{5} \beta_1 \Delta lnTFP_{i,c\neq c(i),t-k} + \eta_c + \delta_t + \mu_i + \eta_c \text{ x } t + \eta_c \text{ x } (business\ cycle\ indicator) + \rho_{i,c,t}$$

$$(2)\ \Delta lnSHARE^{M}{}_{i,c,t} = \beta_0 + \sum_{k=0}^{5} \beta_1 \Delta lnTFP_{i,c\neq c(i),t-k} + \eta_c + \delta_t + \mu_i + \eta_c \text{ x } t + \eta_c \text{ x } (business\ cycle\ indicator) + \nu_{i,c,t}$$

$$(3)\ \Delta lnSHARE^{L}{}_{i,c,t} = \beta_0 + \sum_{k=0}^{5} \beta_1 \Delta lnTFP_{i,c\neq c(i),t-k} + \eta_c + \delta_t + \mu_i + \eta_c \text{ x } t + \eta_c \text{ x } (business\ cycle\ indicator) + \varepsilon_{i,c,t}$$

In which $i$ indicates industries, *c* implies countries and *t* indexes time. *SHARE* represents the overall labor share present in a firm. For example: $SHARE^{H} = \frac{W^{H}N^{H}}{W^{H}N^{H} + W^{M}N^{M} + W^{L}N^{L}}$ is the wage bill share of high-skilled group and *N* is the number of hours worked by this skill group. The composition of these shares is based on the study of Michaels, Natraj & Van Reenen (2014). Logs are taken for interpretation purposes. Furthermore, following Autor & Salomons (2018) the log change in TFP involves the contemporaneous measure as well as the previous five distributed lags. The first-differencing specification is measured at the industry-country-time level. The estimation includes country ($\eta_c$) and year ($\delta_t$) and industry ($\mu_i$) fixed effects. In addition, an interaction term between country and time ($\eta_c$ x $t$) and business cycle dummy indicators, *peak* and *trough* interacted with the respective country are included. $\varepsilon, \nu$ and $\rho$ are the error terms of the estimations.

**Table 6. Estimates of the relation between TFP growth and High-Skilled Wage Bill Share**

**6.1. Unweighted**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | | | |
| | Dependent variable: Δ log High−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 1,466** | 1,223** | 1,121*** | 0,784** | 0,081 | 0,099 |
| | (0,666) | (0,546) | (0,411) | (0,305) | (0,380) | (0,107) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country * Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,028 | 0,024 | 0,007 | 0,010 | 0,830 | 0,355 |
| $R^2$ | 0,345 | 0,392 | 0,687 | 0,401 | 0,474 | 0,471 |
| No. of observations | 6,458 | 5,695 | 5,695 | 5,695 | 2,983 | 2,983 |

**6.2. Weighted**

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| | Weighted by averaged employment share of country and industry | | | | | |
| | Dependent variable: Δ log High−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 4,803 | 5,140*** | 4,049*** | 2,212** | 1,834* | 0,806* |
| | (3,126) | (1,559) | (1,212) | (1,009) | (1,125) | (0,439) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country * Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,125 | 0,001 | 0,001 | 0,036 | 0,105 | 0,068 |
| $R^2$ | 0,221 | 0,291 | 0,673 | 0,299 | 0,495 | 0,506 |
| No. of observations | 6,458 | 5,695 | 5,695 | 6,526 | 2,983 | 2,983 |

*Notes*: Source: EU Klems release of 2019 & 2007. Business cycle indicators: OECD database, peak and trough variables.

a. TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).

b. Standard clustered errors by country-industry pairs in parentheses.

c. Coefficients are the sum of contemporaneous and five annually distributed lags.

d. Statistical significance at a p-value of *10% **5% and ***1%

**Table 7. Estimates of the relation between TFP growth and Medium-Skilled Wage Bill Share**

**7.1. Unweighted**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | | | |
| | Dependent variable: $\Delta$ log Medium−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | -0,348** | -0,321* | -0,306** | -0,029 | 0,024 | 0,056 |
| | (0,206) | (0,192) | (0,153) | (0,099) | (0,145) | (0,054) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country*Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,092 | 0,096 | 0,046 | 0,77 | 0,867 | 0,302 |
| $R^2$ | 0,208 | 0,246 | 0,452 | 0,274 | 0,305 | 0,312 |
| No. of observations | 6,458 | 5,695 | 5,695 | 5,695 | 2,983 | 2,983 |

**7.2. Weighted**

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| | Weighted by averaged employment share of country and industry | | | | | |
| | Dependent variable: $\Delta$ log Medium−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | -0,231 | -0,282 | -0,246 | -1,213** | -0,285 | 0,046 |
| | (0,679) | (0,587) | (0,539) | (0,532) | (0,310) | (0,148) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country*Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,734 | 0,632 | 0,648 | 0,023 | 0,360 | 0,758 |
| $R^2$ | 0,135 | 0,183 | 0,421 | 0,191 | 0,345 | 0,353 |
| No. of observations | 6,458 | 5,695 | 5,695 | 5,695 | 2,983 | 2,983 |

*Notes*: Source: EU Klems release of 2019 & 2007. Business cycle indicators: OECD database, peak and trough variables.
a. TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).
b. Standard clustered errors by country-industry pairs in parentheses.
c. Coefficients are the sum of contemporaneous and five annually distributed lags.
d. Statistical significance at a p-value of *10% **5% and ***1%

**Table 8. Estimates of the relation between TFP growth and Low-Skilled Wage Bill Share**

**8.1. Unweighted**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | | | |
| | Dependent variable: Δ log Low−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | -0,887 | -1,112 | -1,301*** | -0,552** | -0,032 | 0,077 |
| | (1,537) | (0,918) | (0,375) | (0,219) | (0,942) | (0,155) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country*Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,564 | 0,227 | 0,001 | 0,012 | 0,972 | 0,618 |
| $R^2$ | 0,110 | 0,186 | 0,874 | 0,193 | 0,223 | 0,223 |
| No. of observations | 6,458 | 5,695 | 5,695 | 5,695 | 2,983 | 2,983 |

**8.2. Weighted**

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| | Weighted by averaged employment share of country and industry | | | | | |
| | Dependent variable: Δ log Low−Skilled Wage Bill Share | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 0,843 | -0,002 | -1,482 | -2,158 | 1,144 | 0,816 |
| | (3,788) | (2,231) | (0,943) | (1,027) | (2,335) | (0,659) |
| Fixed Effects | | | | | | |
| Country | Yes | Yes | No | No | Yes | No |
| Year | Yes | Yes | No | No | Yes | No |
| Sector | No | No | No | Yes | No | Yes |
| Country*Year | No | No | Yes | Yes | No | Yes |
| Business Cycle indicators | No | Yes | Yes | Yes | Yes | Yes |
| Sample: All industries | X | X | X | X | | |
| Sample: Traded Industries | | | | | X | X |
| P-value | 0,824 | 0,999 | 0,117 | 0,036 | 0,625 | 0,217 |
| $R^2$ | 0,070 | 0,140 | 0,930 | 0,148 | 0,192 | 0,191 |
| No. of observations | 6,458 | 5,695 | 5,695 | 5,695 | 2,983 | 2,983 |

*Notes*: Source: EU Klems release of 2019 & 2007. Business cycle indicators: OECD database, peak and trough variables.
a. TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).
b. Standard clustered errors by country-industry pairs in parentheses.
c. Coefficients are the sum of contemporaneous and five annually distributed lags.
d. Statistical significance at a p-value of *10% **5% and ***1%

## 6. Results

The next section will interpret the results of the analysis. The results of TFP on the different wage bill share shares will be elaborated upon, including the different tests that are performed.

