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Diversify or Not? – The Link Between Global Sourcing of ICT Goods and Firm Performance

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Abstract

Our paper contributes to the discussion about Europe's digital sovereignty. We analyze the relationship between firm performance and the diversification of sourcing countries for imported ICT goods. The analysis is based on administrative data for 3888 German manufacturing firms that imported ICT goods in the years 2010 and 2014. We find that firms that diversify the sourcing of ICT goods across multiple countries perform better than similar firms with a less diversified sourcing structure. This result holds for value added as well as for gross operational surplus as performance measures and for two different indicators of diversification.

Keywords: ICT goods imports, global sourcing, digital sovereignty, firm performance

JEL Classification Numbers: F14, F23, L14, L23, D24

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1 Introduction

Geopolitical developments are drawing attention to Europe's dependence on imports, with China being the main sourcing country for digital goods. The revealed comparative disadvantages of the European Union, and in particular of Germany, with respect to digital technologies as key enabling technologies have spurred the debate about Europe's digital sovereignty (European Commission, 2021*a*,*b*). This topic is of high importance since digital technologies are a driver of technological progress, including other key enabling technologies such as production technologies and life sciences (for example EFI 2022; Kroll et al. 2022). Digital sovereignty, however, does not require producing technologies domestically but rather having access to technologies without unilateral dependencies.

Aksoy et al. (2022) report that 87 percent of the German manufacturing firms adjusted their sourcing strategy in 2022 in response to supply chain disruptions. Apart from increased stockpiling, the second most frequent response was the diversification of suppliers. However, there is limited evidence on how diversification affects firm performance (Cadot et al., 2013). It is not clear *a priori* whether increased diversification has a positive or negative impact, as sourcing from multiple suppliers may be costly, especially for smaller firms, while the benefits of diversified sourcing may outweigh the associated costs by reducing the risk of supply disruptions. Moreover, a broader set of imported intermediate goods might increase firms' output, as argued by De Loecker and Goldberg (2014).

Our paper contributes to the question of how diversification affects firm performance; thus it also contributes to the broader discussion on Europe's digital sovereignty. To this end, we analyze the relationship between firm performance and the diversification of sourcing countries for imported ICT goods in the German manufacturing sector. We focus on ICT goods since they are nowadays key input factors for the production of all kind of manufacturing goods. In the empirical analysis, we consider value added as a measure of firms' output and gross operating surplus as a measure of financial performance. Further, we use two different diversification variables, the Shannon entropy index and the share of ICT goods from the main sourcing country. The analysis is based on administrative data covering 3888 German manufacturing firms for the years 2010 and 2014.

We find that the more diversified the sourcing structure for ICT goods, the better the firms perform. This holds for both measures of firm performance and for both diversification measures. However, considering the limitations present in our data, which hinder the application of econometric techniques capable of establishing causality, it is crucial to refrain from interpreting this result as indicative of a causal relationship. Further, consideration of the degree of digitalization of the firms shows that this correlation only applies to firms with a high degree of digitalization, i.e. the procurement strategy for ICT goods is only relevant for highly digitalized firms. A series of robustness checks support the results found in the baseline regressions. This includes the tests for divergent results for different size classes, the potential influence of the 'Rotterdam' effect, and separate estimations for each year in the data set. All tests confirm the main findings. Thus, diversification of suppliers matters for firm performance.

The paper is structured as follows. Section 2 places the paper in the context of related literature. Section 3 presents the empirical framework. Data and descriptive statistics are shown in Section 4. Section 5 contains econometric results including the robustness checks and it discusses the implications and limitations of the analysis. Section 6 concludes.

2 Related literature

The importance of international sourcing has greatly increased over past decades. China has become an important source of intermediate goods and has increased its global manufacturing shares since 2004, while the shares of the U.S., Japan, and Germany have declined (see Baldwin and Freeman, 2022, p.165).[1] The analysis by Flach et al. (2022, p.5) shows that Germany's involvement in global value chains has been quite stable since 2007. Imported intermediate goods, as a share of domestic production of final goods, was 15 percent in 2007, declined after the financial crisis in 2009, and then increased to about 20 percent in 2019. As providers of intermediate goods for Germany, the most important countries are the U.S., the Netherlands,[2] China, and France. Only five percent of imported goods, however, are so-called "dependent goods;" i.e. these goods are relevant for domestic production. There is limited diversification with respect to the sourcing countries and these goods cannot easily be substituted by domestic production.[3] Dependent goods are basically manufacturing goods, belonging to the chemical and pharmaceutical industry or to oil processing. About 73 percent of these goods are imported from EU countries, whereas seven percent are imported from the U.S., four percent from Switzerland, and three percent from China (Flach et al., 2022, p.16). Although digital goods are considered less critical according to this analysis, dependence on China for ICT goods is relatively high, as 0.69 percentage points of the three percent of dependent goods imported from China are electronic components (Flach et al., 2022, p.17).

In general, there is consensus that the growth of international trade and global supply chains has contributed to productivity growth and the welfare of industrialized countries. At the micro level, several studies show that firms sourcing goods from abroad perform better in terms of productivity than firms operating only domestically (see, among others, Amiti and Konings, 2007, Kasahara and Rodrigue, 2008, and Halpern et al., 2015).[4] This particularly holds for ICT goods and digital technologies in general. Having access to digital technologies and possessing the knowledge and skills to apply them is important for economic performance since digital technologies - as key enabling technologies - can be used in many economic sectors, promoting product and process innovation in these sectors as well as productivity gains. There are several strands of literature addressing the role of digitalization for firm performance. A broad body literature focuses on the relationship between firms' investment in digital technologies and labor productivity; this is thoroughly documented in overviews by Draca et al. (2007), Cardona et al. (2013), Bertschek et al. (2015), and Schweikl and Obermaier (2020).[5]

[1] The impact of China's rise as provider of manufacturing goods on the U.S. labor market is studied by Autor et al. (2016).

[2] To some extent, imports from the Netherlands are in fact imports from other, in particular Asian, countries, as these imports are shipped through the port of Rotterdam. This is the so called 'Rotterdam effect'. See e.g. Bogliacino et al. (2018) and European Commission (2009).

[3] More specifically, according to Flach et al. (2022, p.14-15), dependent goods (i) are relevant for the five most important economic sectors and belong to the three most important inputs for these sectors; (ii) are sourced from a small number of providers or countries; and (iii) the share of imports of these goods is equal to or larger than the share of exports of these goods.

[4] Some studies analyze the link between firm performance and trade more generally. For instance, Bernard et al. (2007) show that firms that are more productive are more likely to start exporting and these firms are also more likely to benefit from exports increasing their productivity again. An overview of the general literature on trade and firm performance is given by Shu and Steinwender (2019). Antràsa and Chor (2022) provide a comprehensive overview about the research on global value chains and a critical evaluation of the macro and micro data sets used for empirical analyses of global value chains.

[5] Positive effects of digitalization are found already in the early 1990s, e.g. by Brynjolfsson and Hitt (1995) and are confirmed in studies by Cette et al. (2022), Dhyne et al. (2021), and Schivardi and Schmitz (2020). Some papers

Moreover, the use of digital technologies such as the Internet or e-commerce applications might reduce information and coordination costs, thus reducing trade costs. As pointed out by Akerman et al. (2022), reduced trade costs enlarge the choice set of exporters and importers, making it easier to substitute if a specific market becomes more expensive to export to or import from.

Yet, the Covid-19 pandemic and the war in the Ukraine have spurred discussions about the vulnerability of global supply chains as well as the effects of disruptions and dependencies on firms and on general economic development. The lack of technological sovereignty and, in particular, of digital sovereignty and its economic and social impact is an ongoing concern of policy-makers (von der Leyen, 2020; European Commission, 2021*a*,*b*; Bauer and Erixon, 2020).[6] The topic is addressed in the preamble of the 2022 European Declaration on Digital Rights and Principles (European Commission, 2022). There are a number of studies attempting to assess the need and the consequences of technological and, in particular, digital sovereignty. Couture and Toupin (2019), for instance, provide an overview of how digital sovereignty is conceptualized by different types of actors. One clear result of this paper is that the understanding of the term digital sovereignty differs widely across actors and countries. For example, as argued by March and Schieferdecker (2021), technological sovereignty does not mean autarky. It rather means that an economy has access to a particular technology either through its own production or through full or partial sourcing from outside without unilateral dependency. Moreover, an economy should have the knowledge and skills with respect to applying a particular technology (EFI, 2022).

