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Working Paper

Labour Markets, Trade and Technological Progress: A Meta-Study

CESifo Working Paper, No. 7719

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Terzidis, Nikos; Brakman, Steven; Ortega-Argiles, Raquel (2019) : Labour Markets, Trade and Technological Progress: A Meta-Study, CESifo Working Paper, No. 7719, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:

<https://hdl.handle.net/10419/201945>

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Impressum:

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

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Editor: Clemens Fuest

www.cesifo-group.org/wp

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Abstract

Technological progress and trade potentially affect wages and employment. Technological progress can make jobs obsolete and trade can increase unemployment in import competing sectors. Empirical evidence suggests that both causes are important to explain recent labour market developments in many OECD countries. Both causes are often mentioned in tandem, but the relative contribution of each cause is less clear. This study presents a meta-analysis to shed light on the relative contribution of technological progress and trade in recent labour market developments and allows us to identify the winners and losers of automation and globalization. Using a sample of 77 studies and 1158 estimates, we find that both effects are important. Automation is beneficial at the firm level, and is more likely to displace low-skilled employment. Trade is more likely to benefit high-skilled employment and affects industry negatively. Somewhat surprisingly, given the consensus in the literature, automation has a positive effect for estimates considering the period before 1995, and trade a negative effect. We also find some evidence of publication biases.

JEL-Codes: F230, J310, J630, O110.

Keywords: labour markets, technological progress, trade, meta-study.

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This version: June 2019

We like to thank Harry Garretsen, Gerdien Meijerink, seminar participants at the 58th ERSA congress and SOM Conference for useful comments on an earlier draft of this paper.

Introduction

Since the 1980s, it became evident that in industrialized countries employment of low-skilled workers relative to high-skilled workers declined. In addition, the wage of unskilled workers compared to high-skilled labour fell. These stylized facts stimulated a debate on the cause of these developments. Two possible explanations were brought forward in the discussion: international trade and domestic technological progress.²

Trade related explanations stressed the growth of import competition from low-wage economies to OECD countries, increasing unemployment in import competing sectors and further wage inequality. Domestic technological growth can have similar effects if *automation* replaces workers. If automation substitutes especially low-skilled workers, the consequences are similar to trade effects and empirically look the same. This raises the question what factor is the most important. Close inspection of the data showed that during the 1980s and early 1990s, demand for skilled workers increased, especially in the US and EU countries. This increase in demand could be explained by the growth of more skill-intensive occupations. The introduction of the computer and high-tech equipment in general has increased demand for high-skilled workers. Furthermore, exports from low-wage countries were too small relative to GDP to explain labour market developments (Krugman, 1995). The consensus – with qualifications – was that although trade was growing, automation was the main cause for the changes on the labour markets in the 1980s and 90s.³

In the early 2000s, stimulated by the Chinese membership of the WTO in 2001 and subsequent steep increase in imports from China, the discussion revisited the role of trade on labour market developments. Import competition was becoming more important as an explanation for labour market developments. In a seminal paper, Autor et al. (2013) take a closer look at the 1990-2007 period. They note that, especially after 2001, imports from China to the US but also other industrialized countries increased enormously. Acemoglu et al., (2016) also conclude that import competition was a major source, compared to technological progress, behind reductions in US manufacturing employment. Gordon (2016) extensively documents for the US that technological progress has substantially slowed down

² There are many surveys of the discussion that took place during the 1990s on the effects of globalization and technological change on labour markets; see for instance Lawrence and Slaughter (1993), Wood (1995), Krugman (1995), Lawrence (1996), Sachs and Shatz (1996), Bernard and Jensen (1997), Borjas et al. (1997). This discussion is summarized in Helpman, (2018).

³ Although there was some consensus on the most important cause of the changes on labour markets, there was discussion what model is best suited to analyse the developments, see for instance the discussion between Krugman (2000) and Leamer (2000). This discussion is evaluated in Feenstra (2016).

from a peak in the 1950s to 2014. This slowdown in productivity growth has also been documented for other industrialized countries (see e.g., Cetto, 2016). Based on studies like these, it seemed that the consensus on the causes of reductions in employment was shifting; trade as a cause of (negative) labour market developments was seen as an important explanation.

To date, many studies exist that estimate the impact of trade and technological progress on labour markets in various countries. Which factor is the most important is not always clear from the available evidence. In this paper, we synthesize this literature and analyze a sample of 1158 estimates from 77 studies. Some of the studies estimate the effects of trade, others of technological progress and some both. The dependent variables in the various estimates are not always the same; some studies focus on wages, others on employment, which can be seen as two sides of the same coin. Sometimes specific skill groups of the labour market were analyzed, but definitions, although often similar, were not identical. A solution to deal with different definitions of the dependent variables found in the literature is to classify estimates in groups: estimates that find a significant negative effect on the labour market (reduction in employment or wages), insignificant effects, and significant positive effects. Therefore, the main analysis concerns an investigation of sign and significance of trade and technological progress on labour markets. The advantage of a meta-study is that we collect estimates that are spread across many studies. This enables us – by adding controls – to provide quantitative information on which factors explain differences in outcomes across estimates. These controls identify, for example, country coverage, time-period of the analysis, the type of trade exposure, the type of sector, etc. A study like this can also shed light on possible publication biases. In general, we find that both effects are important. Automation is beneficial at the firm level, and is more likely to displace low-skilled employment. Trade is more likely to benefit high-skilled employment and affects industry negatively. Somewhat surprisingly, given the consensus in the literature, automation has a positive effect for estimates considering the period before 1995, and trade a negative effect. Furthermore, the impact of technology dampens after 1995, while the impact of trade is more likely to be positive and significant after 1995. With respect to the impact from trade, our analysis shows that the current wave of trade in services is more likely to benefit workers in the domestic, high-income economies. Finally, results need to be qualified with respect to data aggregation (industry-, firm- or worker-level), while we also find some evidence of publication biases.

The remainder of this paper is organized as follows. In section 2, we briefly indicate the theoretical background of the various channels of trade and technological progress on labour markets. This discussion motivates the empirical specification for the meta-analysis. Section 3 explains how papers are selected and provides descriptive statistics. In section 4, we discuss the various aspects of heterogeneity in the sample. Section 5 presents the results. Finally, section 6 concludes.

2. Labour markets, Trade and Technological progress

When it comes to explain relative factor price changes, trade theory relies traditionally on the Stolper-Samuelson (S-S) theorem that follows from the Heckscher-Ohlin (H-O) theory. Countries that have a comparative advantage in some commodity in autarky experience excess demand for that commodity, and thus a relative price increase, when trade is allowed. The theorem states that the relative price increase benefits the reward of the production factor that is intensely used in the production of that commodity. If this production factor is high-skilled labour then a price increase in high-skilled intensive products raises the real wage of high-skilled workers, and reduces the real wage of low-skilled workers; wage changes are larger than price changes, which is a so-called *magnification effect* (see Jones, 1965). In principle, this theorem can explain the change in the skilled workers real wage premium in industrialized countries. The flip side of this reasoning is that in low-skilled worker abundant countries a wage premium for low-skilled workers develops.

According to the H-O model, these price changes also have consequences for the relative factor use in the model; sectors economize on the production factors that have become more expensive. In the industrialized countries, the share of high skilled relative to low-skilled workers should decline, and the opposite should happen in low-skilled abundant countries. The reverse happened; the employment of high-skilled workers relative to low-skilled workers increases in the 1980s, despite higher relative wages. Feenstra (2016, p.99), however, forcefully points out that in the late 1990s developments of relative employment of high versus low-skilled workers is consistent with what one would expect from trade theory; a relative decline of high-skilled employment. The evidence in the 1980s and 1990s with respect to relative employment developments initially does not unambiguously point in the

direction of trade as being the main influence on the labour market developments, but later developments are more consistent with standard trade theory.⁴

In order for the H-O model to work, however, the embodied factor supplies in trade flows should be substantial enough to have economy-wide effects. For the industrialized countries, this implies that the low-skilled labour embodied in imports should be large. Borjas et al. (1997) and Krugman (1995) find that in the 1980s and 1990s the import flows are too small to explain developments on the US labour market. Berman et al. (1998) refer to findings like these and point to the importance of technological developments as an alternative explanation for the labour market developments. Together the evidence does not point to trade as a main explanation. In the period before 2000, the 1980s and early 1990s, the consensus developed that technological change was a main driver to explain relative changes in the position of high-skill workers versus low-skill workers on labour markets.

The reasoning behind technological change and developments on labour markets is straightforward. A typical effect of technological change in most high-income countries is the increased demand for higher skilled workers as more and more occupations become more skill-intensive. If demand increases more rapidly than the supply of high-skilled workers (due to for instance better education), relative wages of high-skilled workers increase. Furthermore, technological progress might make some low-skilled jobs obsolete. Together it explains why high-skilled workers experienced a relative wage increase and increased their share in total employment. This reasoning depends on the type of technological progress (see Helpman 2004 for a survey).⁵ The discussion between Krugman, (2000) and Leamer (2000) on the different consequences of factor related technological progress versus sector biased technological progress is a case in point. Leamer (2000) assumes the small country case where prices are fixed and the *sector* bias of technological progress determines relative wages, whereas Krugman (2000) discusses the large country case, where prices change, and

⁴ Helpman (2018) evaluates how modern developments in trade theory can explain increasing income inequality. These models are based on the concepts of assignment and matching between firms and workers (see Costinot and Vogel, 2010). Trade can re-shuffle workers such that a better matching is possible. In skill-abundant countries this benefits skilled workers.

⁵ Technological progress is said to be high-skill augmenting if it makes high-skilled workers more productive. This is comparable to an increase of high-skill workers at the old level of technology. Similarly, for low-skill augmenting technological progress. If technological progress augments both factors equally, it is neutral technological progress. Depending which type is stronger it can change relative factor rewards. Technological progress can also replace production factors. For example, a reorganization of the production process can economize on low-skilled workers while keeping output constant. Technological progress can also have a sector dimension; benefitting one sector (including all factors of production) more than other sectors. The consequences for each type of production factor thus depends on the type of technological progress.

only the *factor* bias of technological change matters. To add to the estimation problems offshoring can also have effects on labor markets that are difficult to disentangle from technological progress. The theoretical model of Grossman and Rossi-Hansberg (2008) illustrates this. In this model, offshoring of low-skilled activities has three effects: offshoring results in a decline of production costs and lowers prices, as it is low-skilled worker saving and more low-skilled workers become available on the labor market and a productivity enhancing effect because overall the remaining tasks are higher skill intense. The first two effects are similar to the effects discussed above with respect to trade and technological progress. The latter effect is a new element in their model. In the model, offshoring acts like a low-skilled biased technical change and makes these workers more productive, potentially increasing wages, but the excess supply of workers acts in the opposite direction. The product price reduction increases the demand for products as well as the demand for workers. Wright (2014) finds a small net reduction in employment as a result of offshoring (see also Hummels et al., 2018).