### 6.1. Results high-skilled wage bill share

Table 6, 7 & 8 represent the results of the main estimates of this paper. Table 6 shows the relation between TFP growth and the high-skilled wage bill share. Column 1 to 5 are unweighted results, while column 7 to 12 are weighted by time-averaged employment share by country and industry. Column 1 is a simple OLS without fixed effects and is significant with a positive coefficient of 1,47 at the 0,05 p-value level. The reported coefficient is the sum of the change in log value of the contemporaneous and five distributed lags of own industry but other country TFP growth. This coefficient implies that an increase of 1% of TFP growth over the five previous years, results in a growth rate of 1,47 % of high-skilled wage bill share.

Column 2 includes an interaction term between country and business cycle indicators peak and trough retrieved from the OECD. Results remain positive and significant. This implies that cycles within firms do not explain the increase in labor market polarization. Productivity growth due to new technologies remains a relevant explanatory variable. By adding these fixed effects precision increases represented by the decreasing standard errors.

Column 3 adds a country and year interaction term. If a new policy is adopted in for example the Netherlands making it more attractive for workers to become high educated, this may affect the high-skilled workers share. Such trends are accounted for by including the interaction term. The explanatory power seems to increase while adding this term in all regressions. A disadvantage is that it takes away a large part of the variance in TFP. Column 4 furthermore includes fixed effects for the five sectors, increasing precision.

Subsequently time-averaged weights of the employment share by industry and by country are added (column 7-12). Coefficients increase considerably, nevertheless, precision decreases. Results remain predominantly significant. Observing the $R^2$ and significant F-test, explanatory power increases while adding more fixed effects.

Overall, the results indicate that an increase in TFP, or in other words new technological innovations entering a firm, lead to an increased share of high-skilled workers within the labor market in advanced countries in the EU and the USA. This suggests that high-skilled workers benefit from new technologies. However, it remains unclear whether these effects are the result of new jobs that have been created during 1995-2017 or due to a decrease in the share of middle-skilled workers. The section on future research will provide several suggestions elaborating on this.

### 6.1.1. Traded industries

Column 5, 6, 11 & 12 are regressions executed on the subsample of traded industries. As shown the coefficients remain positive, however they lose their statistical significance. This may imply that offshoring has played a considerable role in the change of the wage bill share. As a consequence, the increase in the relative share of high-skilled workers may be explained by jobs of middle-skilled workers that have been outsourced to low-wage countries, rather than the hypothesized effect of new technologies entering the market.

## 6.2. Results medium-skilled wage bill share

Table 7 shows the results for the estimates of TFP growth on the medium-skilled wage bill share. As hypothesized, coefficients are negative. An increase of 1% of TFP results in a negative growth rate of -0,35% in column 1, significant at the 0,05 p-value. This indicates that an increasing TFP is associated with a decline of the share of middle-skilled workers, as was hypothesized in the theoretical framework of this study. However, coefficients remain only moderately significant and small.

Adding weights of the employment share of country and industry result again in small, negative coefficients. Nevertheless, they become statistically insignificant. Similar to the high-skilled wage bill share group, applying employment weights changes the outcomes considerably. An explanation for this may be found in the fact that certain industries receive relatively large weights. Some of these industries are not affected much by new technologies. As discussed in the data section, automation is mainly expected to be prevalent in, for example, the manufacturing industry. Workers in this industry are more likely to be replaced by machines since they perform routine-based tasks while making products. On the other hand, industries such as professional and scientific activities perform non-routine tasks. These industries also represent large shares of the industries of advanced economies (Appendix 11.3.). This may explain why results turn non-significant while applying weights.

To research this argument this paper repeats the analysis on solely the manufacturing industry, identifying large and significant coefficients of TFP on wage bill shares (Appendix 11.8.). Furthermore, the analysis is repeated on a subsample of the professional, scientific, technical, administrative and support service activities. Outcomes show counteracting coefficients (Appendix 11.8.). These results hint towards certain industries in which the effect is prevalent and certain industries that do not experience increased labor market polarization due to increased TFP.

In addition, the USA represents 45% of all employment and may bias the results (Appendix 11.2.1.). Since education levels for the USA are solely available on country level and not industry-level there is less variation in the skills levels of the USA. Therefore, the weighted results should be interpreted with caution.

#### 6.2.1. Traded industries

Traded industries sample set represented in column 5, 6, 11 and 12 again turn statistically non-significant for the middle-skilled wage bill share group and turn positive in the case of the unweighted results. This suggests that part of the decrease of the medium wage bill share may again be explained by the occurrence of offshoring during the time period 1995-2017.

### 6.3. Results low-skilled wage bill share

Results for the low-skilled wage bill share, summarized in table 8, are ambiguous for both samples. Results are not significant and direction changes while applying weights of employment share. Explanatory power remains low while adding fixed effects and standard errors are rather high. Results of the effect of TFP growth on the low wage bill share are therefore inconclusive. As the previous descriptive statistics already showed, low-skilled wage bill share decreased relatively little compared to the medium and high-skilled wage bill share groups. This might explain the lack of a meaningful relation. Furthermore, while adding the year and country interaction term the explanatory power becomes very high. This may be explained by the fact that trends apply to both the dependent variable, wage bill share, and independent variable, TFP causing inflated $R^2$. Therefore, one should focus on the results excluding the time and country interaction term.

Based on these findings one can observe a positive growth rate of the high-skilled wage bill share whenever TFP increases. Growth rate of middle-skilled wage bill share is predominantly declining as a result of an increase in TFP. Results for the low-skilled wage bill share are inconclusive.

## 6.4. Robustness Tests

A number of robustness tests are performed addressing potential pitfalls of this study. Table 9 summarizes the main results of these robustness tests.

### 6.4.1. Sub-samples

The descriptive statistics show that Italy is an outlier in the data. Therefore, as a robustness check the regression analysis is repeated while dropping the variable representing Italy. The results remain similar to the main estimation. However, the unweighted low-skilled wage bill becomes statistically significant with a negative coefficient of -1,34. This may be explained by the fact that Italy was a large positive outlier in the low-skilled wage bill share.