The existing literature does not provide a consensus on the advantages and disadvantages associated with the degree of diversification in the international supply value chain. Criscuolo et al. (2017), for example, argues that firms can reduce their vulnerability to supply shocks by holding additional input inventories or diversifying their range of input suppliers. They also point out that this lead to higher costs and even might reduce productivity. Similarly, Miroudot (2020) points out that holding additional inventory or production capacity in order to mitigate shocks due to crises might outweigh the gains from mitigating risks in the case of low-probability events, like the Covid-19 pandemic. Shu and Steinwender (2019), in contrast, argue that access to imported intermediate goods could, in principle, lower input costs and increase the quality of inputs. Hence, these firms might be able to produce new or higher quality goods, therefore improving their overall performance. A similar argument is provided by De Loecker and Goldberg (2014). They claim that a broader set of imported intermediate goods or higher quality imported intermediate goods are likely to increase firms' output. With regard to our research question on whether the diversification of imported ICT goods is associated with better firm performance, a similar argument might hold. Although sourcing ICT goods from a more diverse range of countries may entail higher administrative costs, it could provide firms with access to higher-quality and potentially more cost-effective goods. Consequently, they may benefit from diversification. A first hint for this claim is provided by Rasel (2017), who finds that the link between labor productivity and global sourcing is only significant for industries with a higher diversity in terms of sourcing from different industries.

In this paper, we focus on the link between firm performance and imports of intermediate ICT

analyze whether there are benefits from using newer types of digital technologies, such as Artificial Intelligence (AI), e.g. Brynjolfsson et al. (2019) and Brynjolfsson et al. (2021), or the heterogeneity of such benefits, e.g. Andrews et al. (2015) and Andrews et al. (2016).

[6] See also Pohle and Thiel (2020).

goods in the German manufacturing sector. We analyze whether a more diversified sourcing strategy for intermediate ICT goods is beneficial for manufacturing firms. We consider value added as a measure of firms' output as well as gross operating surplus as a measure of financial performance.

3 Empirical framework

With our empirical analysis we aim to understand whether firms benefit from regional diversification of their imports of ICT goods or, alternatively, from concentrating on a single country for sourcing. We use a Cobb-Douglas production function approach for the empirical analysis and link indicators of firm performance with measures sourcing diversity. The output variables available to us are sales, value added, and gross operating surplus. Trade data are observed for the years 2010 and 2014 and the overlap in terms of identical firms between the two years is minimal such that panel estimation methods cannot be used. However, we do observe the outcome variables not only for t but also for $t + 1$. Thus, applying pooled OLS, we regress the outcome variables from $t + 1$ onto the control variables from period t in order to mitigate the endogeneity problem to some extent.[7] The estimation function in logs is

$$y_{it+1} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \beta_{Div} Div_{it} + \boldsymbol{\gamma_X} \mathbf{X_{it}} + u_{it} \tag{1}$$

where y_{it+1} represents the outcome variable for firm i at time t, l_{it} captures the labor input, k_{it} represents the capital input, and u_{it} denotes the independently and identically distributed (iid) error term. The matrix $\boldsymbol{X_{it}}$ contains additional control variables, such as dummy variables for two-digit industries, federal states, and years, while the variable Exp_{it} captures the importance of exports for a firm, measured as share of exports in total gross production value and, thus, the activity of firms in international markets. We also need to take into account how relevant ICT imports are for the firms in the first place, both in relation to their total imports and in terms of their importance in production. This is captured by the variables $ICTiTotImp_{it}$ and $ICTiM_{it}$, both of which are also included in $\boldsymbol{X_{it}}$.

The main variable of interest in Eq. (1) is Div_{it}, measuring the regional diversity of the firms' sourcing of ICT goods. We will apply two different measures in the course of the analysis. First, we follow the literature and capture the diversity of sourcing countries by means of the Shannon entropy index (see, inter alia, Teza et al., 2021), which is calculated as

$$Shannon_{it} = -\sum_{j}^{M} S_{jit} log(S_{jit}) \tag{2}$$

with S_{jit} being the share of ICT imports from each country j for each firm i. The value of $Shannon_{it}$ is bounded between 0 and log(N) and depends on the number of countries (M) from which a firm procures its ICT goods and the importance of each country in this sourcing process, i.e. the countries share S_{jit}. Simply put, the $Shannon_{it}$ equals zero if a firm sources all ICT goods from a

[7] We are fully aware of the endogeneity issue that is inherent in production function estimations as first described by Marschak and Andrews Jr. (1944) and the fact that control function approaches along the lines of, *inter alia*, Ackerberg et al. (2015) and Gandhi et al. (2020) are regularly used to address this problem. However, these approaches require observations from at least two consecutive years for each firm, which is not available in the data.

single country, while it approaches -2 when a firm sources equally (*i.e.* $S_{jit} = 0,01$) from a hundred countries. Put differently, the more balanced and over more countries ICT imports are sourced from, the lower the value of the Shannon entropy index. Therefore, a positive coefficient would indicate that firms benefit from focusing on a single country when procuring ICT goods. If the coefficient is negative, the performance of the firms is positively related to an increasing geographic diversity of their ICT goods imports structure.

In addition to the Shannon entropy index, we also perform the entire analysis with a second diversity measure: the share of the value of ICT goods sourced from the main supplier country in a firm's total ICT goods imports ($Share_{it}$). This measure is less comprehensive than the Shannon entropy index. However, it might be more appropriate in scenarios where two firms source the majority of their ICT goods from the same country, say 90% of it, but the first firm imports the remaining 10% from two dozen countries, while the second firm sources the rest from less than a handful of other countries. The value of the Shannon index will be different for the two firms, though not by much, but economically the firms are essentially equally vulnerable. The simple share variable accounts for this as the two firms in the example would enter the analysis with the same value. Thus, a positive coefficient for this diversity measure indicates that the more firms source their ICT goods imports from a single country, the better they perform, and vice versa.

Two outcome variables are used in the main specification of the analysis. The first is value added, which aims at capturing the performance of firms in terms of their output. In addition, Eq. (1) is estimated with gross operating surplus as the dependent variable indicating financial performance.

A series of robustness checks are performed to validate the main results (section 5.2). In a first robustness check, the estimations are conducted separately for the two years available in the dataset to see if any year actually drives the results. In a second robustness check, the sample is split into two groups of firms using the taxonomy of digitally intensive sectors (see Table 3 in Calvino et al., 2018, p.31).[8] This follows the idea that we expect the effect to be more relevant in sectors with a high digital intensity than in sectors with a low digital intensity. The distortion due to the 'Rotterdam effect' is addressed in a third robustness check. The 'Rotterdam effect' describes the fact that many imports are handled via Dutch ports.[9] As a result, they enter customs data as imports from the Netherlands, which can be a significant part of the imports and might have a distorting effect on any diversity variable. We test to what extent this affects our results. In another robustness test, we run the analysis for different size classes to check whether the results are driven by the large firms in the dataset. The last robustness test uses a smaller set of main variables, namely sales as the dependent variable and labor as the only factor of production. The reason for this is that the use of capital stocks, value added, or gross operating surplus in the main specification significantly limits the number of observations, which might raise the suspicion that a selection problem is responsible for the results of the main specification. By conducting the estimations using only labor and sales as well as, of course, the diversity variables and some other firm-level controls, a larger dataset is available such that it is possible to check whether the results of the main specification are due to the selection of firms.

Before turning to the data and the results, it seems appropriate to address the elephant in the room:

[8] For the classification of firms, we follow Calvino et al. (2018). Industries with a medium or high digital intensity according to Calvino et al. (2018) correspond to industries with a high digital intensity in our analysis. Industries with medium or low digital intensity correspond to industries with a low digital intensity in our analysis.

[9] See footnote 2.

selection bias. By focusing on firms engaged in importing ICT goods, the question arises as to whether this choice introduces a selection bias in our analysis. We are confident that this is not the case: (1) We focus on the effects of diversification of ICT goods imports and *not* on the effects of ICT goods imports per se or on the difference between importing and non-importing. Consequently, the study does not claim to say anything about non-importing firms.[10] (2) We claim not to have a data-driven selection bias as we observe the trade data for all German firms, and the second dataset provided by the Federal Statistical Office is based on a stratified random sub-sample. (3) Unobservable characteristics which are associated with both firm performance and the decision to import ICT goods at all would also constitute a selection bias. Management practices or ability might be such characteristics that are unobservable to us. However, as explained in (1), we only analyze the firms currently importing ICT goods and do not draw any conclusions for the firms not importing ICT goods.[11] Yet, management practices could also impact the intensity of diversification. We cannot rule out this possibility in general, which might lead to an upward bias due to an endogeneity issue - hence correlation of our diversification variables and the error term - but not due to selection.