From Jones (1965) it is well known how technological progress can add, reverse, or substitute for the effects of trade on factor markets, which explains to some extent the conflicting evidence on the relative importance of trade versus technological progress. The conclusion of Feenstra (2016, p.90) is therefore something to be expected. After reviewing the evidence for the 1980s and 1990s, he concludes that estimates are ‘*quite sensitive to the data used and the specification of the regression.*’

On balance, the literature favours technology above trade as the main driver of negative labour market developments in the 1980s and early 1990s.

This consensus was put to the test when the first empirical evidence became available on the impact of China joining the WTO in 2001. In a seminal article Autor et al. (2013) analyse the consequences of the China shock on the US labor market. They calculate that an increase in import exposure of \$1000 per worker over a decade reduces manufacturing employment (working population) by 0.596 percentage points. Between 1990 and 2000 the import penetration changed by \$1140 per worker and between 2000 and 2007 by \$1839 per worker. In the first period, manufacturing employment fell by 0.68 percentage points and in the second period by 1.1 percentage points. Acemoglu et al. (2016), using a different methodology find that between 1999 and 2011 job losses in the US amounted to 2.4 million. They find that had import penetration from China not grown after 1999 the number of

manufacturing jobs would have been 560.000 larger (p.144). Dauth et al. (2014) find similar but smaller effects for Germany. As the review of Hummels et al. (2018) stresses, the effects are not always easy to disentangle from technology effects similar to that of offshoring.

Overall, the evidence is mixed. This is why a meta-study might be useful. Various effects on the labour market have been documented and systematically looking at a representative sample of available evidence could be worthwhile to find out what the relative contribution of the effects are and whether the relative importance changed over time.

Investigating the employment impact from technology and/or international trade involves the estimation of either a wage equation (1) or a labour demand equation (2).

$$(1) \ln Wage_{ikjt} = a_0 + a_1 Tech_{jkt} + a_2 Trade_{jkt} + X'_{ijt}\beta + \gamma_i + \varphi_k + \delta_j + \lambda_t + \varepsilon_{ikjt}$$

$$(2) \ln Empl_{ikjt} = a_0 + a_1 Tech_{jkt} + a_2 Trade_{jkt} + X'_{ijt}\beta + \gamma_i + \varphi_k + \delta_j + \lambda_t + \varepsilon_{ikjt}$$

Where the dependent variable is either *wages (or wage shares)*, Eq. (1) or *employment*, Eq. (2) per individual (i), firm (k), industry (j) and year (t), $Tech_{jkt}$ is the factor-biased technical change variable and $Trade_{jkt}$ is the measure of international trade activity. In the above equations, factor-biased technical change and international economic activity are the most common terms used to designate the automation practices and forms of international trade investigated in the selected literature. The set of control variables (X_{ijt}) are usually very similar to ones included in Mincerian equations (Mincer, 1974). In their most comprehensive forms the estimated equations typically include worker γ_i , firm φ_k , industry δ_j and time λ_t fixed effects, while ε_{ikjt} is the error term. The dependent variables, *wages*, and *employment* can refer to different groups, skill levels, sectors and industries, or spatial units. As explained in Feenstra (2016) equations as (1) and (2) can be given a micro-economic foundation.⁶

Variants of both equations are present in the literature. Following Card, Kluve and Weber (2010) we test for *sign* and *significance*. This approach allows us to compare evidence across available studies that have a different dependent variable, but describe the same phenomenon.

More specifically, we have:

$$(3) \quad y_i = x'_i\beta + \varepsilon_i$$

⁶ For example, Feenstra and Hanson (1999) apply a two-step estimation process where they first estimate the impact from technology and trade (structural variables) on prices and productivity. Secondly, they use the first stage estimated coefficients to decompose the change in factor prices that can be explained by technology or trade.

$$\text{where } y_i = \begin{cases} 1 & \text{for significantly negative estimates } (t \geq 1.28) \\ 0 & \text{for insignificant estimates } (-1.28 \leq t \leq 1.28) \\ -1 & \text{for significantly positive estimates } (t \leq -1.28) \end{cases}$$

The central idea is that the unobserved dependent variable falls into three categories based on the associated t-value of the respective coefficient. Furthermore, we assume that the latent variable is a linear combination of our set of predictors (x_i) and the error term ε_i is normally distributed.

A significant negative result reflects either a reduction in employment or wages. Given the three options with respect to the dependent variable, an ordered probit estimate technique is applicable. Table 1 gives the frequencies for Factor-biased Technological Change (Columns 1-3) and International Economic Activity (Columns 4-6). All categories present in the samples.

Table 1. Frequencies of estimates

	Factor-biased technical change			International economic activity		
Dependent Variable (y_i)	Frequency	Percent	Cumulative Percent	Frequency	Percent	Cumulative Percent
	(1)	(2)	(3)	(4)	(5)	(6)
+1	119	46.67%	47.04%	297	32.89%	32.89%
0	86	33.73%	70.24%	300	33.22%	67.11%
-1	50	19.61%	100.00%	306	33.89%	100.00%
Total	255	100.00%		903	100.00%	

Source: own calculations

3. Data Collection

To select a representative and comprehensive database on labour market estimates we proceeded as follows. The primary search engine was *Google Scholar* as it allows for a full-text search and has several additional advantages such as the accommodation of multiple search queries. The search strategy is as follows. First, we developed an appropriate list of relevant terms (Table A1 – Appendix A). These terms were applied both individually and combined with Boolean operators (AND, OR, NOT) and wild card symbols (*) to approximate alternative word endings. In addition, our search was extended over several

additional databases (*EconStor*, *Microsoft Academic Search* and *IDEAS/RePEc*) and key working paper series (*NBER*, *CEPR*, *CESifo*, *IZA* etc.). A detailed list of the search queries and the outcomes per research engine is provided in the online appendix. Finally, we identified a number of relevant papers by reviewing the references of literature surveys (Ramaswami, 2018; Klein, Schuh and Triest, 2002; Gilles and Williams, 2000) and applied ‘snowballing’ literature search techniques by studying reference lists in the studies that we identified.

The search process resulted in around 3500 studies. Upon closer examination, we excluded studies failing to satisfy the following selection criteria (see Table 2). First, we selected empirical studies on *employment* or *wage effects* (level or change) from *technology* or *trade* (investigated individually or at the same empirical model) based on various data aggregations (industry-, firm-, worker-level data). Second, we selected studies with robust econometric techniques (regression analysis) that establish causal relationships and are subject to a referee system (we dropped book chapters).

Table 2. Selection Criteria

INCLUDED	NOT INCLUDED
<ul style="list-style-type: none"> • Studies on equilibrium employment or wage effects (level or change) • Studies using robust econometric techniques (regression analysis establishing causation not mere correlation) • Labour market effects in high income countries • Publications in academic journals, discussion paper series, conference papers 	<ul style="list-style-type: none"> • Studies on productivity, employment security (probability of becoming jobless) etc. • Studies based on non-parametric / descriptive / match sampling etc. techniques • Effects on low-income countries • Book chapters

We excluded studies presenting non-parametric evidence or empirical comparisons between exporters and non-exporters based on the construction of counterfactuals. Third, to accommodate the main discussion in the literature, which focuses on high-income economies, using the *Country and Lending Groups*⁷ classification by the World Bank. Finally, see

⁷ The *Country and Lending Groups* taxonomy (the World Bank), categorises countries based on their Gross National Income. In our sample we include estimates for *High-Income countries*, defined as those with per capita GNI exceeding \$12,056.

equation (3), we need information on the precision of the estimates (standard errors and number of observations). Appendix B lists the studies included in this paper.

This resulted in 77 studies and 1158 estimates in total. A detailed distribution of the selected estimates per category and empirical paper is available upon request, together with a list of excluded papers (with the main reason for exclusion).

The estimates reflect considerable heterogeneity in the ways different countries, industries or firms operationalize factor-biased technical change and international economic activity, resulting in substantial variation in the labour market outcomes. Since it is not possible to homogenize different technology or trade practices, we adopt a two-step typology to classify the estimated effects (Table 3). In the first step, we differentiate between the *technology* and *trade* effects (broad categories). However, these umbrella terms incorporate more disaggregated categories, with potentially differentiated labour market outcomes. Therefore, in our second step we use this sub-division of categories. Specifically, we divide technology estimates between R&D investment and the acquisition of *high tech capital*. Similarly, trade estimates are divided between those referring to trade in intermediate (*international outsourcing* and *in-house offshoring*) and final products (*import competition*). International outsourcing includes trade that is being sourced to an independent supplier as opposed to in-house offshoring where the domestic company owns (a share) of the foreign supplier (multinational enterprises).