Prior literature has shown that labor market polarization occurs in countries in West-European countries and in the USA. The EU Klems database however provides data for East-Europe as well. Therefore, to go beyond the scope of prior literature, this study observes if the effect is prevalent in other parts of Europe. The data analysis is extended to exclude USA and include Czech Republic and Slovak Republic, for which – although somewhat incomplete – data from 1995-2017 is available. Results for the middle-skilled wage bill group remain robust, while the statistical significance disappears for the high-skilled wage bill group. This may indicate that technological innovations do not have the same effect on all European countries. A potential explanation of the different effect of new technologies causing labor market polarization in these countries may be due to the size and state of development of an economy. Whenever an economy is more advanced it is more likely to implement and invest in new technologies.

Furthermore, the analysis is performed on data availability of 22 countries in Europe from 2008-2017 (additional countries: Czech Republic, Estonia, Hungary, Lithuania, Luxembourg, Latvia, Romania, Slovenia & Slovak Republic). Results show similar directions of the coefficients although they lose their statistical significance. This confirms the notion that the effect is mainly occurring in more advanced economies. However, a number of datapoints are lacking from these additional countries, therefore making a legitimate interpretation harder. Lastly, the analysis is repeated on a subsample while excluding 2006 & 2007 due to the missing data on education levels. Results remain positive and significant for the high-skilled wage bill share. However, they unexpectedly turn positive for the middle-skilled group. It would indicate that all shares experience growth with an increase in TFP.

### 6.4.2. Change of dependent and independent variables

A different robustness check that is executed is the replacement of the shares by taking the values of log labor compensation changes by skill group and year. This robustness check is relevant since the economic framework by Acemoglu & Restrepo (2018) predicts that new tasks might be created due to the introduction of new technologies. Observing the shares in the main estimation only analyzes the shifts between these shares, while an analysis of the values takes potentially newly created tasks into account. Results of the robustness check show similar directions of the coefficients. Results are significant, weighted by employment share by industry and country. Other coefficients lose their statistical significance. Nevertheless, further research would be required to make inferences on this topic, as is suggested later on.

The use of TFP may be a disputed proxy for technological innovations. An increase in productivity of a company could be caused by factors other than technological innovations. Furthermore, it relies on assumptions made by Autor & Salomons (2018). Therefore, as a robustness check, the TFP of other countries is replaced by a R&D indicator available from the capital accounts database. R&D is a commonly used proxy for technological innovations (Acemoglu & Autor, 2011). The gross fixed capital formation expenses on R&D index with 2010=100 is used. Results remain robust and statistically significant using R&D as the independent variable for the unweighted and weighted variables of the high and middle-skilled wage bill shares. Surprisingly, low-skilled wage bill shares, both unweighted and weighted, show positive coefficients of 11,62 and 38,63 significant at the 0,01 p-value. This would imply that a growth in R&D expenditures increases the low wage bill share. These results are not in line with the hypotheses of this paper, nonetheless they do support the market polarization hypothesis. This suggests that by making use of different proxies, diverse results in support of the hypotheses can be attained.

### 6.4.3. Different identification strategy

In addition, the study of Michaels, Natraj & Van Reenen (2014) makes use of long differences while observing the EU Klems release of 2007. In order to explore this alternative identification strategy a robustness check is performed by applying long differences of 22 years instead of using the first differencing method. Results remain robust. However, due to the small number of observations these results should be interpreted with caution.

Overall the robustness tests support the findings of the main estimations regarding the high and middle-skilled wage bill shares. Nevertheless, different samples provide different results. This suggests that multiple factors play a role while analyzing labor market polarization.

**Table 9. Robustness checks**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | Weighted by averaged employment share by country and industry | | |
| *Robustness checks* | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share |
| *Dropping outlier Italy* | | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 1,208** | -0,423** | -1,341** | 4,473*** | -0,393 | -1,800 |
| | (0,509) | (0,185) | (0,565) | (1,241) | (0,544) | (1,148) |
| $R^2$ | 0,378 | 0,222 | 0,142 | 0,296 | 0,155 | 0,143 |
| Observations | 6,041 | 6,041 | 6,041 | 6,041 | 6,041 | 6,041 |
| *Data availability 2008-2016* | | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 3,617* | -0,008 | 0,860 | 1,505 | -0,631 | 0,498 |
| | (1,917) | (0,623) | (2,346) | (2,410) | (0,701) | (1,996) |
| $R^2$ | 0,185 | 0,089 | 0,036 | 0,060 | 0,027 | 0,092 |
| Observations | 3,219 | 3,219 | 3,219 | 3,219 | 3,219 | 3,219 |
| *Drop year 2006 & 2007* | | | | | | |
| $\Sigma\Delta\log\ R\&D_{i,c,t-k}$ | 1,376** | 0,141 | 0,033 | 2,789*** | 0,535 | -1,322* |
| | (0,546) | (0,137) | (0,385) | (0,824) | (0,327) | (0,798) |
| $R^2$ | 0,242 | 0,158 | 0,131 | 0,190 | 0,154 | 0,268 |
| Observations | 3,387 | 3,387 | 3,387 | 3,387 | 3,387 | 3,387 |
| *Values of wage bill rather than shares* | *Value* | *Value* | *Value* | *Value* | *Value* | *Value* |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 0,399 | -0,351 | -0,893* | 5,252*** | -0,568 | 0,537 |
| | (0,279) | (0,255) | (0,537) | (1,312) | (0,536) | (2,242) |
| $R^2$ | 0,266 | 0,141 | 0,178 | 0,306 | 0,193 | 0,147 |
| Observations | 6,996 | 6.996 | 6,996 | 6,526 | 6,526 | 6,526 |
| *Exclude USA and include Czech Republic & Slovak Republic* | | | | | | |
| $\Sigma\Delta\ln\ TFP_{i,c,t-k}$ | 0,141 | -0,137** | -0,349 | 4,828*** | -0,769 | -1,451 |
| | (0,136) | (0,053) | (0,217) | (1,472) | (0,669) | (2,789) |
| $R^2$ | 0,413 | 0,260 | 0,197 | 0,523 | 0,298 | 0,246 |
| Observations | 5,919 | 5,919 | 5,919 | 5,919 | 5,919 | 5,919 |
| *Make use of R&D as a proxy for TI* | | | | | | |
| $\Sigma\Delta\log\ R\&D_{i,c,t-k}$ | 3,129*** | -1,132*** | 11,618*** | 3,928* | -1,180 | 38,63*** |
| | (1,005) | (0,414) | (3,198) | (2,345) | (0,758) | (8,929) |
| $R^2$ | 0,452 | 0,298 | 0,212 | 0,339 | 0,229 | 0,205 |
| Observations | 4,923 | 4,923 | 4,923 | 4,923 | 4,923 | 4,923 |
| *Long differences instead of first differences* | | | | | | |
| $\log TFP_{i,c,t} - L22.\log TFP_{i,c,t}$ | 0,276*** | -0,624* | -0,223 | 0,314*** | 0,053 | -0,075 |
| | (0.066) | (0.033) | (0,151) | (0,103) | (0,067) | (0,456) |
| $R^2$ | 0,053 | 0.015 | 0,008 | 0,071 | 0,006 | 0,000 |
| Observations | 306 | 306 | 306 | 306 | 306 | 306 |

*Notes*: TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).
b. Standard clustered errors by country-industry pairs in parentheses.
c. Coefficients are the sum of contemporaneous and five annually distributed lags
d. Statistical significance at a p-value of *10% **5% and ***1%
e. Robustness test: data availability 2008-2016 did not include business cycle indicators due to a lack of data. Robustness test: long differences simple OLS, robust standard errors. All other robustness tests: original regression analysis including fixed effects country, year and business cycle indicators.