4 Data and descriptive statistics

For the econometric analysis, we make use of firm-level data provided by the German statistical offices. The source of firm-level inputs and performance measures is the 'AFiD-Panel Manufacturing Firms' (FDZ der Statistischen Ämter des Bundes und der Länder, 2019). One of the core datasets in this panel is the cost structure survey as it contains all firm-level outcome variables, such as value added, gross operating surplus, and sales, as well as input variables, such as labor and material usage. The cost structure survey is mainly a rotating sample of firms that is kept stable for four years. The sample is designed such that it ensures representativeness at the industry and size class levels. Data on investment comes from the investment survey, which is also part of the AFiD-Panel and a census for manufacturing firms with more than 20 employees. The investment data are used to calculate capital stocks by means of the perpetual inventory method. The AFiD-Panel is used extensively to study various topics, which is why we refrain from a detailed discussion but refer to the existing literature (e.g. Le Mouel and Schiersch, 2020; Axenbeck and Niebel, 2021; Duso and Schiersch, 2022; von Greavenitz and Rottner, 2022).

The second data source is the foreign trade statistic for the years 2010 and 2014. These data capture the transactions of German firms across national borders and are based on customs data. The data are tailor-made by the Statistical Office for this analysis and are provided at the firm-year-

[10] Using a different example might make the argument clearer: We would not compare firms that engage in R&D with those that do not; rather, we would be interested in the effects of different R&D strategies among the firms that do R&D, e.g. whether having a research facility in just one place or doing research at multiple places has different effects. In this paper, we are interested in the role of different sourcing strategies with respect to the number of sourcing countries, not in the amount of ICT goods imported and its link to firm performance.

[11] Suppose a researcher wants to estimate the wage premium associated with higher levels of education. If the sample used for the analysis consists only of individuals with higher education, it would likely overstate the true wage premium (e.g. due to motivation associated with both educational attainment and higher wages). In this case, the selection bias occurs because the sample is not representative. If the study would be on the differences in the way students organize their courses and how this affects the wage differences between students, it would not try to say something on the premium of a university degree. This is also the case in our study. It does not aim to say anything about the benefits of ICT goods imports, or about how differences in the volume of ICT goods imports affect firm performance. Instead, this study is about how the way firms organize their ICT imports relates to their performance.

product-country level, with products distinguished at the 6-digit level according to the Harmonized System (HS6). Wagner (2019) provides an extensive description of the general trade data. Below we describe those aspects that are most relevant to our analysis.

The analysis focuses on those manufacturing firms that globally source ICT goods. We use the respective definition of the OECD to classify any imported good as an ICT or non-ICT good (OECD, 2011).[12] As we do not contrast ICT importing and non-ICT importing firms but focus on the diversity of ICT goods sourcing, the analysis uses only those firms that have imported at least one ICT good within the available two years.

For the analysis, we combine the dataset on outputs and inputs with the transaction data using the unique firm identifier that is available in both datasets. Firms with missings in relevant variables are excluded from the analysis. This leaves a dataset with 3888 observations.

Table 4.1: Descriptive statistics for the main countries of origin of ICT imports

	China	Netherlands	USA	Taiwan	Malaysia
total ICT import volume†	1750.86	764.52	646.77	421.86	568
no. of observations that import ICT from country j	1841	553	1876	1005	958
average value of imports‡	102.98	204.11	33.32	143.82	45.06
no. of observations in which x is main sourcing country	638	179	699	153	138

†: million €. ‡: thousand €. Source: RDC of the Federal Statistical Office and Statistical Offices of the Lander, Trade statistics, 2010 & 2014, own calculations.

For the German economy as a whole, China is the most important country for ICT goods sourcing. This is also reflected in our data. As the first line of Table 4.1 shows, the firms in the final dataset procure by far the largest quantity of their ICT goods from China. In addition, for more than half of all observations, some (or all) of the firms' ICT imports originate from China, as the second row shows.[13] In 638 of these cases, China is even the main country of origin for ICT imports (last row). In our data, the Netherlands is the second most important country in terms of volume. This is again identical to what can be observed for German ICT imports as a whole. It follows that even though our data set is limited in terms of the number of observations, thus deviating in terms of the observed ICT import volume compared to total German ICT goods imports, the structure of the observed imports is close to that observed for the German economy as a whole.

Table 4.2 provides more information on the ICT goods import structure of the firms in the final dataset. On average, firms source from about 4.7 countries. At the bottom of the distribution, at the 10th percentile, firms import their ICT from a single country, whereas at the 90th percentile 12 countries provide ICT imports. The number of ICT products imported is quite heterogeneous, ranging from one at the 10th percentile to 32 at the 90th percentile. On average, firms import roughly twelve ICT goods. The average value of ICT imports across firms is €47,043. About eleven percent of the total imports are ICT imports. Again, there is substantial heterogeneity across firms, as shown by the values at the 10th and 90th percentiles, which range from virtually zero to 47 percent.

[12]The detailed list of ICT goods can be found in Table A.10 in the Appendix.
[13]Note that firms may source from different countries at the same time, so the sum in row two need not add up to 3888.

Table 4.2: Descriptive statistics on ICT import structure

variable	mean	sd	p10	p90	N
no. of countries from which ICT is sourced	4.68	5.93	1	12	3888
number of imported ICT products	12.38	29.64	1	32	3888
average value of ICT imports	47043.05	392398.31	139	46599.1	3888
share of total ICT imports in total imports (ICTiTotImp$_{it}$)	.11	.23	0	.47	3888
Shannon entropy index (Shannon$_{it}$)	.51	.6	0	1.44	3888
share of imported ICT from main sourcing country (Share$_{it}$)	.81	.23	.43	1	3888

Monetary values in thousand €. Source: RDC of the Federal Statistical Office and Statistical Offices of the Lander, Trade statistics, 2010 & 2014, own calculations.

These descriptive statistics demonstrate that while there are a significant number of firms procuring their ICT goods from only a few or even just one country, there are also a significant number of firms that procure their ICT goods in a much more regionally diversified manner. To adequately capture the extent of this diversification, we use the two indicators described above, the Shannon entropy index and the share of ICT imports from the main country of procurement in all ICT imports. The degree to which firms have diversified varies significantly, as the last two rows in Table 4.2 show. The average value of the Shannon index is about 0.50. Again, variation across firms is sizable, as the value is virtually zero at the 10th percentile and 1.44 at the 90th percentile. The average share of ICT imports in all ICT imports from the main country of sourcing shows that the firms purchase on average 80 percent of their ICT goods from their respective main country of sourcing. At least 10 percent of all firms import their total ICT from only one country (90th percentile), while another 10 percent obtain 43 percent or less of their ICT goods from their main trading partner (10th percentile).

Finally, Table 4.3 shows the statistics for each of the remaining variables in the analysis. The averages of the main outcome and input variables are slightly higher in comparison to similar statistics in studies that are based on the same data (e.g. Le Mouel and Schiersch, 2020). This suggests that larger firms are slightly over-represented in the final data set. There are two main reasons for this. First, we focus on ICT importing firms in manufacturing. This reduces the number of observations substantially. Second, for all firms that are actually ICT importers in 2010 and 2014, we also need information on value added, material, and capital. This leads to a further decrease in the number of available observations and to a slight over-representation of larger firms in the final dataset. To address this issue, we run a robustness check using a dataset that only requires sales and labor from the AFiD Panel dataset. This increases number of observations to about 8,600. Looking at the statistics from this larger dataset, we find means and standard deviations that are closer to those observed in other studies. Therefore, we expect that a possible biases due to oversampling of larger firms in the main specification can be checked by this robustness test.