Table 3. Overview of estimated effects

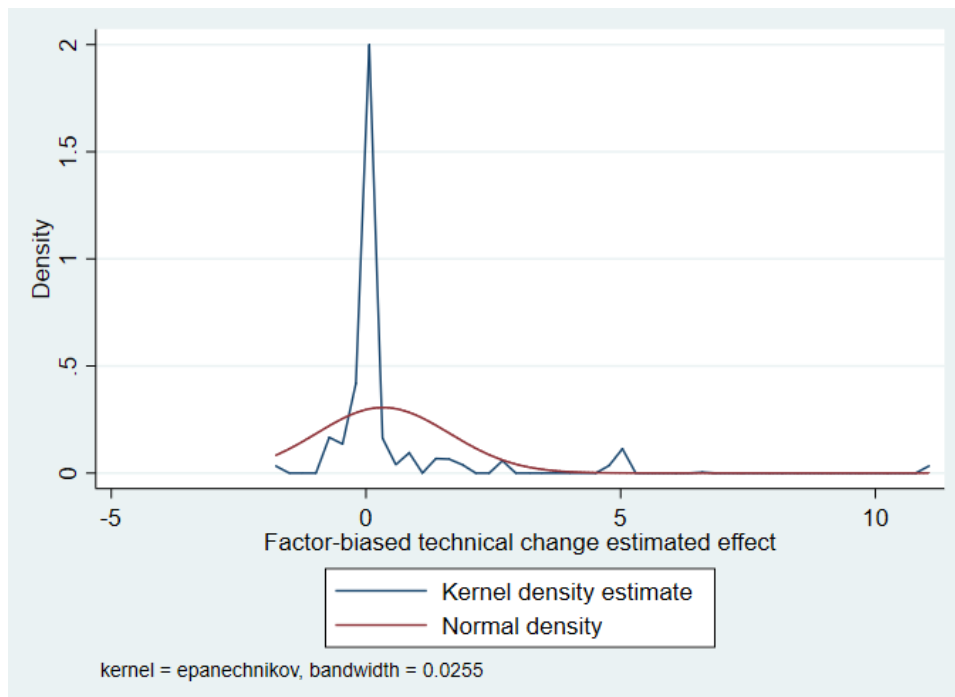
Category	Observations
<i>Panel A – Factor – biased technical change</i>	255
• R&D Investment	142
• High tech capital	88
<i>Panel B – International economic activity</i>	903
• International outsourcing	396
• In-house offshoring	88
• Import competition	343

Note: Numbers refer to the observations after removing the outliers by means of *Grubbs test* and do not completely add-up due to the inclusion of additional individual categories within the broader ones.

Simple non-parametric analysis of the collected samples reveals overall trends of our estimated effects. The 255 factor-biased technical change estimates range from -1.742 to 1.881 with a mean of 0.068 and a median of 0.013. Figure 1 illustrates the kernel density estimates for the factor-biased technical change sample and clearly shows an over-representation of estimated effects around value zero, while both the mean and the median are included within the mode of the distribution⁸.

Figure 2 reveals a similar pattern for the distribution of the 903 international economic activity estimates, which vary from -2.43 to 2.25 with a mean of -0.060 and a median of -0.0025. Once again, we document a relatively high sharpness of the central peak compared to the normal distribution also indicated by the kurtosis value (6.98). Our international economic activity estimates however are relatively symmetrically distributed around the sample mean (Skewness = -0.31) while both the mean and the median are included in the mode of the distribution.

Figure 1. Estimated density of the factor-biased technical change estimates



⁸ Preliminary evidence (detailed summary statistics in the online appendix) shows that the distribution of the factor-biased technical change estimates exhibits relatively higher peak (kurtosis = 6.58) and is skewed to the right (skewness = 1.17); similar analysis for the international economic activity reveals a peak in the distribution (kurtosis = 6.98) accompanied by a relatively symmetric distribution (skewness = -0.31). The above pattern of estimated effects is also accounted for in the literature of both technology and trade, dependent on the skill-level of the workforce (labor saving and labor augmenting effects).

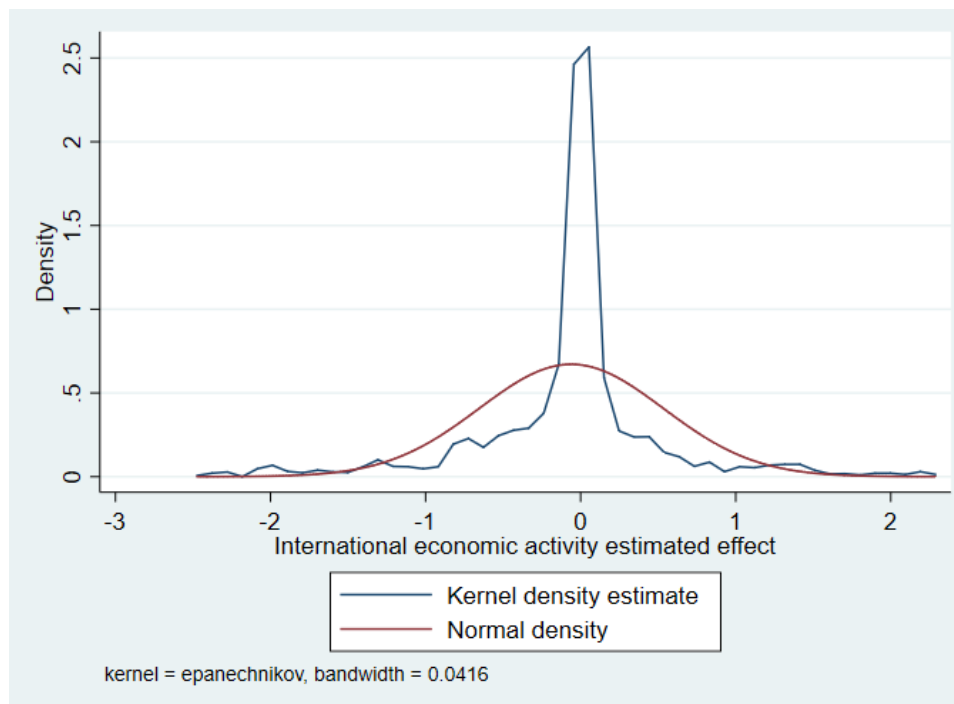
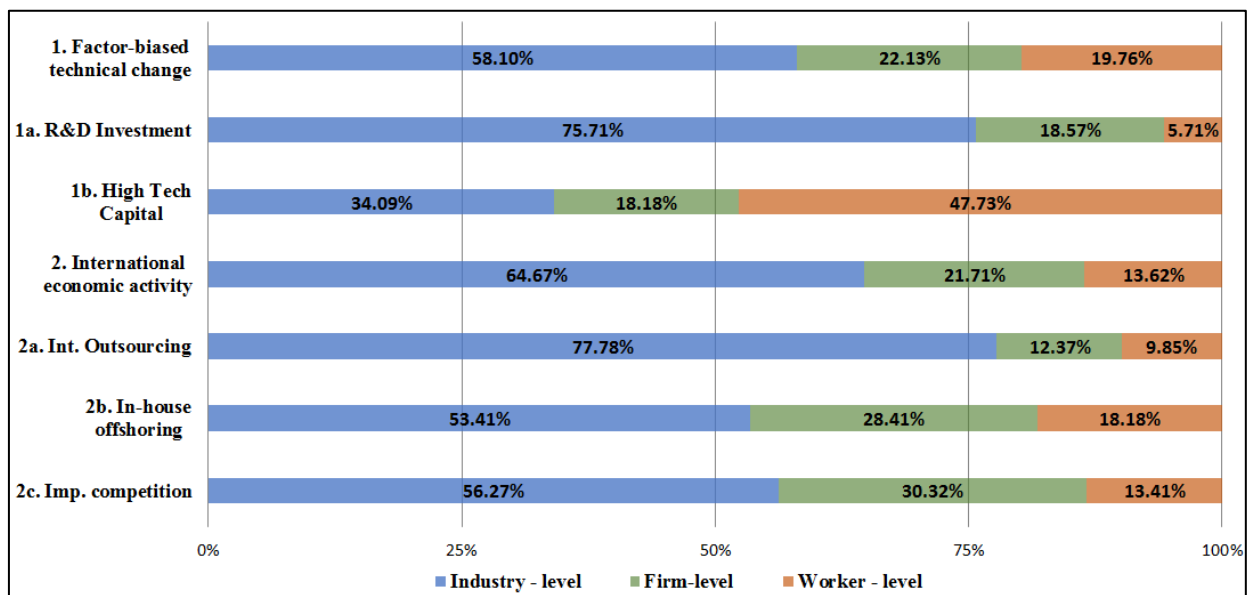
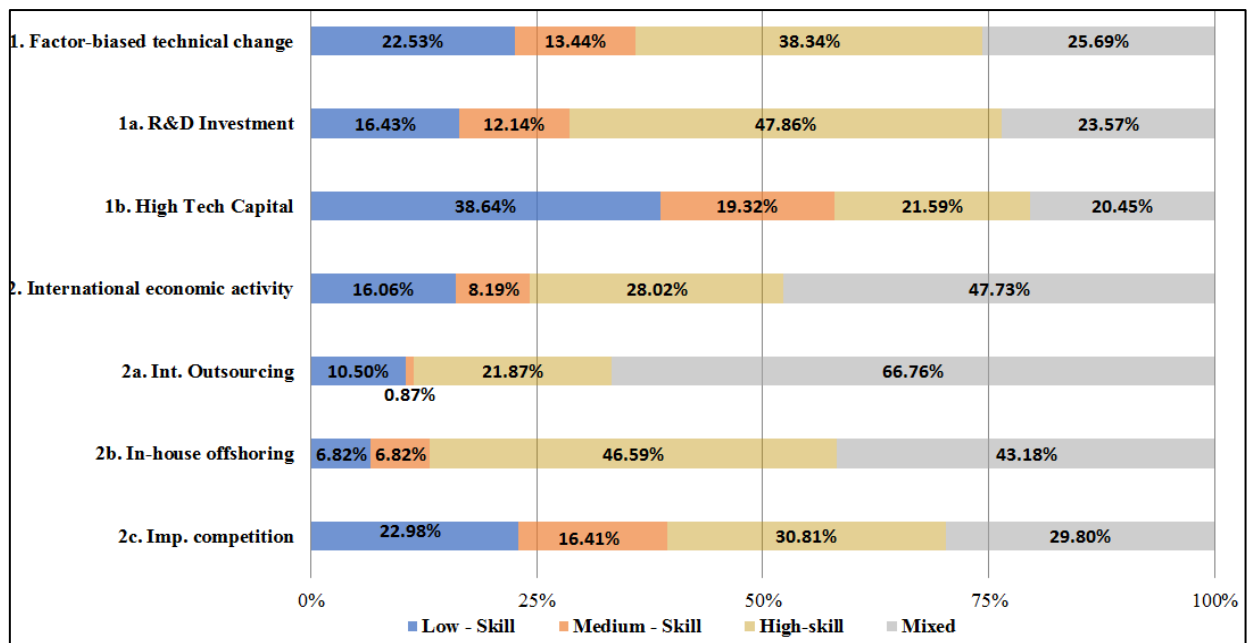
Figure 2. Estimated density of the international trade activity estimates

Figure 3 illustrates the various levels of data disaggregation used in the empirical literature and documents that the majority of the analyses on factor-biased technological change and international economic activity are based on industry-level data. A substantial number of studies apply firm-level analysis, while worker-level empirical applications are the minority. The only exception are analyses on high-tech capital, which is mostly based on worker-level data.