## 7. Discussion & conclusion

By analyzing data ranging from 1995-2017 from the USA and countries in Europe this paper tried to determine and disentangle the effect of new technologies such as robotics and AI on the labor market polarization trend of the past decades in advanced economies. Overall the results of the main estimates are in accordance to the hypotheses predicted in the short run based on the presented theoretical framework of Acemoglu & Restrepo (2018) and the extension this paper makes on their framework.

### 7.1. Findings

Empirical evidence suggests that high-skilled workers experience an increase in their share whenever a new technological innovation is introduced in a firm, taking up to a maximum of five years to reach the steady state. An explanation for this would be the presence of the replacement effect. The high-skilled workers have a comparative advantage in high-indexed tasks, leading to new task opportunities for them to take on. This implies a shift in the demand side of labor (Acemoglu & Restrepo 2018). In this respect, new technologies are represented by TFP, suggesting that an increase in the total productivity is a result of new technologies that have been implemented in a firm. To stress-test this proxy, the analysis was repeated while observing R&D expenditures, resulting in similar outcomes.

Furthermore, results of this study hint towards a decrease of the share of the middle-skilled workers. A possible explanation would be the displacement effect. Middle-skilled workers are more often engaged in performing low-indexed, routine tasks in their jobs, resulting in replacement by machines who can achieve the same outcome more efficiently in the short run. The theoretical framework of this study predicts that in the long run high-indexed tasks arising from new tasks associated with the introduction of new technologies would become standardized. Standardization would allow middle-skilled workers to perform these high-indexed tasks. Nevertheless, due to the limited frame-time observed in this study, results do not allow to make inferences regarding the effects in the long run. This would require more extensive research.

Lastly, the hypotheses of this study assume that the low-skilled workers share remains unaffected by the introduction of new technologies. Such workers perform high-indexed tasks, however, are not expected to benefit from new technologies. Results appear to be ambiguous, neither confirming nor disproving this hypothesis. In general, the growth of the low-skilled workers share shows little relation to TFP. On the other hand, when adopting a different proxy, namely the R&D indicator, the low-skilled share significantly increased. Therefore, the findings for this group remain inconclusive.

An alternative, contrasting, explanation that needs to be considered on the introduction of new technologies would be on the labor supply side. High-skilled workers require more education and training to be able to perform the new tasks associated with the new technologies. They would therefore demand higher wages. As not all high-skilled workers will re-educate, the supply of the high-skilled workers will decline. This subsequently results in an increase of the middle-skilled worker share (Borjas, 2019). This argument is offsetting the hypotheses adopted in this paper. A counterargument to this would be that it will be mainly the middle-skilled laborers who will engage in re-educational programs. The supply effect will affect the middle-skilled group, rather than the high-skilled group, leading to increased polarization. Low-skilled workers, again, remain unaffected. Previous empirical evidence, as well as this paper, would support the latter explanation on the supply side of labor. Nevertheless, more research in regard to allocation of education and trainings should be conducted to be able to confirm this argument.

### 7.2. Causes for caution

The outcomes of this study in general suggest that technological innovations are associated with increased labor market polarization. Nevertheless, there are several reasons why these findings should be interpreted with caution. The results do not remain robust while applying similar methods to different sub-samples. The effects appear to be mainly occurring in certain countries. An explanation could be that countries require an advanced economy for the effects to occur. Developed countries are more likely to have the capacity to develop, invest in and implement new technologies. Therefore, such technologies have the potential to replace routine-task based occupations, prevalent in the middle-skilled labor share.

Furthermore, results hint towards a discrepancy between specific industries. Certain industries, such as manufacturing, experience a much larger effect of automation causing labor market polarization. This reinforces the conjunction of results identified by Breemersch, Damijan & Konings (2017). On the other hand, industries such as educational services or sciences only benefit from new technologies and will therefore experience overall growth in their industry. Based on the findings of this study the effect of new technologies would be much larger on labor market polarization in for example the manufacturing industry present in an advanced economy, such as the Netherlands, compared to an education industry present in Czech Republic. Autor, Dorn, Katz, Patterson & Van Reenen (2018) tried to prove the different effects of technology on different industries. This study seems to be in accordance with their findings.

Furthermore, new technologies entering firms is not the sole possible factor that explains the labor market polarization trend of the past decades. Estimates of the subsample on traded industries in this study suggest that offshoring is another important explanatory factor, hereby confirming prior academic literature (Breemersch, Damijan & Konings 2017; Goos, Manning & Salomons 2014). An increase of routine-based tasks that are performed in low-wage countries cause a decline of jobs for middle-skilled workers in advanced countries. Since the findings of this study turn non-significant when only traded industries are observed, this presumption appears to be supported. Another explanation that could lead to increased labor market polarization in advanced economies is increased import competition from low-wage countries. Take as an example the accession of China to the World Trade Organisation (WTO) in 2001. This caused a sudden surge in advanced economies importing from China. Prior literature however indicated these effects are prevalent at mainly the between-industry level (Breemersch, Damijan & Konings, 2017). This study only focuses on within-industry level and is therefore not able to confirm this. However, both factors potentially explain why the analysis in this study is only moderately significant. It implies that there are other important time varying developments occurring besides technological innovations that potentially explain the trend of the labor market polarization observed in the past decades.

Lastly, one should keep in mind that this paper makes use of a specific interpretation representing the high, medium and low-skilled workers, which were elaborated upon in the data and methodology sections. The skills levels are based on the prior education levels of laborers. Nonetheless, if one would adopt a different interpretation of, for example, the low-skilled workers, this would affect the findings considerably. It could indicate that there has been a decline in the share of low-skilled workers, rather than middle-skilled workers. Therefore, one should be aware of the definitions used in the different papers before being able to compare results.

In conclusion, although the findings of this study would suggest that there is an effect of technological innovations on the labor market, there are many other factors to take into consideration. Certain industries and countries may experience much larger effects compared to others, offshoring, import competition and other time-varying developments may explain part of the labor market polarization trend and the findings of this study depend on the adopted definitions.

Nonetheless, based on the findings of this study people should continue to think about the potential impact of new technologies on the future of jobs. Although there are certain hurdles arising whenever new technologies such as robotics or AI continue to enter the market, opportunities lie ahead. In the long run new technologies have the ability to benefit all, including the middle-skilled workers, as new tasks arise and become standardized over time. After all, robots and other automated technologies require the guidance of humankind. Our goal should be to seize these provided opportunities to be able to provide prosperity for all labor-groups.

