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How the three Ds affect firm pricing, markups and productivity

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Editorial

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Digitalization and international competitiveness: A cross-country exploration of the relation between firm-level ICT use, productivity and export*

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Abstract: We study the relationship between ICT, total factor productivity and export at the firm level in Belgium, France and the Netherlands. In particular, we look at whether ICT has both a direct effect on export and an indirect effect via productivity improvements. We allow for endogeneity, unobserved heterogeneity, dynamic feedback, initial conditions and correlations between the time-invariant random effects and between the idiosyncratic random effects. We find similarities but also differences in the effects of ICT on export between the three countries.

JEL classification: C23, D24, F14, O30
Keywords: ICT, productivity, export, firm data, panel data, international comparison

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1 Introduction

The adoption and use of information and communication technologies (ICT, henceforth) is widely considered as a major driving force behind competitiveness and economic growth (Romer (1991); Jorgenson, Ho, and Stiroh (2008)). The ICT advance is different from general technological progress and has triggered a new round of upgrading, not only of products but also of production processes and the organization of production. Indeed, current research suggests that increased investment in ICT, especially in the so-called Fourth Industrial Revolution technologies (AI, robotics) and the organizational impact associated with ICT, enable firms to improve their productivity through innovation and efficiency gains (Brynjolfsson, Rock, and Syverson (2021); Atkin, Khandelwal, and Osman (2017)). Moreover, this productivity gain may induce firms to export or to increase their sales abroad (Bernard and Jensen, 1999). In addition, since ICT reduces costs and trade barriers, recent but scarce studies have also looked into the impact of ICT on exports (e.g., Fernandes et al. (2019), Kneller and Timmis (2016); Añón Higón and Bonvin (2024); Higón and Bournakis (2024) and Añón Higón and Bonvin (2022)).

This paper aims to deepen our understanding of the effect of ICT on firms' exports and of the role that total factor productivity (TFP) growth plays in shaping firms' international operating environment. Research into drivers of ICT, TFP and export at the firm-level is important because that is where the decisions about technology adoption and trade are made, and where the effects of globalization and technological change play out (Harrigan, Reshef, and Farid (2023)). What makes a firm trade more? Which firm-specific characteristics influence the decision to adopt ICT? Is selection at work? And can it be explained by a self-selection mechanism whereby the most productive firms export? Or can it be explained by ICT? To what extent can productivity gains be explained by ICT? Are there any variations between industries? Do we observe cross-country differences? These are the main questions that we address.

Theoretically, there are several channels through which ICT might positively affect export (allowing for possible dynamics). Our empirical framework allows us to firstly disentangle two mechanisms: (A) ICT$\rightarrow$TFP $\rightarrow$export, (B) ICT$\rightarrow$export. Mechanism A characterize the endogenous productivity setting of firms due to ICT adoption, while mechanism B characterizes all other mechanisms that explain the link between ICT adoption and exports which are not related to TFP. The interest of our analytical framework is that we identify each of these mechanisms conditionally to the others. Second, we add an ICT adoption equation to the framework to overcome potential selection problems. Third, by comparing three countries, Belgium, France and the Netherlands, we explicitly take into account the institutional and contextual framework in our analysis. For instance, country-specific channels by which ICT translate into export and productivity can related to the specific modes of ICT applications, availability of human capital and the structure of the economy itself (Hagsten and Kotnik (2017)).

Focusing on the direct and the indirect impact of ICT on export through TFP, we draw on empirical studies from three strands of literature. First, we contribute to the literature on the role of ICT in explaining productivity (e.g., Draca Mirko (2007); Acemoglu et al. (2014); Li et al., 2022). Second, we add to the existing literature that relates to productivity and trade (Melitz (2003); De Loecker (2013)). Third, we add to the scarce literature that looks at evidence on the role of ICT and digitalization for trade ((e.g., Kneller and Timmis (2016); Añón Higón and Bonvin (2024); and Añón Higón and Bonvin (2022)). Generally, it has been postulated that trade flows are driven primarily by the utilization of technological innovations including ICT, through creating competitive advantages and through costs advantages when entering foreign markets. Firm-level studies are scarce but confirm the theoretical prediction that ICT related innovation is positively correlated with exports. By bringing these strands together, this paper aims to deepen our understanding of the complex relationship between digitalization, productivity and trade. In contrast to previous studies, we propose that ICT endogenously affects TFP and export in a simultaneous process.

The discussion above clearly demonstrates that detecting the causal effect of ICT on export is not straightforward. Indeed, firms with high productivity are likely to self-select into export markets making it difficult to disentangle treatment effects of ICT from self-selection. The empirical literature suggests several approaches to deal with this endogeneity problem (see for instance, Aghion et al. (2022)). However, to accommodate the endogeneity, our empirical strategy differs from those generally observed in the literature. More specifically, our model consists of a three-equation nonlinear dynamic simultaneous model that includes individual effects and idiosyncratic errors correlated across equations. We use a full information maximum likelihood estimator for the model. The novelty of the approach is that we handle multiple integration due to the correlations of individual effects and idiosyncratic errors across equations using simulated maximum likelihood. We use total factor productivity – TFP – and the method for productivity measurement based on the production approach, and will take into account price biases, markups and the usual endogeneity problems between inputs and outputs (see e.g., Dobbelaere, Fuss, and Vancauteren (2023), for a recent discussion).