Distributing the empirical estimates based on the skill-level of the domestic workforce (Figure 4) indicates that the focus is often on high-skilled workers and/or low-skilled employees, rather than medium-skilled employment. Again, in the sub-sample of high-tech capital estimates, the focus is on low-skilled employment. Finally, an important part of the empirical studies does not apply any skill-based differentiation of the domestic workforce.

Figure 3. Distribution of estimates based on data aggregation**Figure 4.** Distribution of estimates based on the skill level of the workforce

A concern in meta-analyses is the possible presence of publication bias. The search selects papers that are published in refereed journals and high-quality (refereed) working paper series. These papers might be more readily accepted if they show significant and expected results. Unfavourable results or results that show the opposite effect of the main hypotheses

might be suppressed or only briefly mentioned in footnotes as ‘available upon request’ (Rosenthal, 1979). In addition, authors of small sample studies might accommodate the implicit request for significant results by engaging in specification search until they obtain large enough estimates to offset the high standard errors associated with the small variation in their sample (Havranek and Irsova, 2011; Doucouliagos and Stanley, 2009). Hence, evidence for publication bias might be the outcome of such practices, often referred to as ‘small-study effects’ (Doucouliagos and Stanley, 2013). Selectivity of empirical estimates is a longstanding threat in empirical economics (Ashenfelter and Greenstone, 2004; Card and Krueger, 1995), where a recent survey of meta-analyses (Doucouliagos and Stanley, 2013) documents extensive occurrence of publication selection.

A simple graphical indication for publication biases are funnel plots (Sutton et al., 2000). Funnel graphs are scatter diagrams of the estimated effect on the horizontal axis against some measure of precision, such as standard errors or the sample size, on the vertical axis. In the absence of publication bias, the plot should show a ‘funnel’ shape centered around the true effect. The underlying rationale is straightforward. The top part of the graph features estimates with low standard error (therefore high precision) which should reflect the true effect and therefore be concentrated around it. In contrast, less-precise estimates lie at the bottom of the graph and are expected to be more widely spread around the true effect, providing an overall ‘funnel’ shape.

Figures 5 and 6 illustrate contour-enhanced funnel plots for the main categories of the analysis (Appendix C presents our results for the more disaggregated categories). The shaded contours are plotted for the typical levels of significance ($\alpha=1\%$, 5% and 10%) and highlight the regions where estimated effects need to lie in order to achieve a certain level of significance. They provide useful insight, since absence of estimated effects in an area of non-significance (white area in the Figures) is a strong indication of publication bias (Langan et al., 2012).

In the case of factor-biased technical change, the funnel plot (Figure 5) illustrates that more precise estimates (top of the graph) are concentrated around the true effect, while estimates with larger standard errors (bottom of the graph) are relatively more dispersed. A symmetric pattern is also evident, including effects of both signs and all levels of statistical significance. Positive effects are consistent with the *labour-augmenting technological progress*, while negative ones follow from concept of *labour-displacing technological progress*. Combined

with the substantial presence of estimates in the non-significant contour, Figure 5 offers preliminary evidence that publication selection is not a concern with respect to factor-biased technical change.

Figure 5. Factor biased technical change

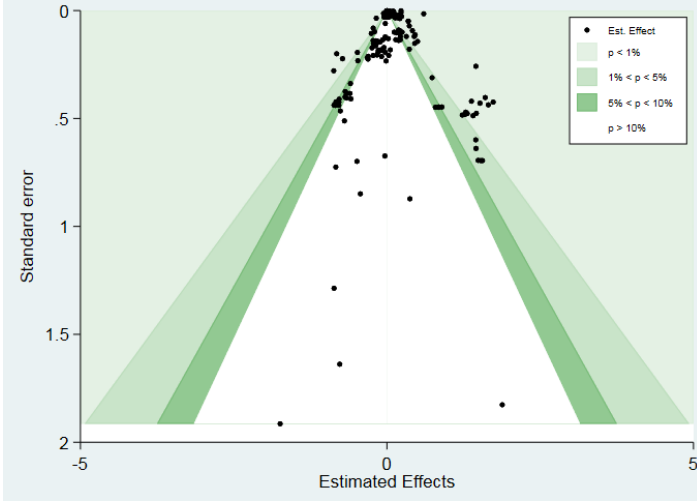
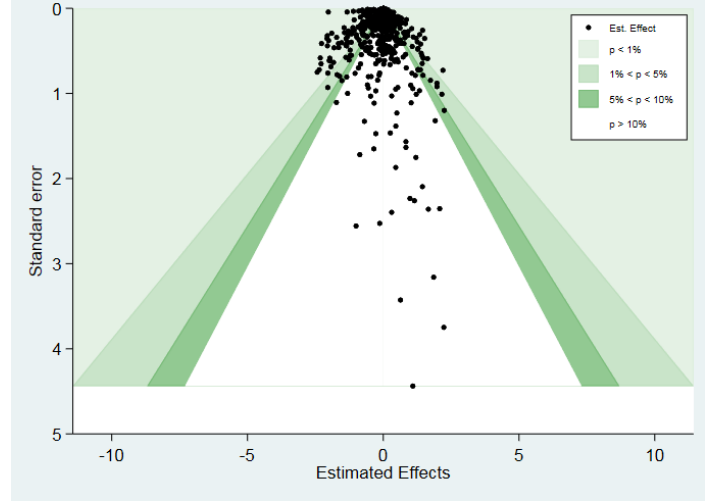


Figure 6. International economic activity



The funnel plot for international trade activity (Figure 6) reveals substantial dispersion as well. Estimates at the top of the graph are concentrated around the true effect, while less precise estimates are on both sides of the true effect. Such pattern is preliminary evidence of absence of publication bias.

Eye-balling funnel plots can be subjective and statistical tests are necessary. A test for publication selection starts with simple regressions of the estimated effects (e_i), against their corresponding standard errors ($SE(e_i)$):

$$(4) \quad e_i = e_0 + a_1 SE(e_i) + u_i$$

where e_0 is the true effect, a_1 measures the strength of the publication bias and u_i is the normally distributed error term. In the absence of publication selection, the estimates should randomly vary across the true effect. However, Eq. (4) suffers from heteroscedasticity, since the explanatory variable is a sample estimate of the standard deviation of the dependent variable. To obtain efficient estimates, we weigh Eq. (4) with the standard errors of the reported estimates as follows:

$$(5) \quad t_i = e_0 \left(\frac{1}{SE(e_i)} \right) + a_1 + \varepsilon_i$$

where the dependent variable is the t -statistic of the reported estimates. Note that in Eq. (5) compared to Eq. (4) the intercept and the slope coefficients are reversed. Egger et al. (1997)

argue that a conventional t-test of the intercept of Eq. (5) (a_1) is a test for publication bias (*funnel asymmetry test* - *FAT*). Furthermore, the absolute value of the associated estimated coefficient indicates the direction and the extent of the estimated bias. Following Doucouliagos and Stanley (2013) we have:

- i. If $|\hat{a}_1| < 1$ and significant, then selectivity bias is ‘little to modest’
- ii. If $1 < |\hat{a}_1| < 2$ and significant, then selectivity bias is ‘substantial’
- iii. If $|\hat{a}_1| > 2$ and significant, then selectivity bias is ‘severe’.

Table 4 reports the results of funnel asymmetry tests and presents estimates of a_1 , split between the entire samples of estimated effects (Column 1) and the samples of estimates published in peer reviewed journals (Column 2).⁹ For the entire sample (Column 1), the bias coefficient for the factor-biased technical change estimates is insignificant, indicating the absence of bias and confirms the visual interpretation of the corresponding funnel plot (Figure 5). The test for the international economic activity rejects the null hypothesis of non-bias, indicating evidence of publication selectivity. Nevertheless, the absolute value of the bias coefficient is less than one, which corresponds to ‘little to modest’ bias. In the sub-samples of the disaggregated categories, we have mixed evidence. The *R&D investment* sample potentially suffers from selectivity bias, while *high-tech capital* estimates show no pattern of publication bias. In the international trade sub-categories, *international* outsourcing and *import competition* reveal evidence of little and substantial bias respectively. Finally, our *in-house offshoring* sample shows no indication of selectivity.

Selectivity efforts are more prominent in peer-reviewed journals (Column 2). Considering the general categories, funnel asymmetry tests show evidence of bias in the case of factor-biased technical change estimates and a bias in the international economic activity sample. Similar conclusions are drawn when we focus on individual categories. In particular, funnel asymmetry tests for the R&D investment and high-tech capital sub-samples show evidence of little and more pronounced bias respectively. The international trade sub-categories also

⁹ Tests of funnel plot asymmetry should be treated with caution and only for a relatively large number of studies (no less than 10). However, even then their power might be quite low, since false-positive results might arise due to multiple reasons (substantial between-study heterogeneity, selection bias, language bias, true heterogeneity, data irregularities or simply by chance (Sterne and Harbord, 2004).

suffer from publication bias, which in the cases of international outsourcing and in-house offshoring is modest, while in the case of import competition is more severe.

Table 4. Egger's test of publication bias

Category of estimated effects	All Estimates (1)		Estimates in peer-reviewed journals (2)	
	Observations	Bias Coefficient	Observations	Bias Coefficient
1. Factor-biased technical change	255	-1.288 [0.978]	143	-4.592 [1.332]***
1.1 R&D investment	142	0.942 [0.314]**	85	0.836 [0.453]*
1.2 High – tech capital	88	-0.153 [0.212]	34	-1.342 [0.409]**
2. International economic activity	903	-0.725 [0.172]***	602	-1.245 [0.249]***
2.1 International outsourcing	396	-0.501 [0.192]**	281	-0.687 [0.267]**
2.2 In – house offshoring	88	0.116 [0.250]	61	0.563 [0.278]**
2.3 Import competition	343	-1.953 [0.366]***	219	-2.867 [0.542]***

Note: The reported coefficients refer to the bias estimated coefficient using the egger parameter in the test for small-study effects. St. errors reported in brackets, significance pattern: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4. Meta-Analysis

4.1 Why do estimates differ?

In this paper, we account for differences in the empirical estimates in the literature by exploring two potential sources of variation so-called *operational* and *methodological* heterogeneity. The first term refers to the various forms of factor-biased technical change and international economic activity (Table 3), while the latter reflects differences in the estimation model (2 aspects), data characteristics (6 aspects) and publication status (2 aspects). For operational heterogeneity we construct a sample for each sub-category. For most cases of methodological heterogeneity we use an appropriate dummy variable to distinguish between different categories. We complement our models with a variable for the

number of years in the dataset to control for the duration of the analysis and the 10-year recursive impact factor to account for publication quality. Detailed information on dummy variables are reported in Table D1 - Appendix D.