## 8. Limitations of the study

There are certain limitations associated with this study. A first limitation is the broad interpretation while making use of TFP as a proxy for technological innovations. A critique imposed on TFP may be that it is too broad to determine whether an increase in productivity of a firm is caused by newly introduced technologies. For example, scaling of businesses may greatly affect the productivity of a firm. Another example would be reorganizing business structures, herby making firms much more efficient (Autor & Salomons, 2018). Although this study tries to account for such factors by adding business cycle effects it is possible not all factors are captured. Furthermore, the small sample size reduces the statistical power of this study.

Making use of first-differencing and fixed effects takes away the unobserved, time invariant variables. Nevertheless, there might still be unobserved time varying variables not accounted for by making use of the current analysis. This leads to potential endogeneity issues in the identification strategy. Making use of an Instrumental Variable (IV) strategy would result in the most accurate determination of the true effect. The study of Acemoglu & Restrepo (2018) makes use of an IV strategy to unravel the effect of robots on the USA and EU labor market.

The used instrument is the adoption of robot development in other advanced countries. Possibly, a similar approach could be applied in a future study on overall technological innovations on labor market polarization.

Another potential limitation is the presence of measurement error. The values of the education levels of the years 2006 & 2007 are estimated since this data was lacking in the EU Klems dataset of 2019. In addition, USA education level data was only available on the country level, rather than industry level. Nevertheless, measurement error in the dependent variable is often considered less of a concern compared to measurement error in the independent variable (Wooldridge, 2016).

Lastly, the wage bill share comprises of the hours worked by the respective skilled groups and the respective labor compensation the different skills groups receive. A disadvantage of making use of wage bill share as the dependent variable is the fact that it oversimplifies the different factors that represent the labor market. There are many other factors that ought to be considered when estimating labor market effects at firm-level. For example, the household composition may alter the supply and demand of labor. In addition, labor conditions, benefits and income taxes are not considered. The nominal value and the real value added furthermore also contribute to the labor market (Autor & Salomons, 2018). Therefore, solely analyzing hours worked and compensation is an oversimplification of reality. Based on prior literature and due to limited data availability and time constraints this study makes use of the wage bill share. As a consequence, results may be somewhat literature-driven, which is a limitation of this study.

## 9. Future research

Certain future recommendations can be derived from this study. Following the findings of the shift-share analysis, this study only observes within-industry changes. However, the results imply that the influence of between-industry seems to be of considerable importance as well. Chinese import competition for example may explain large parts of labor market polarization between industries and is currently not identified in this study. Therefore, future research would require an inclusion of a between-industry analysis to gain a comprehensive understanding of the overall effect. This could be achieved by including the different countervailing channels proposed by Autor & Salomons (2018) to determine the eventual net effect.

Furthermore, this study is not able to determine why the high-skilled wage bill share increases. This relation could be clarified by introducing proxies for the creation of new tasks. Acemoglu & Restrepo (2020b) used the share of new job titles, number of emerging tasks and the share of employment growth in a year as proxies for new tasks. By analyzing such proxies and including them into the regression analysis of the high-skilled wage bill share, the motivation behind the growth of the share could be explained. Nevertheless, this falls outside the scope of this research paper and is therefore suggested for future research.

New technologies are continuously entering markets. Due to the recent Covid-19 developments digitalization has become even more important. An increasing amount of people are losing their jobs and the threat of replacement by technologies has never been this real. Therefore, more future research on this topic is required and expected to help shed light on what digital developments will mean for the future of work.

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# 11. Appendix

## 11.1. Economic framework derivations

Autor & Salomons (2018) derivations leading to net demand of replacement and displacement effect of formula 3.

Labor Market Equilibrium:

$$\frac{a_L y_L(N)}{a_M y_M(N-1)} > \frac{W}{R} > \frac{a_L y_L(I)}{a_M y_m(I)}$$

The model in equilibrium is expressed like:

$$Y = B\left(\frac{a_M M}{I-N+1}\right)^{I-N+1}\left(\frac{a_L L}{N-I}\right)^{N-I}$$

Where

$$B = exp\left(\int_{N-1}^{1} \ln y_m\,(x)dx + \int_{I}^{N} \ln y_m(x)dx\right)$$

Demand for labor can be written as

$$W = (N-I)\frac{Y}{L}$$

Four distinct forms of technological change (1) conventional factor-augmenting technical changes (2) extensive margin (labor-displacing) technical changes (3) intensive margin capital- or labor augmenting technical changes, (4) task-creating technical change.

(1) Conventional factor-augmenting technical changes. A rise in either $a_L$ or $a_M$, signifying labor or capital augmenting technical change.

$$\frac{d\ln W}{d\ln a_L} = \frac{d\ln\left(\frac{y}{L}\right)}{d\ln a_L} = (N-I)d\ln a_L > 0$$

And similarly:

$$\frac{d\ln W}{d\ln a_M} = \frac{d\ln(\frac{y}{L})}{d\ln a_M} = (I - N + 1)d\ln a_M > 0$$

(2) Extensive margin (labor-displacing) technical change

$$\frac{d\ln W}{dI} = \left[-\frac{1}{N-I}\right] + [\ln(\frac{W}{a_L y_L(I)}) - \ln(\frac{R}{a_M y_M(I)})]$$

(3) Intensive margin capital- or labor augmenting technical changes

$$d\ln W = d\ln\frac{Y}{L} = (I - N + 1)\, d\ln y_M > 0$$

(4) Creation of new tasks.

Combining (1) (2) and (3) to create the total effect of task-replacing technical change and new task creation to get to formula 3 on page 14:

$$d\ln W = \left[\ln\left(\frac{R}{a_m y_m(N-1)}\right) - \ln\left(\frac{W}{a_l y_l(N)}\right)\right] d\mathrm{N} + \left[\ln\left(\frac{W}{a_l y_l(I)}\right) - \ln\left(\frac{R}{a_m y_m(I)}\right)\right] dI + \left[\frac{1}{N-I}\right](d\mathrm{N} - d\mathrm{I})$$

## 11.2. Time-averaged country weights employment and value added

### 11.2.1. Country weights

**Table 10. Country weights TFP, Employment & Value Added.**

| *Country* | *Country weight employment* | *Country weight Value Added* |
|---|---|---|
| (AT) Austria | 0,013 | 0,009 |
| (BE) Belgium | 0,014 | 0,012 |
| (DK) Denmark | 0,009 | 0,055 |
| (ES) Spain | 0,06 | 0,032 |
| (FI) Finland | 0,008 | 0,006 |
| (FR) France | 0,087 | 0,064 |
| (DE) Germany | 0,135 | 0,088 |
| (IT) Italy | 0,080 | 0,052 |
| (NL) The Netherlands | 0,028 | 0,019 |
| (SE) Sweden | 0,01 | 0,109 |
| (UK) United Kingdom | 0,09 | 0,051 |
| (US) United States | 0,451 | 0,500 |