5 Econometric results

5.1 Main results

Our main specification corresponds to Eq. (1) for both value added and gross operating surplus as dependent variable, and once using the Shannon entropy index and once using the share of ICT imports from the firms' main sourcing country to capture the level of diversity of ICT sourcing. The results

Table 4.3: Descriptive statistics remaining variables

variable	mean	sd	p10	p90	N
sales‡	146.42	508.61	6.9	324.12	3888
value added‡	46.43	140.39	2.94	106.85	3888
gross operating surplus‡	14.05	36.77	.48	33.82	3888
labor (l_{it})	484.8	1335.11	46	1085	3888
capital (k_{it})	81.55	272.29	4.13	186	3888
export intensity (Exp_{it})	.4	.26	.03	.75	3888
importance in production ($ICTiM_{it}$)	.03	.09	0	.05	3888

Monetary values in million €. ‡: values from t+1. Source: RDC of the Federal Statistical Office and Statistical Offices of the Lander, Trade statistics, AFiD-Panel Manufacturing, 2010 & 2011 & 2014 & 2015, own calculations.

are presented in Table 5.1, where the first four columns show the results for value added and the last four columns show the results when gross operating surplus is the dependent variable. All estimations are performed with stepwise addition of further controls. Due to space limitations, only the results of the estimations with the minimum set of control variables (columns 1, 3, 5, and 7) and all control variables (columns 2, 4, 6, 8) are presented here. The remaining results are found in Tables A.1 to A.4.

First, we can state that the coefficients for labor and capital make perfect sense and are close to what is found in the literature. This is an indication that the estimations generally produce reasonable results. For the Shannon entropy index, the coefficients are always positive and significant in all specifications, regardless of whether we include all control variables or only a minimum variable set and regardless of the dependent variable. It follows that the more diversified ICT imports are, the better the firm performance. This result is more pronounced in case of using gross operational surplus than in case of using value added as performance measure.

The general finding that diversity is beneficial for firms is supported by estimations with the share variable as alternative diversification measure. As a reminder, a share of one means that a firm sources all its ICT imports from one country. In contrast, a value of 0.01 means that the share of the country from which a firm sources the most of its ICT goods is just one percent. The coefficients of $Share_{it}$ in Table 5.1 are significantly negative in all specifications. That is, the more a firm relies on a single source of ICT goods import, the worse it performs in terms of both output and gross operational surpluses. In other words, and using the descriptive statistics from Table 4.2, moving from single-country sourcing (90th percentile) to a situation where ICT sourcing is distributed as it is for the firm at the 10th percentile, i.e., from a share of 1 to 0.43, is associated with a 6.2 percent increase in output and a 13.7 percent increase in gross operating surplus.[14]

In sum, we conclude that diversification of ICT sourcing across countries is positively linked to firm performance. This is true regardless of which measure of firm performance we look at or which measure of diversification is applied.

[14] A change from the 90th percentile to the 10th percentile means a delta in Share_{it} of -0.57, resulting in a change in y_{it} of 0.0612 and 0.1368, using coefficients -0.109 and -0.24, respectively, when all other factors remain fixed.

Table 5.1: Regression results, main specification, pooled OLS

	y_{it} = ln(value added)				y_{it} = ln(gross operating surplus)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l_{it}	0.782***	0.780***	0.784***	0.782***	0.462***	0.461***	0.467***	0.466***
	(0.0155)	(0.0153)	(0.0155)	(0.0153)	(0.0367)	(0.0367)	(0.0367)	(0.0366)
k_{it}	0.261***	0.246***	0.261***	0.246***	0.531***	0.506***	0.531***	0.506***
	(0.0132)	(0.0131)	(0.0132)	(0.0131)	(0.0315)	(0.0316)	(0.0315)	(0.0316)
Shannon_{it}	0.0553***	0.0506***			0.129***	0.114***		
	(0.0115)	(0.0115)			(0.0291)	(0.0297)		
Share_{it}			–0.126***	–0.109***			–0.284***	–0.240***
			(0.0288)	(0.0287)			(0.0731)	(0.0739)
Exp_{it}		0.281***		0.284***		0.499***		0.506***
		(0.0259)		(0.0259)		(0.0657)		(0.0656)
ICTiTotImp_{it}		–0.184***		–0.175***		–0.237**		–0.214**
		(0.0412)		(0.0408)		(0.0928)		(0.0921)
ICTiM_{it}		0.353***		0.351***		0.620***		0.614***
		(0.102)		(0.102)		(0.227)		(0.226)
Constant	7.381***	7.485***	7.499***	7.583***	2.458***	2.618***	2.721***	2.832***
	(0.178)	(0.184)	(0.182)	(0.187)	(0.497)	(0.511)	(0.506)	(0.519)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	3,888	3,888	3,888	3,888	3,888	3,888	3,888	3,888
R-squared	0.932	0.935	0.932	0.935	0.676	0.683	0.675	0.682

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

5.2 Robustness checks

As described in section 3, we perform a series of additional estimations to test the robustness of this finding. The first is to run the estimations separately for each of the two years in the dataset, again looking at both value added and gross operating surplus, and running the estimations once with the Shannon entropy index and once with the share variable, while using the full set of control variables. The coefficients of the two diversity measures are shown in Panel A of Table 5.2.[15] All eight coefficients are very close to the respective coefficients presented in Table 5.1. With all caution, since these are results from OLS estimations, this at least suggests that our results are not influenced by a single year in the dataset.

For the second robustness check, we divide the dataset into two groups of firms by digital intensity based on the firms' industry affiliation using the corresponding OECD definition (Calvino et al., 2018). The results are presented in Panel B of Table 5.2 and are consistent with our expectations. First, there are only significant effects in the estimations when using the subset of highly digitalized industries. In contrast, the diversity of ICT procurement is statistically irrelevant for firm performance in low-digitalization industries. In other words: the procurement strategy matters only when ICT plays an important role due to the degree of digitalization of a firm.

[15]Full result tables are shown in the Appendix.

Table 5.2: Regression results, robustness tests

	y_{it} = ln(value added)		y_{it} = ln(gross operating surplus)	
	Panel A: different years			
	2010	2014	2010	2014
Shannon$_{it}$	0.0497***	0.0507***	0.105**	0.124***
	(0.0172)	(0.0155)	(0.0429)	(0.0412)
Share$_{it}$	-0.106**	-0.112***	-0.220**	-0.263**
	(0.0429)	(0.0386)	(0.104)	(0.104)
	Panel B: digital intensity of industries			
	high digital intens. ind.	low digital intens. ind.	high digital intens. ind.	low digital intens. ind.
Shannon$_{it}$	0.0547***	0.0222	0.123***	0.0509
	(0.0126)	(0.0279)	(0.0326)	(0.0714)
Share$_{it}$	-0.122***	-0.0399	-0.266***	-0.0978
	(0.0318)	(0.0651)	(0.0823)	(0.166)
	Panel C: 'Rotterdam effect'			
	no NL	NL to CN	no NL	NL to CN
Shannon$_{it}$	0.0483***	0.0530***	0.122***	0.120***
	(0.0116)	(0.0117)	(0.0299)	(0.0300)
Share$_{it}$	-0.102***	-0.113***	-0.261***	-0.249***
	(0.0288)	(0.0289)	(0.0741)	(0.0743)
	Panel D: different firm sizes			
	SME	large	SME	large
Shannon$_{it}$	0.0590***	0.0491***	0.129***	0.0965**
	(0.0174)	(0.0154)	(0.0434)	(0.0413)
Share$_{it}$	-0.132***	-0.0983**	-0.285***	-0.179*
	(0.0425)	(0.0386)	(0.106)	(0.104)

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

The potentially distorting impact of the 'Rotterdam effect' is addressed with the third robustness check. To this end, we manipulate the data as follows. First, we created a scenario in which all ICT imports from the Netherlands are relabeled in the data as imports from China - since it is very likely that a significant share of these imports actually come from China via Dutch ports - then recalculated the two diversity variables. Second, we set all imports from the Netherlands to missing, as if these imports never existed. This second approach is widely applied to avoid "biases stemming from the so-called 'Rotterdam effect´, which relates to the fact that trade in goods with the Netherlands is artificially inflated by those goods being dispatched from or arriving in Rotterdam despite the ultimate destination or country of origin being located elsewhere" (Bogliacino et al., 2018, p.789). We believe that these two approaches cover the two most extreme scenarios and, if the results still hold, the main results cannot be caused by the 'Rotterdam effect´, regardless of how much of the imports from the Netherlands really come from there and not from another country. After we recalculated the two diversity variables for these two scenarios, all the estimations are repeated. The respective results are reported in Panel C. They reveal that the Rotterdam effect does not qualitatively affect the results. The coefficients of the Shannon entropy index remain significant, regardless of whether imports from the Netherlands are excluded or treated as if they were imports from China. The same is true for the share variable.