Most of the technology estimates are obtained from empirical models that also include a measure of international trade, while trade estimates are often obtained from models that do not include a measure of technology. The samples also differ with respect to the dependent variable; employment or wage effects (either in levels or in changes). This choice reflects to some extent differences in labor market institutions (Balsvik, Jensen and Salvanes, 2015; Hakkala and Huttunen, 2016). If binding minimum wages or similar labor market rigidities are in place, authors are more likely to analyse employment effects. Both our technology and international trade samples present similar distributions in terms of employment and wage effects.

A first issue regarding heterogeneity concerns the level of aggregation; industry-, firm- or worker-level each with different implications. For instance, Amiti and Wei (2005) argue that the employment effects of trade can only be detected at the finest sectoral level, since in more aggregate industrial classifications compensatory adjustments in labor demand might offset any impact from trade. In contrast, Mastrostefano and Pianta (2009) suggest that only broad-based, industry-level studies are able to provide a comprehensive picture of the impact from automation and trade and therefore constitute the most promising approach.

Firm-level applications are informative of direct labor market effects on enterprises. However, they potentially suffer from sample selection bias if they focus on firms that are active on international markets, since firms operating in the international markets are more productive than firms that are only active domestically. Worker-level estimates are potentially the most informative and capable of reflecting the most direct labor market outcomes. Such studies however are often constrained by the limited availability of reliable data. This is reflected in our technology and international trade samples, where studies based on industry-level data outnumber the firm-level ones, while lack of extensive and reliable worker-level data accounts for the relatively smaller representation of individual-level studies.

Estimates are also differentiated depending on skill-level. A large part of the literature distinguishes low-, medium- and high-skilled employees. This distinction is clearly visible in

the samples, where most estimates refer to high-skilled workforce, followed by the ones referring to low-skilled employees. Only few studies also include medium-skilled employees.

Table 5. Descriptive statistics

Dependent variable	Factor-biased technical change				International Economic Activity			
	Before 1995		After 1995		Before 1995		After 1995	
	Obs.	Mean Value	Obs.	Mean Value	Obs.	Mean Value	Obs.	Mean Value
Entire sample of estimates	93	0.111	162	0.043	242	-0.028	661	-0.072
Elasticity	25	-0.214	101	0.041	72	0.003	237	0.080
Marginal Effect	-	-	9	0.049	-	-	11	-0.008
Est. Coefficient (no interpretation)	68	0.231	52	0.047	170	-0.042	413	-0.160
<i>Panel A - Operational heterogeneity</i>								
R&D investment	63	0.244	79	0.034				
High – tech capital	19	-0.300	69	0.002				
International outsourcing					106	-0.040	290	0.025
In-house offshoring					49	-0.016	39	0.169
Import competition					73	-0.034	270	-0.308
<i>Panel B – Methodological heterogeneity</i>								
Estimation method heterogeneity								
Factor-biased technical change only	14	-0.025	20	0.079				
International economic activity only					144	-0.090	441	-0.142
Both FBTC and IEA	79	0.136	142	0.038	98	0.062	290	0.070
Employment effect	44	0.160	54	0.049	140	-0.145	329	-0.180
Monetary effect	49	0.049	108	0.041	102	0.132	332	0.035
Data heterogeneity								
Industry-level data	60	0.079	89	0.022	168	-0.008	390	-0.153
Firm-level data	33	0.171	23	0.206	66	-0.085	104	0.069
Individual-level data	-	-	50	0.006	8	0.000	89	0.019
Manufacturing effect					220	-0.074	421	-0.073
Services effect					9	1.046	89	0.085
Economy-wide effect					13	0.008	151	-0.160
Low-skilled labor	21	-0.288	36	-0.209	38	-0.283	107	-0.019
Medium-skilled labor	3	-0.074	31	-0.129	15	-0.040	59	-0.018
High-skilled labor	58	0.101	39	0.408	110	0.131	143	0.127
Mixed Labor	11	0.983	56	0.047	79	-0.125	352	-0.177
Effect on Europe	47	0.067	146	0.041	118	-0.038	548	-0.038
Effect on North America	43	0.164	14	0.054	116	-0.054	108	-0.229
Effect on Rest of the world	-	-	-	-	8	0.489	5	-0.346
High-income trade partner	5	1.495	-	-	25	-0.090	46	0.184
Low-income trade partner	30	0.111	12	0.237	76	-0.059	297	-0.249
Unspecified trade partner	44	-0.002	132	0.020	141	-0.001	318	0.057
Number of years in the analysis	93	17.9	162	9.26	242	13.4	661	11.29
Publication heterogeneity								
Peer-reviewed journals	85	0.113	60	0.038	222	-0.003	380	-0.162

Working paper	8	0.094	102	0.047	20	-0.307	281	0.050
10 year recursive impact factor	93	24.62	166	5.22	242	15.84	661	6.76

Note: Author's calculations

In addition, most studies differentiate trade effects on manufacturing or services separately, while a smaller subdivision refers to the entire economy.¹⁰ Most estimates concentrate on trade effects in the manufacturing sector.

Studies are also differentiated geographically (see Maps D1 and D2 in the Appendix for a detailed country coverage). The majority of the estimates refer to European labor markets (where Germany, the United Kingdom and Sweden stand out), followed by estimates for the United States. Only a small part of the sample refers to other high-income economies, such as Japan or Canada. As stated above, different countries involve different labor market institutions, therefore we expect a differentiated impact from technology and trade between various high-income countries.

To address the evolution of labor market effects from automation and trade over time, we calculate the midpoint (average year) in each study and separate estimates with midpoint before or after 1995. Our choice is based on the well-documented fact that from the mid-1990s trade between high-income and low-income countries increased substantially (Krugman, 2008). Our sample is relatively biased to more recent estimates.

An additional aspect of data heterogeneity involves the economic status of the trade partner. This distinction is applicable to our trade sample and the technology estimates from empirical models also including a measure of trade and reflects the different types of trade between heterogeneous countries. Trade with low-income countries is more likely to be of the inter-industry type, while trade between high-income countries is expected to be of the intra-industry type (Debaere et al. 2009). Almost half of our trade estimates captures this distinction. This differentiation is only valid for a relative small part of our technology estimates, with most of them involving trade with a low-income partner.

We control for the quality of publication in two ways: First, we use a dummy variable to distinguish between a paper published in a refereed journal or in a working paper series. This indicator variable captures the higher level of methodological rigor in a refereed journal. The majority of our sample is obtained from refereed journals; however, estimates published in

¹⁰ In the empirical estimations of automation, such a distinction is rarely clear in the literature, therefore we do not apply it in our empirical models.

key working paper series (*NBER*, *CEPR*, *CESifo*, *IZA* etc.) are also represented. The 10-year recursive impact factor from the *IDEAS/RePEc* database captures the quality of the publication.

Finally, an additional source of heterogeneity originates from the estimated functional forms. Some authors report employment or wage elasticities, either directly obtained from a linear-in-logs functional form, or calculated on the basis of the estimated coefficients. Few authors report marginal effects.

Table 5 summarizes the independent variables and reports the mean for each sub-period. In line with the literature, we illustrate that more recent studies tend to report a (larger) labor market impact from trade, while estimates regarding technology decrease in absolute value over time. Also, the evidence indicates that the skill-level is an important determinant of the overall outcome, for both technology and international trade. In general, low-skilled employment is the loser of automation and trade, while high-skilled labor is the winner. In addition, trade is beneficial for services, but detrimental for manufacturing. Finally, the choice of the dependent variable is also important; trade effects on employment are more likely to be negative compared to the ones for wages.

5. Meta-Analysis: results

5.1 Sign and significance analysis; descriptive statistics

In this section, we provide some descriptive statistics. First, we will discuss the effects of automation. Figure 5 illustrates the distribution of estimated effects across various categories of operational heterogeneity. All categories are represented in the data. R&D investment and Factor biased technological change yields mostly positive labour market effects.

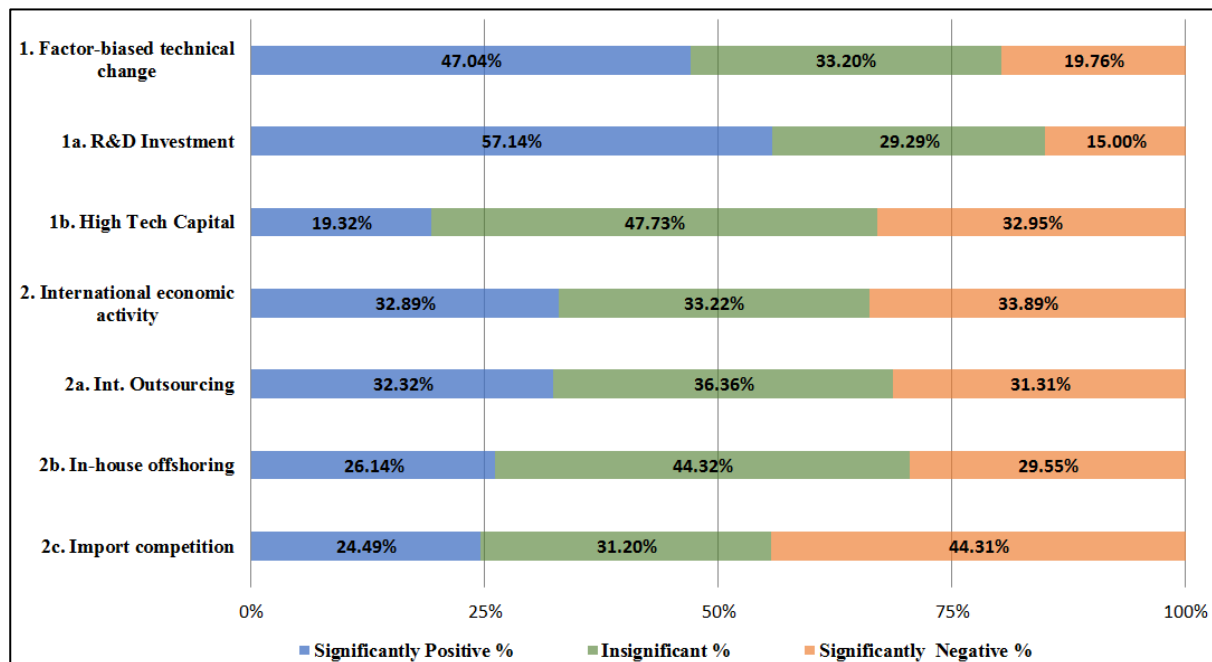
Figure 5 Sign and significance analysis of general and individual categories

Table 6 provides more disaggregate sources of heterogeneity. In particular, technology is mostly negative for low-skilled employment, while the majority of estimates referring to high-skilled employees is positive. In addition, industry- and firm-level studies are more likely to report significantly positive labour market outcomes, especially compared to worker-level studies that are more likely to yield insignificant effects.