### 11.2.2. Country weights sample excluding USA and including CZ and SR

**Table 11. Country weights TFP, Employment & Value Added.**

| *Country* | *Country weight employment* | *Country weight Value Added* |
|---|---|---|
| (AT) Austria | 0,023 | 0,015 |
| (BE) Belgium | 0,025 | 0,019 |
| (CZ) Czech Republic | 0,029 | 0,194 |
| (DK) Denmark | 0,016 | 0,089 |
| (ES) Spain | 0,105 | 0,051 |
| (FI) Finland | 0,013 | 0,009 |
| (FR) France | 0,153 | 0,103 |
| (DE) Germany | 0,236 | 0,153 |
| (IT) Italy | 0,140 | 0,083 |
| (NL) The Netherlands | 0,049 | 0,032 |
| (SK) Slovak Republic | 0,013 | 0,003 |
| (SE) Sweden | 0,023 | 0,175 |
| (UK) United Kingdom | 0,168 | 0,082 |

## 11.3. Time-averaged industry weights employment and value added

**Table 12. Industry weights TFP, Employment & Value Added.**

| *Code & Industry* | *Employment weights, averaged across countries* | *VA weights, averaged across countries* |
|---|---|---|
| (4) Agriculture, forestry and fishing | 0,033 | 0,018 |
| (5) Mining and quarrying | 0,002 | 0,009 |
| (6) Total manufacturing | 0,145 | 0,171 |
| (20) Electricity, gas, steam and air conditioning supply | 0,005 | 0,019 |
| (21) Water supply; sewerage; waste management and remediation activities | 0,005 | 0,008 |
| (22) Construction | 0,069 | 0,059 |
| (23) Wholesale trade and retail trade: repair of motor vehicles and motorcycles | 0,153 | 0,121 |
| (27) Transportation & storage | 0,052 | 0,052 |
| (33) Accommodation and food service activities | 0,049 | 0,028 |
| (34) Information and communication | 0,030 | 0,051 |
| (38) Financial and insurance activities | 0,030 | 0,055 |
| (39) Real estate activities | 0,115 | 0,108 |
| (40) Professional, scientific, technical, administrative and support service activities | 0,126 | 0,104 |
| (43) Education | 0,069 | 0,053 |
| (44) Health and social work | 0,124 | 0,079 |
| (46) Arts, entertainment and recreation | 0,017 | 0,012 |
| (47) Other service activities | 0,029 | 0,017 |

*Notes:* Regressions and tables in Author’s calculations make use of industry share of employment or Value Added (VA) by country. Figure above displays industry shares averaged across countries.

### 11.4. EU Klems NACE revision 2, industries

**Table 13. NACE Revision 2**

| Sort_ID | Indnr | Code | Description |
|---|---|---|---|
| 1 | Agg | TOT | TOTAL ECONOMY (A-U) |
| 2 | *Agg | TOT_IND | TOTAL INDUSTRIES (A-S) |
| 3 | *Agg | MARKT | MARKET ECONOMY (all industries excluding L, O, P, Q, T and U) |
| 4 | 1 | A | Agriculture, forestry and fishing |
| 5 | 2 | B | Mining and quarrying |
| 6 | Agg | C | TOTAL MANUFACTURING |
| 7 | 3 | 10-12 | Food products, beverages and tobacco |
| 8 | 4 | 13-15 | Textiles, wearing apparel, leather and related products |
| 9 | 5 | 16-18 | Wood and paper products; printing and reproduction of recorded media |
| 10 | 6 | 19 | Coke and petroleum products |
| 11 | 7 | 20 | Chemicals and chemical products |
| 12 | 8 | 21 | Basic pharmaceutical products and pharmaceutical preparations |
| 13 | 9 | 22-23 | Rubber and plastics products, and other non-metallic mineral products |
| 14 | 10 | 24-25 | Basic metals and fabricated metal products, except machinery and equipment |
| 15 | 11 | 26 | Computer, electronic and optical products |
| 16 | 12 | 27 | Electrical equipment |
| 17 | 13 | 28 | Machinery and equipment n.e.c. |
| 18 | 14 | 29-30 | Transport equipment |
| 19 | 15 | 31-33 | Other manufacturing; repair and installation of machinery and equipment |
| 20 | 16 | D | Electricity, gas, steam and air conditioning supply |
| 21 | 17 | E | Water supply; sewerage; waste management and remediation activities |
| 22 | 18 | F | Construction |
| 23 | Agg | G | WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES |
| 24 | 19 | 45 | Wholesale and retail trade and repair of motor vehicles and motorcycles |
| 25 | 20 | 46 | Wholesale trade, except of motor vehicles and motorcycles |
| 26 | 21 | 47 | Retail trade, except of motor vehicles and motorcycles |
| 27 | Agg | H | TRANSPORTATION AND STORAGE |
| 28 | 22 | 49 | Land transport and transport via pipelines |
| 29 | 23 | 50 | Water transport |
| 30 | 24 | 51 | Air transport |
| 31 | 25 | 52 | Warehousing and support activities for transportation |
| 32 | 26 | 53 | Postal and courier activities |
| 33 | 27 | I | Accomodation and food service activities |
| 34 | Agg | J | INFORMATION AND COMMUNICATION |
| 35 | 28 | 58-60 | Publishing, audio-visual and broadcasting activities |
| 36 | 29 | 61 | Telecommunications |
| 37 | 30 | 62-63 | IT and other information activities |
| 38 | 31 | K | Financial and insurance activities |
| 39 | 32 | L | Real estate activities |
| 40 | 33 | M-N | Professional, scientific, technical, administrative and support service activities |
| 41 | Agg | O-Q | PUBLIC ADMINISTRATION, DEFENCE, EDUCATION, HUMAN HEALTH AND SOCIAL WORK ACTIVITIES |
| 42 | 34 | O | Public administration and defence, compulsory social security |
| 43 | 35 | P | Education |
| 44 | 36 | Q | Health and social work |
| 45 | *Agg | R-S | ARTS, ENTERTAINMENT, RECREATION; OTHER SERVICES AND SERVICE ACTIVITIES, etc |
| 46 | 37 | R | Arts, entertainment and recreation |
| 47 | 38 | S | Other service activities |
| 48 | 39 | T | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use |
| 49 | 40 | U | Activities of extraterritorial organizations and bodies |

| | | | |
|---|---|---|---|
| 991 | *Agg | C20_C21 | Chemicals; basic pharmaceutical products |
| 992 | *Agg | C26_C27 | Computer, electronic, optical products; electrical equipment |
| 993 | *Agg | D_E | Electricity, gas, steam; water supply, sewerage, waste management |