Although we explicitly account for firm size in the main specification by controlling for labor and capital stocks, another conjecture might be that our results are driven mainly by large firms. These firms are known to be more productive and more embedded in global value chains. Therefore, one may suspect that the diversity measures in the estimates also capture, at least in part, the differences in the dependent variables that result from firm size. Hence, we performed the estimations separately for different size classes. Panel D in Table 5.2 shows the results for SMEs and large firms, where the first group includes firms with 10 to 249 employees, while the second group has 250 or more employees.[16] The results refute the suspicion that it is mainly the large firms that are responsible for the results of our analysis. The coefficients of the Shannon entropy index and the share variable in the analysis based on SMEs have the same sign as in all other estimations and are always significant at the one percent level. When comparing the results between large companies and SMEs, we even find that the coefficients for diversification are slightly larger for SMEs and that the coefficient of the share variable in case of gross operating surplus is only weakly significant for large firms. Overall, these results ensure that our main results are not driven by the large firms in the sample.

Table 5.3: Regression results for sales, pooled OLS

	Shannon_{it}	Share_{it}
l_{it}	1.080***	1.082***
	(0.00601)	(0.00589)
Div_{it}	0.0438***	–0.0930***
	(0.0113)	(0.0284)
ICTiTotImp_{it}	–0.102***	–0.0953***
	(0.0281)	(0.0278)
ExpIntensSALES	0.358***	0.361***
	(0.0245)	(0.0245)
Constant	11.80***	11.88***
	(0.145)	(0.149)
dummy var.	yes	yes
N	8,605	8,605
R-squared	0.863	0.863

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Another concern is the limited number of observations, with large firms being over-represented compared to other studies based on the same data source for firms' inputs and outputs. To address this issue, we repeat the estimations with a set of variables that allows for a larger sample size. Specifically, this entails that we use only the sales and employment variables from the AFiD panel.[17] The remaining control variables are retained in the analysis. The respective results in Table 5.3 show that coefficients of the Shannon entropy index and the share variable are very similar to those of the main specification. This indicates that the results in Section 5.1 are not due to the over-representation of large firms or some form of unobserved selection.

By and large, we thus conclude that diversification of ICT goods sourcing across countries is positively linked to firm performance. This relationship holds no matter which indicator of diversity

[16] We show the full results in Tables A.8 and A.9 in the Appendix, where we additionally provide the results for medium and small firms separately.

[17] We also omit the $ICTiM_{it}$ variable because it requires the material and intermediate goods variable, which would severely limit the number of factor available.

or firm performance we use. The only exception is when we distinguish between digitally intensive and less intensive industries where the coefficients for diversification become insignificant in digitally less intensive industries. This might be explained by the fact that, in these industries, ICT generally plays a less important role in the production process.

5.3 Limitations

Although we perform a number of different robustness checks that support our main result, the analysis has some limitations originating from inherent limitations in the data. First, the analysis might be prone to endogeneity issues as omitted variables might confound the relationship between diversification of ICT sourcing and firm performance. We use available control variables to mitigate this issue as far as possible. Second, our analysis might be affected by reverse causality. More successful firms might have more resources to undertake efforts to diversify the sourcing of ICT goods. To alleviate this problem to some extent, we regress outcome variables from $t + 1$ onto the control variables from period t.[18]

Third, the data does not allow for distinguishing whether the imported ICT goods are indeed used as an intermediate input (or as final good) or whether they are investment goods. For intermediate inputs (and final goods), we expect that the mechanism for better performance of more diversified firms is driven by better quality products or a broader product portfolio. With respect to imported ICT investment goods, we cannot rule out the possibility that our effect is captured by the variable for total capital input. Furthermore, German manufacturing firms might not only directly source ICT goods from abroad but also buy ICT goods from German wholesale firms for ICT goods that are produced abroad. We do not have any information on the level of country diversification of the ICT goods sourced from German wholesale firms. Thus, the actual level of diversification for German manufacturing firms in terms of ICT goods used could be higher or lower than shown in our measures of the regional diversity of the firms' sourcing of ICT goods solely based on direct imports. Despite these limitations that lead to more noise in the diversity variables, we find a robust significant link between the diversification of ICT goods sourcing and firm performance.

Finally, one additional concern results from the fact that our dataset only has information on ICT goods. An important factor when it comes to digital sovereignty might also be the procurement of ICT services as well as software. Thus, having access to ICT services and software without unilateral dependencies could also be relevant for the long-term performance of German manufacturing firms. Another minor drawback of our analysis might be the observation period. Our explanatory variables are available for the years 2010 and 2014. The former refers to the period right after the global financial crisis, which generally might have disturbed the way firms operate. However, focusing just on the year 2014 (with dependent variables in 2015) still shows a robust significant relationship between diversification with respect to ICT sourcing countries and firm performance.

[18] We also conducted several IV estimates to overcome potential endogeneity issues. However, all estimations were lacking statistical power in the first stage.

6 Conclusions

Our analysis shows that diversification of suppliers matters. Manufacturing firms with a higher diversification of their suppliers of imported ICT goods across countries have a better performance in terms of value added and gross operating surplus. This holds for both indicators of diversification considered in the analysis and for firms operating in industries with a high level of digitalization. For manufacturing firms with a low level of digitalization, the link between firm performance and diversification is insignificant, probably because ICT goods play a less important role for these firms in general. Thus, diversifying the sourcing of ICT goods across different countries as a measure to increase digital sovereignty seems beneficial for firms.

To decide on the sourcing strategy of imports is first, and foremost, the decision of firms. However, in case of unforeseen crises characterized by disruptions of value chains, such as the Covid-19 pandemic or the Ukrainian war, firms expect governmental help when they feel unable to maneuver through the crisis. Given the lessons learned from of recent crises, the government could make its support more contingent on whether firms have taken adequate precautions to diversify their supply chains and also argue that this can support firms' development outside of times of crisis.

The limitations of our results are mainly due to the shortcomings of the data. Therefore, future research would benefit significantly from more and more recent administrative data. This would allow panel analysis to take unobserved heterogeneity into account. Moreover, covering a longer period would improve the possibilities to conduct event studies to estimate causal effects. Furthermore, not only unilateral dependencies for imported ICT goods but also for imported ICT services such as cloud services might exist, but this kind of information is not available in our firm-level data.[19] Thus, improving the availability of administrative firm-level data for research is crucial for more concise and causal analyses.

[19] In principle, data on ICT services are available. See, for example, the study by Hafner and Kleinert (2021). However, these data cannot currently be merged with administrative data. Changes in the regulation to facilitate the merging of data are also an important issue to enable better research.