Employment versus wage effects do not appear to affect the sign of the significant empirical estimates. For both types of variables, the distribution of the estimates is similar. The analysis also illustrates that geography plays a role; European labour markets are more likely to benefit from technological change compared to the US labor market, for which we report a substantial part of negative effects. This reflects the differences in labor market institutions; in particular, the greater flexibility of the US labour markets (Amiti and Wei, 2005).

Table 6. Sign and significance analysis: Factor – biased technical change estimates

	Percent of estimates that are:			
	Number of estimates	Significantly Positive	Insignificant	Significantly Negative
1. Type of data used				
a. Industry – level	149	47.65%	29.53%	22.82%
b. Firm – level	56	67.8%	14.3%	17.9%
c. Worker – level	50	20.0%	68.0%	12.0%
2. Effect type				
a. Employment effect	98	48.98%	29.59%	21.43%
b. Wage effect	157	45.2%	36.3%	18.5%
3. Labour skill type				
a. Low – skill	57	3.4%	44.0%	52.6%
b. Medium – skill	34	20.6%	58.8%	20.6%
c. High – skill	97	74.2%	23.7%	2.1%
d. Mixed labour	67	56.72%	26.87%	16.42%
4. Geographical level				
a. Europe	193	47.15%	36.27%	16.8%
b. North America	57	40.3%	28.1%	31.6%
c. Rest of the world	5	100%	-	-
5. Economic status of trade partner (if applicable)				
a. High income	5	100.0%	-	-
b. Low income	42	78.6%	19.0%	2.4%
c. Mixed	174	31.82%	40.34%	27.84%

Table 7 reports the sign and significance of various categories for international trade. The skill level of the labor force appears as an important determinant of the sign of the overall effect. Trade is beneficial for high-skilled employment and harmful to low-skilled employment. International trade estimates at the individual level are more likely to be positive. Industry- and firm-level estimates, on the other hand, are more equally distributed but negative findings outnumber positive ones. In contrast, employment-based studies are less likely to report significantly negative outcomes, compared to wage-based empirical studies that tend to show positive or insignificant evidence.

Table 7. Sign and significance analysis: International economic activity estimates

	Percent of estimates that are:			
	Number of estimates	Significantly Positive	Insignificant	Significantly Negative
1. Type of data used				
a. Industry – level	598	28.0%	33.0%	39.0%
b. Firm – level	190	30.0%	39.4%	30.6%
c. Worker – level	115	55.7%	22.7%	21.6%
2. Effect type				
a. Employment effect	469	26.6%	39.2%	34.2%
b. Wage effect	434	39.6%	36.2%	24.2%
3. Labour skill type				
a. Low – skill	145	22.8%	30.3%	46.9%
b. Medium – skill	74	25.7%	50.0%	24.3%
c. High – skill	253	49.0%	35.2%	15.8%
d. Mixed labour	431	28.1%	30.1%	41.8%
4. Geographical level				
a. Europe	666	34.7%	35.6%	29.7%
b. North America	224	26.8%	26.3%	46.9%
c. Rest of the world	13	38.5%	38.5%	23%
5. Development status of trade partner				
a. High income	71	29.6%	49.3%	21.13%
b. Low income	373	25.3%	30.2%	44.5%
c. Mixed	459	39.7%	33.1%	27.2%

From a geographical/institutional perspective, European workforce is more likely to benefit from international trade compared to the US where significantly negative outcomes are more frequent. Finally, with respect to the development status of the trade partner, trade between high income countries are more likely to yield insignificant labour market outcome, while trade between a high income (domestic) economy and a low income trade partner are more likely to result in a negative labour market outcome.

5.2 Ordered Probit Analysis

This section reports the main findings from an ordered probit analysis (Table 8). Table 8 shows how the heterogeneity present in the literature (see Table 5 for an overview) determines the probability of obtaining significant labour market outcomes; either positive or negative. The models are well specified (the Wald test always rejects the null hypothesis that all parameters are jointly equal to zero) and exhibit substantial predictive power (R^2

coefficients vary between 16 and 37%). Column 1 refers to factor biased technical change. Column 2 reports the results for international economic activity. The reported models refer to the general categories of estimates (Table 3) and include dummies for the disaggregate categories, different types of effects (employment or wages) and additional controls (see detailed results in Tables E1 and E2 - Appendix E).

Focusing on the factor-biased technical change sample, the following conclusions stand out. First, with respect to the choice of the dependent variable; employment impacts from technology are more likely to yield negative and significant results compared to wage effects. Second, the analysis shows that the level of aggregation affects the results. Firm-level studies are more likely to produce significantly negative labour market outcomes compared to industry- or worker-level ones. Third, we verify the earlier conclusions that the skill level of the workforce also determines the labour market outcome. Table 8 illustrates that technology is more likely to have a negative effect on low- and medium-skilled workers, as opposed to high-skilled ones. Finally, the analysis shows that the labour market impact from technology dampens over time, since earlier empirical estimates (those with average year in their sample period before 1995) exhibit greater probability to yield significantly positive outcomes.

A sub-sample analyse the effects of technology, but also includes a measure of trade. The labour market effects from technology obtained from these studies are more likely to be negative than those that only include measures of technology. Development status does not seem to play an important role, since the probability for a positive labor market outcome from technology is independent of the development status of the trade partner (when included). However, the probability is higher when trade involves developed countries, rather than developing ones.

In addition, we conclude that the impact of factor-biased technological change in Europe and North America is more likely to be negative compared to the impact on the rest of the world (mostly Japan). In addition, estimates using economy-wide wages, assuming labour mobility, do not alter the probability for obtaining significant results of any sign than models that assume labour immobility. Finally, -in line with Table 4- we do not find serious evidence of publication bias in the (broad) factor-biased technological change category, since estimates published in peer-reviewed journals do not exhibit greater probability to be significant than the ones published in working paper series or derived from unpublished manuscripts.

Table 8. Ordered probit models for the sign and significance of the empirical estimates

	Factor – Biased Technical Change (1)	International economic activity (2)
Estimated equation type (<i>omitted: FBTC only or IEA only</i>)		
a. FBTC and International Economic Activity	-0.889 [0.289]**	0.012 [0.194]
Effect Type (<i>omitted: Wage Effect</i>)		
a. Employment Effect	-0.693 [0.295]**	-0.336 [0.174]*
Data Type (<i>omitted: Worker - level</i>)		
a. Industry	0.027 [0.354]	-0.718 [0.406]*
b. Firm	1.447 [0.465]**	0.068 [0.360]
Labour Type (<i>omitted: Mixed</i>)		
a. Low Skilled	-2.181 [0.641]**	-0.444 [0.330]
b. Medium Skilled	-1.154 [0.576]**	-0.045 [0.332]
c. High Skilled	0.002 [0.652]	0.727 [0.202]***
Economic Sector (<i>omitted: Both</i>)		
a. Material / Manufacturing		-0.084 [0.257]
b. Services		0.802 [0.315]**
Origin Country (<i>omitted: Rest of the World</i>)		
a. Europe	-3.857 [0.195]***	-0.930 [0.682]
b. North America	-5.183 [0.366]***	-1.237 [0.676]*
Destination Country Type (<i>omitted: Mixed / Not Specified</i>)		
a. High-Income	4.674 [0.472]***	0.058 [0.254]
b. Low-Income	0.855 [0.459]*	-0.379 [0.217]*
Time Frame (<i>omitted: after 1990</i>)		

a. Before 1995	1.311 [0.521]**	-0.851 [0.341]**
Wage Level (<i>omitted: Mixed / Not Specified</i>)		
a. Economy	0.432 [0.445]	-0.017 [0.302]
b. Industry	0.547 [0.317]*	-0.517 [0.248]**
Publication Type (<i>omitted: Discussion Paper</i>)		
a. Peer-reviewed journals	-0.084 [0.289]	-0.205 [0.231]
Dummies for type of data	yes	yes
Dummies for individual categories	yes	yes
Dummies for different types of estimated effects	yes	yes
Additional controls	yes	yes
Observations	255	903
Wald (p-value)	0.000	0.000
Pseudo R – squared	0.3758	0.1644

Standard errors clustered by study in brackets, Models are ordered probit, fit to ordinal data with value of +1 for significant positive estimate, 0 for insignificant estimate, and -1 for significant negative estimate. Estimated cut points (2 for each model) are not reported in the Table. The Wald test is performed in robust but non-clustered st. errors, since clustering the st. errors per study results in an insufficient rank to perform the test. Results remain unchanged. Additional controls include indicators for publication year, regional analysis (local labour markets), publication quality (ten year impact factor) and number of years covered by the time period of analysis. *Omitted* stands for the reference category in each set of dummy variables

Turning to the effect of international economic activity (Table 8 - Column 2) the results indicate the following: First, analysing employment effects of international trade decreases the probability of a significantly positive outcome compared to wage effects. Second, data aggregation matters for empirical estimates of international trade in a –qualitatively- different way than the estimated effects from technology. In particular, we show that industry-based studies are more likely to provide significantly negative outcomes than firm- or worker- level ones.

Comparing labour market effects with respect to the skill level of the workforce, trade is more likely to benefit high-skilled employment than low skilled employment. This result shows a clear differential effect between technology and trade, since technology is more likely to harm low- and medium-skilled employees while trade is more likely to benefit high-skilled labor. In addition, the results indicate that the second wave of international trade

(trade in services) is more likely to benefit high-income labour markets compared to the first wave (trade in manufacturing).