*Notes*: Source: Methodology EU Klems Report, 2019

## 11.5. Transformation of NACE revision 2 to NACE revision 1.

**Table 14. Transformation NACE Revision**

| Sort_ID | Nace Revision 2 | Nace Revision 1.1. Code: |
|---|---|---|
| 4 | A | 1 & AtB & A & B |
| 5 | B | C & 10t12 & 13t14 |
| 6 | C | D |
| 7 | 10-12 | 15t16 |
| 8 | 13-15 | 17t19 |
| 9 | 16-18 | 20 & 21t22 |
| 10 | 19 | 23t25 |
| 11 | 20 | 23t25 |
| 12 | 21 | 23t25 |
| 13 | 22-23 | 25 & 26 & 36 |
| 14 | 24-25 | 27t28 |
| 15 | 26 | 30t33 |
| 16 | 27 | 30t33 & 29 |
| 17 | 28 | 29 & 32 & 34t35 |
| 18 | 29-30 | 34t35 |
| 19 | 31-33 | 36t37 & 29 |
| 20 | D | 40 & E & 40x & 402 |
| 21 | E | 41& 90 |
| 22 | F | 70 & 45 & F |
| 23 | G | 50 & 51 & G |
| 24 | 45 | 50 |
| 25 | 46 | 51 |
| 26 | 47 | 52 |
| 27 | H | 60t63 & I |
| 28 | 49 | 60 |
| 29 | 50 | 61 |
| 30 | 51 | 62 |
| 31 | 52 | 63 |
| 32 | 53 | 64 |
| 33 | I | H |
| 34 | J | 22 & 72 |
| 35 | 58-60 | 92 & 74 & 64 |
| 36 | 61 | 64 |
| 37 | 62-63 | 72 & 92 & 74 |
| 38 | K | 65 & 66 & 67 & J |
| 39 | L | 70 & K |
| 40 | M-N | 71 & 73 & 74 & 90 |
| 41 | O-Q | |
| 42 | O | 75 & L |
| 43 | P | M |
| 44 | Q | N |
| 45 | R-S | |
| 46 | R | 92 & 52 |
| 47 | S | 93 & O |
| 48 | T | P |
| 49 | U | Q |

*Notes*: Source: Methodology EU Klems Report, 2019 & NACE revision 1.1

## 11.6. Unweighted cross-country variation

Unweighted Cross-Country Variation of Annualized High, Medium and Low Skilled Wage Bill Share Change and TFP growth, 1995-2017.

**Figure 5. High-skilled Wage Bill Share**

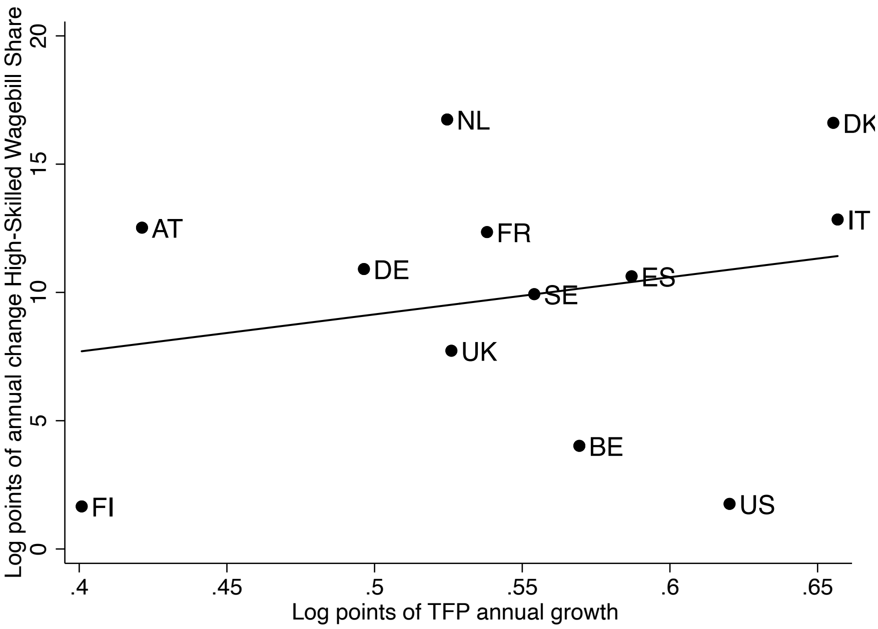



**Figure 6. Medium-skilled Wage Bill Share**

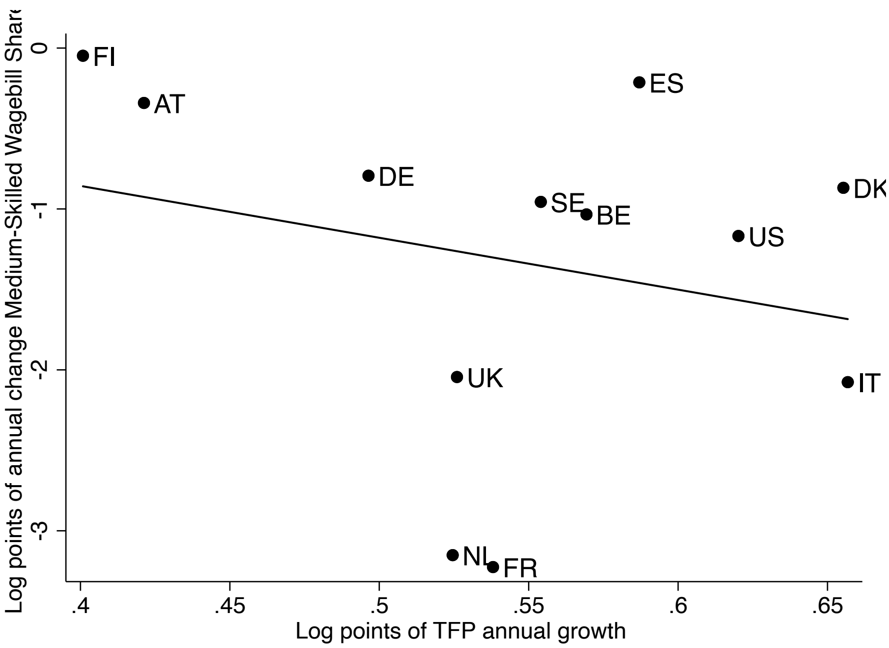
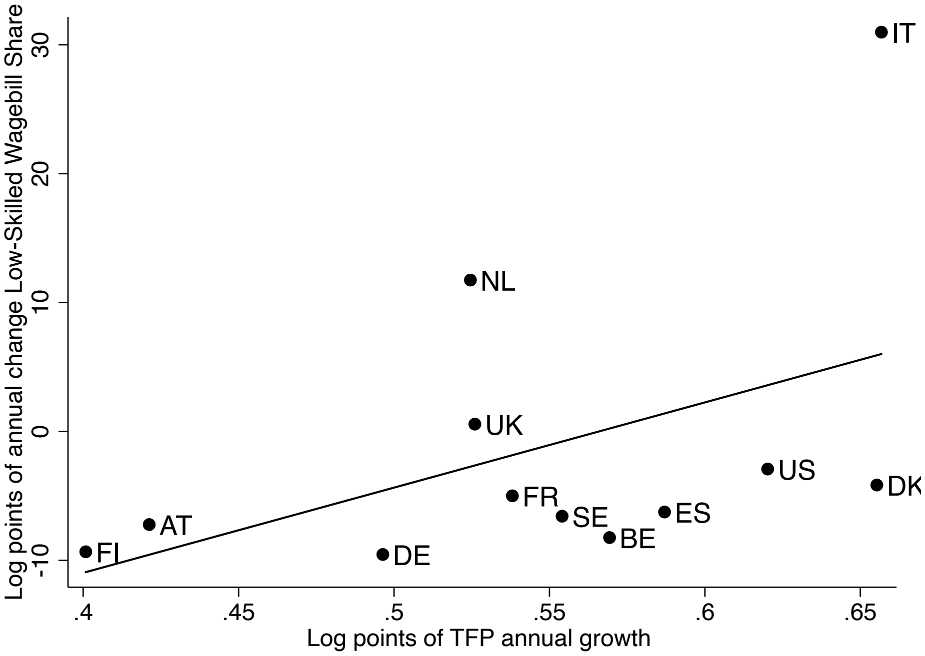