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A Appendix

Table A.1: Regression results, value added, Shannon entropy index, pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l_{it}	0.782***	0.782***	0.778***	0.783***	0.779***	0.783***	0.779***	0.780***
	(0.0155)	(0.0153)	(0.0155)	(0.0156)	(0.0153)	(0.0154)	(0.0154)	(0.0153)
k_{it}	0.261***	0.250***	0.259***	0.260***	0.249***	0.249***	0.254***	0.246***
	(0.0132)	(0.0131)	(0.0132)	(0.0132)	(0.0131)	(0.0131)	(0.0131)	(0.0131)
$\text{Shannon}_{ICT,it}$	0.0553***	0.0418***	0.0680***	0.0530***	0.0499***	0.0399***	0.0677***	0.0506***
	(0.0115)	(0.0111)	(0.0118)	(0.0117)	(0.0116)	(0.0113)	(0.0117)	(0.0115)
Exp_{it}		0.312***			0.296***	0.311***		0.281***
		(0.0256)			(0.0258)	(0.0256)		(0.0259)
ICTiTotImp_{it}			–0.171***		–0.0990***		–0.287***	–0.184***
			(0.0365)		(0.0361)		(0.0407)	(0.0412)
ICTiM_{it}				0.128		0.111	0.503***	0.353***
				(0.0940)		(0.0896)	(0.104)	(0.102)
Constant	7.381***	7.406***	7.426***	7.393***	7.431***	7.416***	7.503***	7.485***
	(0.178)	(0.185)	(0.178)	(0.178)	(0.184)	(0.185)	(0.178)	(0.184)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.932	0.935	0.932	0.932	0.935	0.935	0.933	0.935
N	3,888	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.2: Regression results, value added, share of imported ICT from main sourcing country, pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l_{it}	0.784***	0.783***	0.780***	0.785***	0.781***	0.784***	0.782***	0.782***
	(0.0155)	(0.0153)	(0.0155)	(0.0156)	(0.0153)	(0.0153)	(0.0154)	(0.0153)
k_{it}	0.261***	0.250***	0.259***	0.259***	0.249***	0.249***	0.254***	0.246***
	(0.0132)	(0.0131)	(0.0132)	(0.0132)	(0.0131)	(0.0131)	(0.0131)	(0.0131)
$\text{Share}_{ICT,it}$	–0.126***	–0.0939***	–0.149***	–0.121***	–0.108***	–0.0898***	–0.148***	–0.109***
	(0.0288)	(0.0280)	(0.0293)	(0.0292)	(0.0288)	(0.0283)	(0.0293)	(0.0287)
Exp_{it}		0.313***			0.299***	0.312***		0.284***
		(0.0256)			(0.0258)	(0.0256)		(0.0259)
ICTiTotImp_{it}			–0.161***		–0.0906**		–0.276***	–0.175***
			(0.0361)		(0.0357)		(0.0404)	(0.0408)
ICTiM_{it}				0.137		0.118	0.501***	0.351***
				(0.0934)		(0.0891)	(0.104)	(0.102)
Constant	7.499***	7.494***	7.562***	7.507***	7.529***	7.501***	7.637***	7.583***
	(0.182)	(0.187)	(0.182)	(0.182)	(0.187)	(0.187)	(0.182)	(0.187)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.932	0.935	0.932	0.932	0.935	0.935	0.933	0.935
N	3,888	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.3: Regression results, gross operating surplus, Shannon entropy index, pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l_{it}	0.462***	0.461***	0.456***	0.465***	0.459***	0.464***	0.458***	0.461***
	(0.0367)	(0.0366)	(0.0368)	(0.0368)	(0.0367)	(0.0367)	(0.0369)	(0.0367)
k_{it}	0.531***	0.512***	0.529***	0.528***	0.511***	0.510***	0.520***	0.506***
	(0.0315)	(0.0315)	(0.0315)	(0.0316)	(0.0315)	(0.0315)	(0.0317)	(0.0316)
$\text{Shannon}_{ICT,it}$	0.129***	0.106***	0.145***	0.123***	0.113***	0.100***	0.145***	0.114***
	(0.0291)	(0.0287)	(0.0300)	(0.0295)	(0.0297)	(0.0290)	(0.0300)	(0.0297)
Exp_{it}		0.540***			0.527***	0.538***		0.499***
		(0.0643)			(0.0653)	(0.0643)		(0.0657)
ICTiTotImp_{it}			–0.215***		–0.0866		–0.419***	–0.237**
			(0.0825)		(0.0824)		(0.0917)	(0.0928)
ICTiM_{it}				0.339		0.309	0.886***	0.620***
				(0.206)		(0.201)	(0.227)	(0.227)
Constant	2.458***	2.502***	2.515***	2.489***	2.524***	2.530***	2.650***	2.618***
	(0.497)	(0.510)	(0.497)	(0.498)	(0.510)	(0.511)	(0.499)	(0.511)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.676	0.682	0.676	0.676	0.682	0.682	0.678	0.683
N	3,888	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.4: Regression results, gross operating surplus, share of imported ICT from main sourcing country, pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l_{it}	0.467***	0.466***	0.463***	0.470***	0.464***	0.468***	0.465***	0.466***
	(0.0367)	(0.0365)	(0.0368)	(0.0367)	(0.0366)	(0.0366)	(0.0368)	(0.0366)
k_{it}	0.531***	0.512***	0.529***	0.528***	0.511***	0.509***	0.520***	0.506***
	(0.0315)	(0.0315)	(0.0315)	(0.0316)	(0.0315)	(0.0315)	(0.0317)	(0.0316)
$\text{Share}_{ICT,it}$	–0.284***	–0.228***	–0.312***	–0.271***	–0.238***	–0.216***	–0.309***	–0.240***
	(0.0731)	(0.0721)	(0.0747)	(0.0739)	(0.0740)	(0.0728)	(0.0746)	(0.0739)
Exp_{it}		0.543***			0.533***	0.541***		0.506***
		(0.0644)			(0.0653)	(0.0644)		(0.0656)
ICTiTotImp_{it}			–0.191**		–0.0664		–0.395***	–0.214**
			(0.0818)		(0.0816)		(0.0911)	(0.0921)
ICTiM_{it}				0.362*		0.329	0.883***	0.614***
				(0.205)		(0.200)	(0.227)	(0.226)
Constant	2.721***	2.711***	2.796***	2.742***	2.737***	2.731***	2.927***	2.832***
	(0.506)	(0.518)	(0.507)	(0.506)	(0.519)	(0.518)	(0.508)	(0.519)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.675	0.682	0.676	0.676	0.682	0.682	0.677	0.682
N	3,888	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.5: Regression results, by years, pooled OLS

	y_{it} = value added				y_{it} = gross operating surplus			
	2010		2014		2010		2014	
l_{it}	0.730***	0.731***	0.809***	0.812***	0.411***	0.501***	0.494***	0.415***
	(0.0249)	(0.0250)	(0.0192)	(0.0191)	(0.0556)	(0.0490)	(0.0491)	(0.0555)
k_{it}	0.285***	0.286***	0.225***	0.224***	0.546***	0.480***	0.481***	0.547***
	(0.0217)	(0.0217)	(0.0162)	(0.0162)	(0.0479)	(0.0422)	(0.0422)	(0.0479)
$\text{Shannon}_{ICT,it}$	0.0497***		0.0507***		0.105**		0.124***	
	(0.0172)		(0.0155)		(0.0429)		(0.0412)	
$\text{Share}_{ICT,it}$		–0.106**		–0.112***		–0.263**		–0.220**
		(0.0429)		(0.0386)		(0.104)		(0.104)
Exp_{it}	0.245***	0.248***	0.318***	0.320***	0.380***	0.611***	0.603***	0.387***
	(0.0382)	(0.0382)	(0.0352)	(0.0352)	(0.0931)	(0.0929)	(0.0930)	(0.0931)
ICTiTotImp_{it}	–0.179***	–0.170***	–0.172***	–0.163***	–0.276**	–0.175	–0.200	–0.255*
	(0.0630)	(0.0625)	(0.0535)	(0.0531)	(0.133)	(0.128)	(0.129)	(0.132)
ICTiM_{it}	0.218	0.217	0.415***	0.411***	0.447	0.712**	0.723**	0.445
	(0.156)	(0.156)	(0.126)	(0.126)	(0.324)	(0.305)	(0.306)	(0.323)
Constant	8.186***	8.266***	8.085***	8.197***	4.389***	3.865***	3.608***	4.554***
	(0.323)	(0.326)	(0.235)	(0.240)	(0.699)	(0.683)	(0.668)	(0.706)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	1,745	1,745	2,143	2,143	1,745	2,143	2,143	1,745
R-squared	0.933	0.933	0.939	0.939	0.701	0.673	0.673	0.701

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.6: Regression results, by ICT intensity of industries, pooled OLS

	y_{it} = value added				y_{it} = gross operating surplus			
	high-tech industries		low-tech industries		high-tech industries		low-tech industries	
l_{it}	0.826***	0.824***	0.680***	0.679***	0.826***	0.824***	0.680***	0.679***
	(0.0184)	(0.0185)	(0.0262)	(0.0262)	(0.0184)	(0.0185)	(0.0262)	(0.0262)
k_{it}	0.203***	0.203***	0.348***	0.348***	0.203***	0.203***	0.348***	0.348***
	(0.0157)	(0.0157)	(0.0227)	(0.0227)	(0.0157)	(0.0157)	(0.0227)	(0.0227)
$\text{Shannon}_{ICT,it}$		0.0547***		0.0222		0.0547***		0.0222
		(0.0126)		(0.0279)		(0.0126)		(0.0279)
$\text{Share}_{ICT,it}$	–0.122***		–0.0399		–0.122***		–0.0399	
	(0.0318)		(0.0651)		(0.0318)		(0.0651)	
VARIABLES	ICTHigh	ICTHigh	ICTLow	ICTLow	ICTHigh	ICTHigh	ICTLow	ICTLow
Exp_{it}	0.318***	0.314***	0.224***	0.223***	0.318***	0.314***	0.224***	0.223***
	(0.0315)	(0.0315)	(0.0445)	(0.0446)	(0.0315)	(0.0315)	(0.0445)	(0.0446)
ICTiTotImp_{it}	–0.162***	–0.173***	–0.295**	–0.295**	–0.162***	–0.173***	–0.295**	–0.295**
	(0.0430)	(0.0435)	(0.121)	(0.120)	(0.0430)	(0.0435)	(0.121)	(0.120)
ICTiM_{it}	0.335***	0.341***	1.092***	1.071***	0.335***	0.341***	1.092***	1.071***
	(0.103)	(0.104)	(0.359)	(0.360)	(0.103)	(0.104)	(0.359)	(0.360)
Constant	8.308***	8.198***	6.536***	6.500***	8.308***	8.198***	6.536***	6.500***
	(0.213)	(0.210)	(0.320)	(0.311)	(0.213)	(0.210)	(0.320)	(0.311)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	2,709	2,709	1,179	1,179	2,709	2,709	1,179	1,179
R-squared	0.935	0.935	0.934	0.934	0.935	0.935	0.934	0.934