Evaluating the international trade estimates by time-period of estimation; earlier empirical applications (those before 1995) exhibit greater tendency to provide negative results compared to more recent ones. This is possibly an indication of the beneficial impact of international trade organizations and multilateral trade agreements that helped high-income labour markets to mitigate potential negative effects from trade (Kohl et al.2018).

Finally, US labour markets are more likely to experience negative outcomes from trade, potentially reflecting institutional differences between Europe and the US.

6. Conclusions and Discussion

During the last four decades, high-income countries have experienced a relative decline of manufacturing employment, typically accompanied by a decline in the wage share of medium- and low-skilled employees. The ongoing globalization debate point towards domestic technological progress and various forms of international trade as the main explanations for these developments. As a result, a considerable body of literature analysing the labour market impact (wages and employment) of technology and trade has developed, but the evidence remains inconclusive as to which factor dominates.

We synthesize this literature in a meta-analysis and analyze a sample of 1158 estimates from 77 studies. Some of these studies estimate the effects of trade, others of technological progress and some both of them. The dependent variables in the various estimates are not always the same; some studies focus on wages others on employment. Sometimes specific skill groups of the labour market are analyzed, and definitions, although often similar, are not identical. We analyze these findings by an ordered probit framework that explains *sign* and *significance* to evaluate the relative contribution of technology and international trade on labor market developments (Card, Kluve and Weber, 2010). The advantage of a meta-study is that we collect estimates that are spread across many studies. This enables us – by adding controls – to determine which factors explain differences in outcomes. These controls identify, for example, country coverage, time-period of the analysis, the type of trade exposure, skill level, etc.

In general, we find that both effects are important. Automation is beneficial at the firm level, and is more likely to displace low-skilled employment. Trade is more likely to benefit high

skilled employment and affects industry negatively. The negative effects are more pronounced for the US than for Europe. Somewhat surprisingly, given the consensus in the literature, automation has a positive effect for estimates considering the period before 1995. Furthermore, the impact of technology dampens after 1995, while the impact of trade is more likely to be positive and significant after 1995.

Finally, the meta-analysis also offers an analysis of publication bias. Standard meta-analytic techniques for estimating publication selectivity (funnel plot analysis, Egger test of small-study effects) indicate, in general, *little or modest* bias.

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APPENDIX A: The Literature search – Descriptive evidence**Table A1. – Search Terms**

General terms	Technology	International Trade
employment, elasticity, regression analysis	automation, computerization, innovation, research and development, technical change	outsourcing, offshoring, foreign direct investment (FDI), export (import) competition

Table A2. Frequencies of estimated effects per category
(general categories only)

Criteria	Technology	International Trade
<i>Panel A – Estimation model</i>		
Technology approximation (Individual)	32	-
Trade approximation (Individual)	-	585
Simultaneous approximations	221	318
Employment effect	96	469
Monetary effect	157	434
<i>Panel B – Data characteristics</i>		
Industry – level	147	598
Firm – level	56	190
Worker - level	50	115
Annual data	247	842
Quarterly data	0	61
Monthly data	6	0
Manufacturing sector		641
Services sector		98
Both sectors		164
Low – skilled labour	57	145
Medium –skilled labour	34	74
High – skilled labour	97	253
Mixed labour	65	431
European country	191	666
North American country	62	224
Rest of the world	0	13
High-income trade partner	5	71
Low-income trade partner	42	373
Mixed trade partner	206	459
Before 1995	93	242

After 1995	160	661
Economy – level wages	44	56
Industry – level wages	105	298
Not specified wage level	104	549
<i>Panel B – Publication characteristics</i>		
Working paper	110	301
Academic publication	143	602
Conference paper	0	0

Note: D* refers to the number of the dummy variable controlling for the respective category in our empirical analysis, while RC stands for *Reference Category*

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APPENDIX C – Funnel plots for individual categories of factor-biased technical change and international economic activity.

C1. Funnel plots for factor biased technical change sub-categories

Figure C1.1 R&D investment

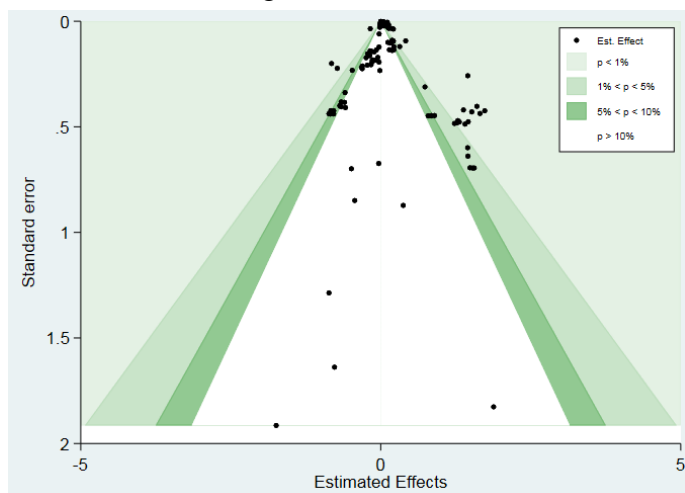
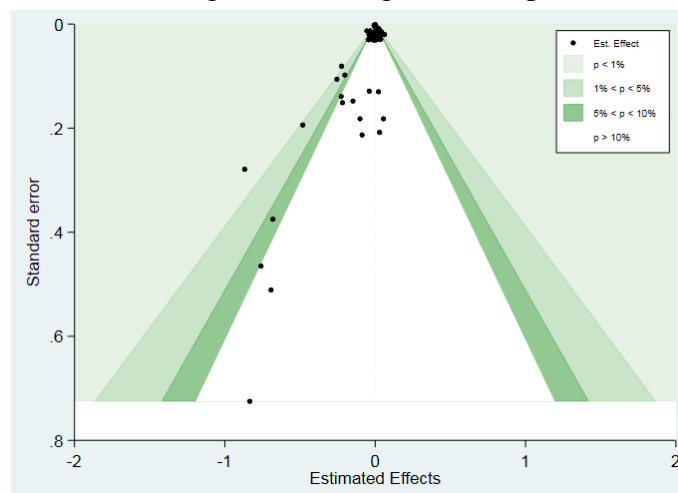


Figure C1.2. High Tech Capital



C2. Funnel plots for international economic activity sub-categories

Figure C2.1. International outsourcing

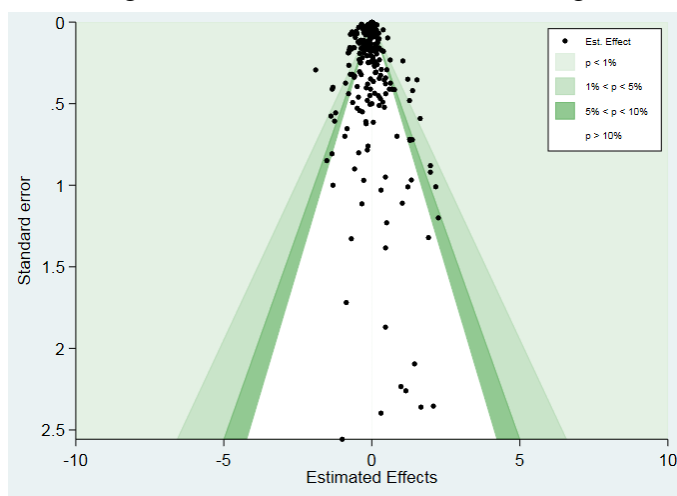


Figure C2.2. In-house offshoring

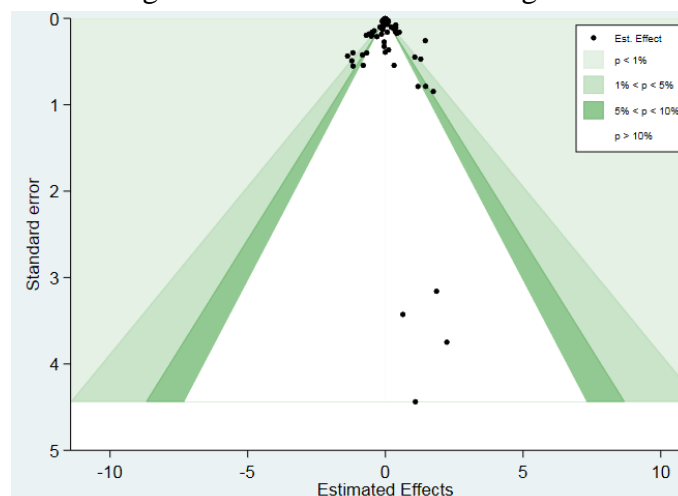
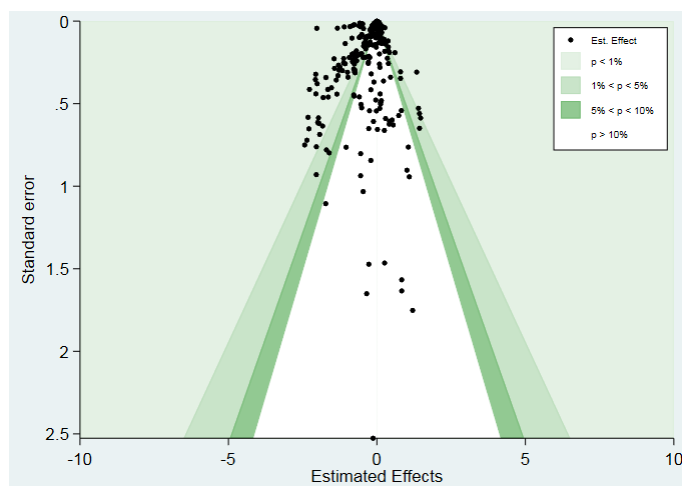