**Figure 7. Low-skilled Wage Bill Share**




*Notes*: source EU Klems 2019

## 11.7. Shift-share analysis of high, medium and low-skilled share

Specifications different skills levels:

$$\Delta \bar{L}^{H}_{c,\tau} = \sum_{i} \bar{\omega}_{i,c,\tau} \Delta l^{H}_{i,c,\tau} + \sum_{i} \bar{l}^{H}_{i,c,\tau} \Delta \omega_{i,c,\tau}$$

$$\Delta \bar{L}^{M}_{c,\tau} = \sum_{i} \bar{\omega}_{i,c,\tau} \Delta l^{M}_{i,c,\tau} + \sum_{i} \bar{l}^{M}_{i,c,\tau} \Delta \omega_{i,c,\tau}$$

$$\Delta \bar{L}^{L}_{c,\tau} = \sum_{i} \bar{\omega}_{i,c,\tau} \Delta l^{L}_{i,c,\tau} + \sum_{i} \bar{l}^{L}_{i,c,\tau} \Delta \omega_{i,c,\tau}$$

**Table 15. Shift-Share Analysis between and within industry.**

| | *High Skilled Labor Share* | | | *Medium Skilled Labor Share* | | | *Low Skilled Labor Share* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Year* | *Total* | *Between* | *Within* | *Total* | *Between* | *Within* | *Total* | *Between* | *Within* |
| 1995-2000 | 0,260 | -0,11 | 0,34 | 0,09 | -0,12 | 0,19 | -0,09 | -0,10 | -0,01 |
| | | (-0,40) | (1,32) | | (-1,4) | (2,21) | | (1,14) | (0,07) |
| 2000-2005 | -0,189 | -0,08 | 0,34 | -0,39 | -0,10 | 0,21 | -0,41 | -0,09 | 0,08 |
| | | (0,42) | (-1,81) | | (0,26) | (-0,53) | | (0,25) | (-0,20) |
| 2005-2010 | 2,24 | -0,06 | 0,64 | 1,48 | -0,07 | -0,11 | 1,81 | -0,07 | 0,36 |
| | | (-0,02) | (0,28) | | (-0,05) | (-0,07) | | (-0,04) | (0,20) |
| 2010-2015 | 0,37 | -0,04 | 0,33 | 0,32 | 0,03 | 0,28 | 0,10 | 0,03 | -0,07 |
| | | (0,11) | (0,86) | | (-0,10) | (0,89) | | (0,30) | (0,69) |

*Notes:* Values are annualized log changes *100 of every five years. Labor shares are weighted by averaged country weights of value added.

## 11.8. Robustness check sub-samples industries

In order to analyze whether certain sub-samples experience a larger effect of TFP on wage bill shares two subsamples were analyzed representing two large industries. Manufacturing representing 14,5% of the total economy was expected to experience large effects in support of the hypotheses. On the other hand, professional, scientific, technical, administrative and support service activities (12,6%) were not expected to experience a decrease in middle-skilled workers due to new technologies necessarily. Although, logically, little variables remain, one is able to observe the trends in the following table.

**Table 16. Robustness Check Sub-samples Industries**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | Weighted by time-averaged employment share by country | | |
| *Robustness checks* | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share |
| *Subsample manufacturing Industry* | | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 125,47** | -30,74*** | 141,86 | 128,88** | -38,439*** | 393,263* |
| | (50,105) | (9,189) | (119,39) | (58,244) | (8,641) | (208,774) |
| $R^2$ | 0,575 | 0,495 | 0,244 | 0,599 | 0,512 | 0,243 |
| Observations | 179 | 179 | 179 | 179 | 179 | 179 |
| *Subsample professional, scientific, technical, administrative and support service activities* | | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | 7,721 | 10,329 | -33,986 | -9,683 | 24,832 | -50,207 |
| | (22,521) | (15,599) | (27,951) | (7,698) | (14,750) | (39,567) |
| $R^2$ | 0,322 | 0,329 | 0,338 | 0,413 | 0,378 | 0,419 |
| Observations | 119 | 119 | 119 | 119 | 119 | 119 |

*Notes*: TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).
b. Standard clustered errors by country-industry pairs in parentheses.
c. Coefficients are the sum of contemporaneous and five annually distributed lags
d. Statistical significance at a p-value of *10% **5% and ***1%
e. original regression analysis including fixed effects country, year and business cycle indicators.

## 11.9. Robustness check own country own industry TFP rather than other country own industry TFP

Furthermore, a robustness check was executed while replacing other country, own industry TFP by own country, own industry TFP to ensure the use of this independent variable. Results change considerably. An explanation is potentially provided by reviewing the motivation why this paper makes use of other country, own industry TFP, which is the fact that labor composition enters the right-hand side of the equation while calculating the TFP. TFP other country, own industry is highly predictive of TFP own country and industry but avoids the problem of the simultaneity issue. These results therefore support the use of TFP other country, own industry indicator.

**Table 17. Robustness Check Own Country Own industry TFP**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Unweighted | | | Weighted by averaged employment share by country and industry | | |
| *Robustness checks* | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share | Δ Log High Skilled Wage Bill Share | Δ Log Medium Skilled Wage Bill Share | Δ Log Low Skilled Wage Bill Share |
| *Replace TFP by own industry & country TFP* | | | | | | |
| $\Sigma\Delta\log\ TFP_{i,c,t-k}$ | -0,218 | -0,106 | -1,527** | 1,276 | -0,069 | -3,489 |
| | (0,399 | (0,185) | (0,590) | (1,021) | (0,378) | (1,705) |
| $R^2$ | 0,395 | 0,232 | 0,181 | 0,306 | (0,191) | 0,149 |
| Observations | 5,969 | 5,969 | 5,969 | 5,969 | 5,969 | 5,969 |

*Notes*: TFP is the value of other-country, same industry TFP, standardized to have a standard deviation of 1 (rather than the previous 1.038 standard deviation).
b. Standard clustered errors by country-industry pairs in parentheses.
c. Coefficients are the sum of contemporaneous and five annually distributed lags
d. Statistical significance at a p-value of *10% **5% and ***1%
e. original regression analysis including fixed effects country, year and business cycle indicators.