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.7: Regression results, imports from Netherlands ignored or added to Chinese imports, pooled OLS

	y_{it} = ln(value added)				y_{it} = ln(gross operating surplus)			
	NL to CN		no NL		NL to CN		no NL	
l_{it}	0.780***	0.782***	0.783***	0.785***	0.460***	0.466***	0.460***	0.466***
	(0.0153)	(0.0152)	(0.0154)	(0.0154)	(0.0367)	(0.0366)	(0.0372)	(0.0372)
k_{it}	0.246***	0.246***	0.243***	0.243***	0.506***	0.506***	0.501***	0.501***
	(0.0131)	(0.0131)	(0.0132)	(0.0132)	(0.0316)	(0.0316)	(0.0320)	(0.0320)
$\text{Shannon}_{ICT,it}$	0.0530***		0.0483***		0.120***		0.122***	
	(0.0117)		(0.0116)		(0.0300)		(0.0299)	
$\text{Share}_{ICT,it}$		–0.113***		–0.102***		–0.249***		–0.261***
		(0.0289)		(0.0288)		(0.0743)		(0.0741)
Exp_{it}	0.280***	0.283***	0.285***	0.288***	0.498***	0.505***	0.503***	0.509***
	(0.0259)	(0.0259)	(0.0262)	(0.0262)	(0.0657)	(0.0657)	(0.0662)	(0.0662)
ICTiTotImp_{it}	–0.185***	–0.176***	–0.178***	–0.169***	–0.238**	–0.216**	–0.242***	–0.220**
	(0.0411)	(0.0408)	(0.0407)	(0.0404)	(0.0928)	(0.0921)	(0.0916)	(0.0909)
ICTiM_{it}	0.357***	0.353***	0.352***	0.350***	0.628***	0.620***	0.622***	0.617***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.227)	(0.226)	(0.228)	(0.228)
Constant	7.486***	7.587***	8.077***	8.166***	2.621***	2.843***	3.754***	3.983***
	(0.184)	(0.187)	(0.187)	(0.190)	(0.510)	(0.519)	(0.479)	(0.487)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	3,888	3,888	3,814	3,814	3,888	3,888	3,814	3,814
R-squared	0.935	0.935	0.936	0.936	0.683	0.683	0.684	0.683

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.8: Regression results, SME versus large firms, pooled OLS

	y_{it} = ln(value added)				y_{it} = ln(gross operating surplus)			
	SME		large firms		SME		large firms	
l_{it}	0.766***	0.768***	0.748***	0.753***	0.410***	0.415***	0.374***	0.385***
	(0.0212)	(0.0212)	(0.0252)	(0.0251)	(0.0519)	(0.0518)	(0.0639)	(0.0641)
k_{it}	0.236***	0.236***	0.263***	0.262***	0.451***	0.451***	0.584***	0.583***
	(0.0169)	(0.0169)	(0.0201)	(0.0201)	(0.0405)	(0.0405)	(0.0494)	(0.0495)
$\text{Shannon}_{ICT,it}$	0.0590***		0.0491***		0.129***		0.0965**	
	(0.0174)		(0.0154)		(0.0434)		(0.0413)	
$\text{Share}_{ICT,it}$		–0.132***		–0.0983**		–0.285***		–0.179*
		(0.0425)		(0.0386)		(0.106)		(0.104)
Exp_{it}	0.316***	0.318***	0.214***	0.220***	0.552***	0.555***	0.408***	0.421***
	(0.0348)	(0.0348)	(0.0381)	(0.0380)	(0.0849)	(0.0849)	(0.104)	(0.104)
ICTiTotImp_{it}	–0.164***	–0.155***	–0.222*	–0.204*	–0.234**	–0.215**	–0.193	–0.154
	(0.0442)	(0.0438)	(0.121)	(0.120)	(0.102)	(0.101)	(0.255)	(0.254)
ICTiM_{it}	0.216*	0.214*	0.615***	0.605***	0.434	0.428	0.897*	0.878*
	(0.115)	(0.114)	(0.222)	(0.223)	(0.271)	(0.270)	(0.460)	(0.462)
Constant	8.224***	8.338***	8.342***	8.422***	4.752***	4.998***	3.356***	3.499***
	(0.268)	(0.273)	(0.268)	(0.270)	(0.633)	(0.647)	(0.654)	(0.666)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	2,205	2,205	1,683	1,683	2,205	2,205	1,683	1,683
R-squared	0.778	0.778	0.879	0.879	0.368	0.367	0.510	0.509

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.9: Regression results, small firms versus medium-sized firms, pooled OLS

	y_{it} = ln(value added) small firms		medium-sized firms		y_{it} = ln(gross operating surplus) small firms		medium-sized firms	
l_{it}	0.766***	0.775***	0.724***	0.726***	0.431**	0.448**	0.301***	0.306***
	(0.0913)	(0.0914)	(0.0267)	(0.0267)	(0.203)	(0.203)	(0.0670)	(0.0668)
k_{it}	0.163***	0.163***	0.252***	0.252***	0.294***	0.296***	0.486***	0.486***
	(0.0380)	(0.0380)	(0.0186)	(0.0186)	(0.0984)	(0.0982)	(0.0445)	(0.0445)
$\text{Shannon}_{ICT,it}$	0.0846**		0.0583***		0.166*		0.125**	
	(0.0392)		(0.0197)		(0.0917)		(0.0495)	
$\text{Share}_{ICT,it}$		–0.198**		–0.132***		–0.373		–0.284**
		(0.0990)		(0.0476)		(0.231)		(0.120)
Exp_{it}	0.428***	0.430***	0.285***	0.286***	0.666***	0.669***	0.517***	0.519***
	(0.0823)	(0.0820)	(0.0388)	(0.0388)	(0.190)	(0.190)	(0.0956)	(0.0957)
ICTiTotImp_{it}	–0.126	–0.115	–0.172***	–0.163***	–0.215	–0.190	–0.201	–0.183
	(0.0805)	(0.0805)	(0.0547)	(0.0540)	(0.175)	(0.175)	(0.131)	(0.129)
ICTiM_{it}	0.149	0.146	0.268**	0.264*	0.298	0.287	0.490	0.483
	(0.217)	(0.217)	(0.136)	(0.135)	(0.454)	(0.453)	(0.335)	(0.333)
Constant	9.325***	9.896***	7.656***	7.772***	6.325***	7.044***	3.620***	3.869***
	(0.642)	(0.681)	(0.285)	(0.291)	(1.690)	(1.785)	(0.730)	(0.747)
dummy var.	yes	yes	yes	yes	yes	yes	yes	yes
N	467	467	1,738	1,738	467	467	1,738	1,738
R-squared	0.433	0.433	0.669	0.668	0.219	0.218	0.265	0.265

Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A.10: ICT goods categories and composition (HS 2007)