Figure C2.3. Import competition



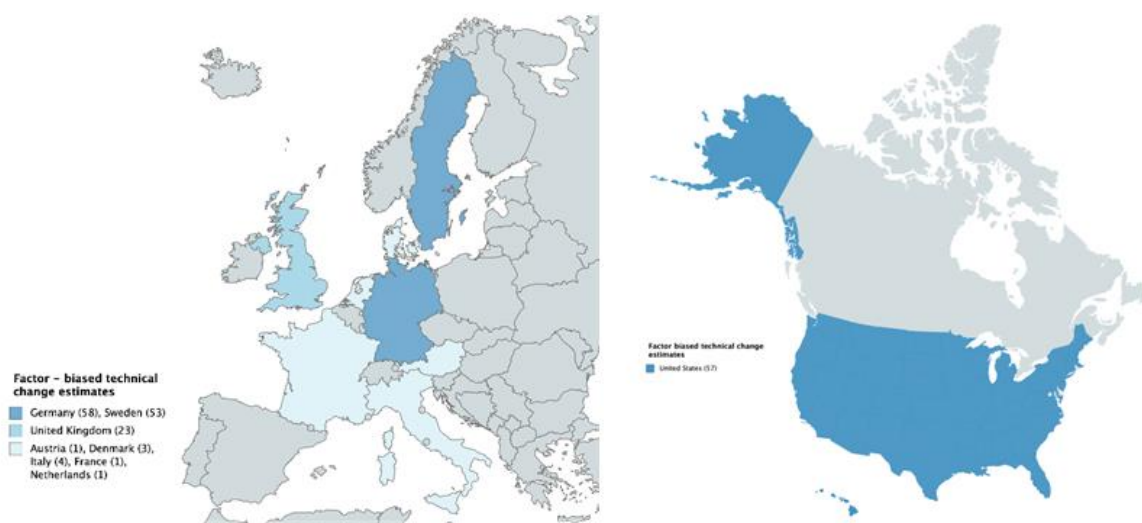
APPENDIX D – Heterogeneity of estimates and geographical distribution

Table D1. Methodological heterogeneity

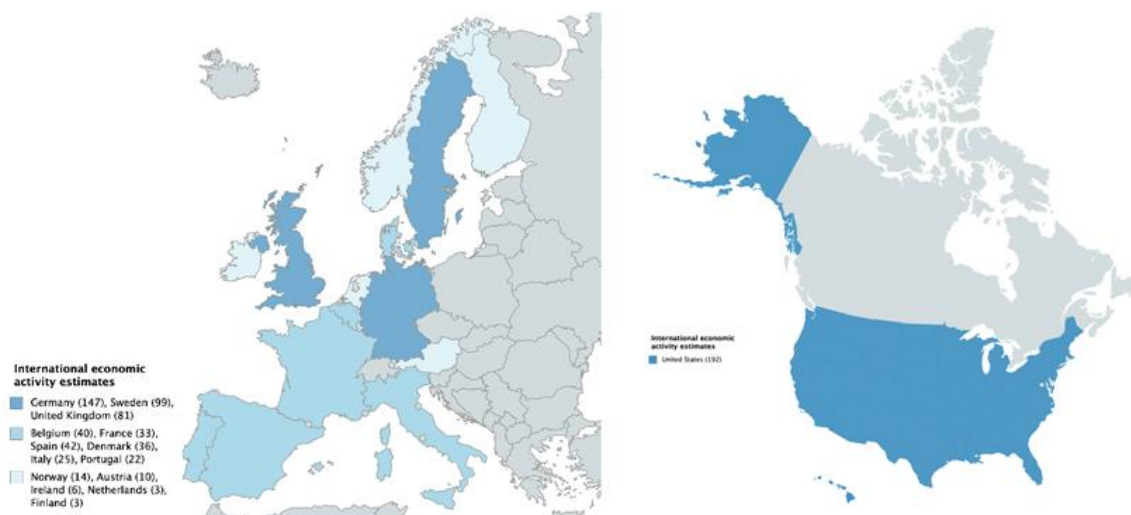
Criteria	Categories and variable structure
<i>Panel A – Estimation model</i>	
Variables of interest	Factor-biased technical change only (D1), international economic activity only (D2) and both (RC)
Type of estimated effects	Employment (D1) and monetary (RC)
<i>Panel B – Data characteristics</i>	
Data aggregation	Industry-level (D1), firm-level (D2) and individual-level (RC)
	Annual (D1), quarterly (RC), monthly (D2)
Industry of interest	Manufacturing (D1), services (D2) or both (RC)
Labor type	High-skilled (D1), low-skilled (D2) or mixed (RC)
Country of interest	Europe (D1), North America (D2) or Rest of the World (RC)
	High income (D1), low income (D2) or both (RC)
Time frame	Before 1995 (D1) or after 1995 (RC)
Duration	Number of years in the analysis
Wage level	Economy (D1), industry (D2) or not specified (RC)
<i>Panel B – Publication characteristics</i>	
Publication status	Working paper (D1), academic publication (D2), conference paper (RC)
Publication quality	10-year recursive impact factor (IDEAS / RePEc)

Note: D* refers to the number of the dummy variable controlling for the respective category in our empirical analysis, while RC stands for *Reference Category*

Map D1. Distribution of factor biased technical change estimates by country



Map D2. Distribution of international economic activity estimates by country



APPENDIX E – Ordered probit analysis (individual categories)

Table E1 – Ordered probit models for the sign and significance of the empirical estimates – factor –biased technical change individual categories

	R&D investment	High-tech capital
	(1)	(2)
Estimated equation type (<i>omitted: FBTC only</i>)		
a. FBTC and International Economic Activity	-1.308 [0.674]*	0.516 [1.076]
Effect Type (<i>omitted: Wage Effect</i>)		
a. Employment Effect	-0.216 [0.133]	0.000 [1.137]
Data Type (<i>omitted: Worker - level</i>)		
a. Industry	-2.329 [2.280]	-2.238 [1.509]
b. Firm	-0.311 [1.508]	-2.330 [1.912]
Labour Type (<i>omitted: Mixed</i>)		
a. Low Skilled	-2.948 [1.217]**	-1.534 [1.506]
b. Medium Skilled	-2.152 [0.842]**	-0.475 [1.503]
c. High Skilled	0.449 [0.513]	-0.393 [1.448]
Origin Country (<i>omitted: Rest of the World</i>)		
a. Europe	-3.708 [0.335]***	-
b. North America	-4.613 [0.480]***	-
Destination Country Type (<i>omitted: Mixed / Not Specified</i>)		
a. High-income	2.775 [0.879]**	-

b. Low-income	-0.015 [0.690]	-
Time Frame (<i>omitted: after 1990</i>)		
a. Before 1995	1.896 [1.010]*	-
Wage Level (<i>omitted: Mixed / Not Specified</i>)		
a. Economy	0.758 [0.752]	1.086 [1.364]
b. Industry	0.386 [0.650]	0.903 [1.214]
Publication Type (<i>omitted: Discussion Paper</i>)		
a. Academic Publication	-0.898 [0.597]	-
Dummies for different types of data	yes	yes
Dummies for different types of estimated effects	yes	yes
Additional controls	yes	yes
Observations	140	88
Wald (p-value)	-	35.76
Pseudo R – squared	0.4960	0.1960

Standard errors clustered by study in brackets, Models are ordered probit, fit to ordinal data with value of +1 for significant positive estimate, 0 for insignificant estimate, and -1 for significant negative estimate. Estimated cut points (2 for each model) are not reported in the Table. The Wald test is performed in robust but non-clustered st. errors, since clustering the st. errors per study results in an insufficient rank to perform the test. Results remain unchanged. Additional controls include indicators for publication year, regional analysis (local labour markets), publication quality (ten year impact factor) and number of years covered by the time period of analysis. *Omitted* stands for the reference category in each set of dummy variables

Table E2 – Ordered probit models for the sign and significance of the empirical estimates – international trade activity individual categories

	International outsourcing	In-house offshoring	Import competition
	(1)	(2)	(3)
Estimated equation type (<i>omitted: IEA only</i>)			
a. International Economic Activity and FBTC	-0.417 [0.213]*	0.070 [0.122]	0.607 [0.284]**
Effect Type (<i>omitted: Wage Effect</i>)			
a. Employment Effect	-0.347 [0.238]	1.231 [0.117]***	0.384 [0.239]
Data Type (<i>omitted: Worker - level</i>)			
a. Industry	0.375 [0.429]	-1.874 [0.421]***	-0.466 [0.418]
b. Firm	1.619 [0.741]**	-1.378 [0.406]**	0.148 [0.423]
Labour Type (<i>omitted: Mixed</i>)			
a. Low Skilled	-0.072 [0.582]	-1.450 [0.308]***	0.049 [0.307]
b. Medium Skilled	0.688 [0.550]	-1.072 [0.284]***	1.469 [0.218]***
c. High Skilled	1.524 [0.494]**	0.466 [0.195]**	0.973 [0.253]***
Economic Sector (<i>omitted: Both</i>)			
a. Material / Manufacturing	0.121 [0.513]	-8.885 [0.500]***	-0.460 [0.408]
b. Services	1.016 [0.547]*	-8.401 [1.044]***	1.388 [0.528]**
Origin Country (<i>omitted: Rest of the World</i>)			
a. Europe	-0.499 [0.597]	-10.026 [1.913]***	-0.309 [0.177]*
b. North America	-0.883 [0.864]	-10.298 [0.948]***	-0.796 [0.281]**
Destination Country Type (<i>omitted: Mixed / Not Specified</i>)			
a. High-income	-0.268 [0.281]	0.933 [0.390]**	-0.376 [0.395]
b. Low-income	0.285 [0.339]	-1.344 [0.264]***	-0.196 [0.184]
Time Frame (<i>omitted: after 1990</i>)			

a. Before 1995	-1.375 [0.390]***	-0.908 [0.520]*	-2.364 [0.769]**
Wage Level (<i>omitted: Mixed / Not Specified</i>)			
a. Economy	0.106 [0.484]	-0.017 [0.302]	4.515 [0.642]***
b. Industry	-0.115 [0.420]	-0.517 [0.248]**	0.253 [0.636]
Publication Type (<i>omitted: Discussion Paper</i>)			
a. Academic Publication	-0.276 [0.446]	9.207 [0.620]***	-0.227 [0.265]
Dummies for different types of data	yes	yes	yes
Dummies for different types of estimated effects	yes	yes	yes
Additional controls	yes	yes	yes
Observations	396	88	343
Wald (p-value)	-	-	-
Pseudo R – squared	0.2356	0.4266	0.2697

Standard errors clustered by study in brackets, Models are ordered probit, fit to ordinal data with value of +1 for significant positive estimate, 0 for insignificant estimate, and -1 for significant negative estimate. Estimated cut points (2 for each model) are not reported in the Table. The Wald test is performed in robust but non-clustered st. errors, since clustering the st. errors per study results in an insufficient rank to perform the test. Results remain unchanged. Additional controls include indicators for publication year, regional analysis (local labour markets), publication quality (ten year impact factor) and number of years covered by the time period of analysis. *Omitted* stands for the reference category in each set of dummy variables