Code	***Label***
ICT01	**Computers and peripheral equipment**
844331	Machines which perform two/more of the functions of printing, copying/facsimile transmission, capable of connecting to an automatic data processing machine/to a network
844332	Other printers, copying machines & facsimile machines, whether/not combined , exclud the ones which perform two/more of the functions of printing, copying/facsimile transmission; capable of connecting to an automatic data processing machine/to a network
847050	Cash registers
847130	- Portable automatic data processing machines, weighing not more than 10 kg, consisting of a least a central processing unit, a keyboard & a display
847141	Other automatic data processing machines : Comprising in the same housing at least a central processing unit & an input & output unit, whether/not combined
847149	Other automatic data processing machines , presented in the form of systems.
847150	Processing units other than those of sub-heading 8471.41/8471.49, whether/not containing in the same housing one/two of the following types of unit : storage units, input units, output units
847160	Input/output units, whether/not containing storage units in the same housing
847170	Storage units
847180	Other units of automatic data processing machines, exclud. 8471.50, 8471.60, 8471.70.
847190	Magnetic/optical readers, machines for transcribing data onto data media in coded form & machines for processing such data, n.e.s.
847290	Other office machines (eg. hectograph/stencil duplicating machines, addressing machines, automatic banknote dispensers, coin-sorting machines, coin-counting/wrapping machines, pencil-sharpening machines, perforating/stapling machines), exclud. 8472.10 & 8
847330	Parts & accessories of the machines of heading 84.71
847350	Parts & accessories equally suitable for use with machines of two/more of the headings 84.69 to 84.72
852841	Cathode-ray tube monitors , of a kind solely/principally used in an automatic data processing system of heading 84.71
852851	Other monitors, of a kind solely/principally used in an automatic data processing system of heading 84.71
852861	Projectors, Of a kind solely/principally used in an automatic data processing system of heading 84.71
ICT02	**Communication equipment**
851711	Line telephone sets with cordless handsets
851712	Telephones for cellular networks/for other wireless networks, other than Line telephone sets with cordless handsets

851718	Other telephone sets, incl. telephones for cellular networks/for other wireless networks, other than 8517.11 & 8517.12
851761	Base stations for transmission/reception of voice, images/other data, incl. apparatus for communication in a wired/wireless network (such as a local/wide area network)
851762	Machines for the reception, conversion & transmission/regeneration of voice, images/other data, incl. switching & routing apparatus
851769	Other apparatus for transmission/reception of voice, images/other data, incl. apparatus for communication in a wired/wireless network (such as a local/wide area network) , other than 8517.61 & 8517.62
851770	Parts of telephone sets, incl. telephones for cellular networks/for other wireless networks; other apparatus for the transmission/reception of voice, images/other data, incl. apparatus for communication in a wired/wireless network
852550	Transmission apparatus for radio-broadcasting/television
852560	Transmission apparatus for radio-broadcasting/television incorporating reception apparatus
853110	Burglar/fire alarms & similar apparatus
ICT03	**Consumer electronic equipment**
851810	Microphones & stands therefor
851821	Single loudspeakers, mounted in their enclosures
851822	Multiple loudspeakers, mounted in the same enclosure
851829	Loudspeakers n.e.s. in 85.18, whether/not mounted in their enclosures
851830	Headphones & earphones, whether/not combined with a microphone, & sets consisting of a microphone & one/more loudspeakers
851840	Audio-frequency electric amplifiers
851850	Electric sound amplifier sets
851890	Parts of the apparatus & equip. of 85.18
851920	Apparatus operated by coins, banknotes, bank cards, tokens/by other means of payment
851930	Turntables (record-decks)
851950	Telephone answering machines
851981	Other sound recording/reproducing apparatus, using magnetic, optical/semiconductor media, other than 8519.20, 8519.30, 8519.50
851989	Other sound recording/reproducing apparatus, other n.e.s. in Ch. 85.19
852110	Video recording/repr. apparatus, whether/not incorporating a video tuner, magnetic tape-type
852190	Video recording/repr. apparatus other than magnetic tape-type, whether/not incorporating a video tuner
852210	Pick-up cartridges for use solely/principally with the apparatus of 85.19-85.21
852290	Parts (excl. pick-up cartridges) & accessories suit. for use solely/principally with the apparatus of 85.19-85.21
852580	Television cameras, digital cameras & video camera recorders
852712	Pocket-size radio cassette-players
852713	Radio-broadcast receivers capable of operating without an external source of power, combined with sound recording/repr. apparatus (excl. of 8527.12)
852719	Radio-broadcast receivers capable of operating without an external source of power (excl. of 8527.12 & 8527.13)
852721	Radio-broadcast receivers not capable of operating without an external source of power, of a kind used in motor vehicles...combined with sound recording/reproducing apparatus
852729	Radio-broadcast receivers not capable of operating without an external source of power,of a kind used in motor vehicles, incl. apparatus capable of receiving also radio-telephony/radio-telegraphy, other(excl.of 8527.21)
852791	Other reception apparatus for radio-broadcasting, combined with sound recording/reproducing apparatus.
852792	Other reception apparatus for radio-broadcasting, not combined with sound recording/reproducing apparatus but combined with a clock.
852799	Other reception apparatus for radio-broadcasting, excl. 8527.91 & 8527.92
852849	Other cathode-ray tube monitors , not of a kind solely/principally used in an automatic data processing system of heading 84.71
852859	Other monitors, not of a kind solely/principally used in an automatic data processing system of heading 84.71
852869	Projectors, not of a kind solely/principally used in an automatic data processing system of heading 84.71
852871	Reception apparatus for television, Not designed to incorporate a video display/screen
852872	Other colour reception apparatus for television, whether/not incorporating radio-broadcast receivers/sound/video recording/reproducing apparatus,
852873	Other reception apparatus for television, whether/not incorporating radio-broadcast receivers/sound/video recording/reproducing apparatus, black & white/other monochrome.
950410	Video games of a kind used with a television receiver
ICT04	**Electronic components**
852321	Magnetic media for the recording of sound/of other phenomena, but excl. products of Ch. 37., cards incorporating a magnetic stripe
852352	Semi-conductor media, "Smart cards" for the recording of sound/of other phenomena, but excl. products of Ch. 37.

853400	Printed circuits
854011	Cathode-ray television picture tubes, incl. video monitor cathode-ray tubes, colour
854012	Cathode-ray television picture tubes, incl. video monitor cathode-ray tubes, black & white/other monochrome
854020	Television camera tubes; image converters & intensifiers; other photo-cathode tubes
854040	Data/graphic display tubes, colour, with a phosphor dot screen pitch smaller than 0.4mm
854050	Data/graphic display tubes, black & white/other monochrome
854060	Cathode-ray tubes n.e.s. in 85.40
854071	Magnetrons
854072	Klystrons
854079	Microwave tubes n.e.s. in 85.40
854081	Receiver/amplifier valves & tubes
854089	Valves & tubes n.e.s. in 85.40
854091	Parts of cathode-ray tubes
854099	Parts of the tubes of 85.40 other than cathode-ray tubes
854110	Diodes (excl. photosensitive/light emitting diodes)
854121	Transistors (excl. photosensitive transistors), with a dissipation rate of <1W
854129	Transistors (excl. photosensitive transistors), other than those with a dissipation rate of <1W
854130	Thyristors, diacs & triacs (excl. photosensitive devices)
854140	Photosensitive semiconductor devices, incl. photovoltaic cells whether/not assembled in modules/made up into panels; light emitting diodes
854150	Semiconductor devices n.e.s. in 85.41
854160	Mounted piezo-electric crystals
854190	Parts of the devices of 85.41
854231	Electronic integrated circuits, processors & controllers, whether/not combined with memories, converters, logic circuits, amplifiers, clock & timing circuits,/other circuits
854232	Electronic integrated circuits, memories
854233	Electronic integrated circuits, amplifiers
854239	Other Electronic integrated circuits, other than Amplifiers/Memories/Processors & controllers
854290	Parts of electronic integrated circuits
ICT05	**Miscellaneous**
852351	Semi-conductor media, solid-state non-volatile storage devices, for the recording of sound/of other phenomena, but excl. products of Ch. 37.
852359	Other semi-conductor media, for the recording of sound/of other phenomena, but excl. products of Ch. 37., other than "Smart Cards" & Solid-state non-volatile storage devices
852380	Discs, tapes, solid-state non-volatile storage devices, "smart cards" & other media for the recording of sound/of other phenomena, whether/not recorded, incl. matrices & masters for the production of discs, but excl. products of Ch.37., other n.e.s.
852910	Aerials & aerial reflectors of all kinds suit. for use solely/principally with the apparatus of 85.25-85.28; parts suit. for use therewith
852990	Other parts suitable for use solely/principally with the apparatus of headings 85.25 to 85.28., other than aerials & aerial reflectors of all kinds
901320	Lasers (excl. laser diodes)

Source: OECD (2011) and https://unctadstat.unctad.org/EN/Classifications.html.