Using highly comparable data drawn from Business registers, VAT declarations, Trade databases and ICT Innovation Surveys, we are then able to estimate our model for three countries with a strong international focus and engagement in ICT activities. Several novel findings emerge. First, we find that ICT increases export (both at the intensive and extensive margin) everywhere, but the transmission mechanism differs across the three countries. In Belgium and in the Netherlands it is to a large extent due to ICT-driven improved productivity whereas in France, although there also exists the indirect effect, ICT affects exporting mainly through other unidentified channels. Second, when we replace TFP by markups in the system equation, we find that the indirect effect of ICT on export is not significant. Hence, the ICT-TFP-export mechanism does not reflect any changes in prices (or quality upgrading) but is due to an actual productivity effect. Third, we obtain results that may be indicative of heterogeneous effects among specific ICT technologies. Fourth, we show that human skills are an important determinant affecting ICT, TFP and export jointly, thereby confirming the importance of key workers within innovative and trade-oriented firms. Fifth, ICT use is negatively correlated to past TFP in Belgium, positively in France and not significantly in the Netherlands. This suggests different dynamic effects across the three countries. Sixth, the correlations between random effects are generally insignificant while the correlations of the idiosyncratic effects are significant suggesting that the simultaneous process of ICT, export and TFP is important.

The remaining sections of the paper are organized as follows. Section 2 reviews the literature that addresses the impact of ICT on productivity, productivity on export and ICT on exporting and provide some background information on the use of digital related technologies in Belgium, France and the Netherlands. In Section 3, we presents the firm panel data for the three countries. Section 4 outlines the empirical framework and the estimation method, while Section 5 presents the results. Finally, Section 6 concludes.

2 Background

2.1 Digitalization and export: direct and indirect relationship

Our research weaves together various lines of research, focusing on specific two-way relations in the ICT-export-productivity triangle. We discuss the relevant literature below, noting that this is necessarily an incomplete overview given the sheer volume of academic work on these topics.

A. From ICT to productivity

A potential indirect effect of ICT on export behavior hinges on an effect of ICT on the firm's productivity. Although the early absence of a contribution of ICT to productivity in the statistics (famously alluded to by Solow) seemed to have been resolved and replaced by a widely held believe that ICT increases productivity, the current combination of historically low productivity growth with a new wave of new technology such as AI, cloud and robotics seems to have revived the debate about the 'productivity paradox'.

As noted by Syverson (2011), country- and industry-level studies have documented that IT-related productivity gains played an important role in explaining aggregate U.S. productivity growth up to the early 2000s (Jorgenson, Ho, and Stiroh (2008)), and the comparably sluggish productivity growth over the same period in European economies (Timmer et al. (2011)). At the firm-level the evidence is more mixed, see Draca Mirko (2007), and Biagi and Falk (2017) for takes on the literature. Brynjolfsson and Hitt (2000) point out that ICT positively affects firm performance, but that the business value generated by ICT is largely determined by complementary organizational changes in business processes and work practices through reduction of communication costs and improved monitoring. Brynjolfsson et al. (2007) argue that ICT has enabled firms to replicate and scale up successful business process, increasing productivity and market share for 'winners' but also the variance between winners and losers in the same market. The relation between productivity dispersion and ICT has also been highlighted in other research, see e.g. Dunne et al. (2004) for the U.S.; Polder, Bondt, and Leeuwen (2018) for the Netherlands; and Dhyne et al. (2018) for Belgium.

Bloom, Sadun, and Van Reenen (2012) found evidence that US multinationals in Europe owe their productivity lead to better use of IT. For the Netherlands, Borowiecki et al. (2021) show that productivity benefits from ICT hardware investment and the uptake of high-speed broadband are positive and sizeable. Intangibles such as software and digital skills also have a positive and statistically significant impact on firm-level productivity growth, although there is variation in the impact by sector, age and initial productivity level.

Recently, however, Acemoglu et al. (2014) show that there is reason to be skeptical about the early growth accounting evidence, noting that for the US manufacturing sector the evidence for faster productivity growth in more IT-intensive industries is in fact somewhat mixed, and strikingly that a more rapid growth of labor productivity in IT-intensive industries is associated with both output and employment declining. Moreover, at first sight, it seems to be difficult to maintain the idea that ICT and digitalization increase productivity, given its ubiquitous presence in all facets of business and society together with sluggish productivity growth in most developed economies. However, a characteristic of a new General Purpose Technologies (GPTs, such as steam power, electricity, and earlier advances in ICT) is that there is a time lag before the productivity benefits materialize, because it takes time to diffuse and be absorbed (Ark, Vries, and

Erumban (2020), as well as to invest in complementary intangible assets and spawn further innovation (Brynjolfsson, Rock, and Syverson (2021)). Dhyne et al. (2018) find that the returns to ICT investment are much lower in the post financial crisis period due to under-investment and misallocation of IT, suggesting that this has contributed to the aggregate productivity slowdown. Nevertheless, an infant literature on firm-level use of AI has started to reveal positive associations between AI and productivity (Czarnitzki, Fernández, and Rammer (2023)).

A separate line of literature recently explores the relation between productivity and automation or robotization; e.g. Koch, Manuylov, and Smolka (2021) find a positive effect of robotization on productivity. In general, information about which type of ICT applications are used appears to be more relevant for determining the relationship with business performance than information about investments in ICT resources alone, where no distinction can be made between, for example, more and less advanced applications (Biagi and Falk (2017);Gal et al. (2019).

We contribute to this literature by revisiting the endogenous relation between ICT usage and productivity, considering a measure of the intensity of ICT usage and adoption, including more novel aspects such as AI, cloud, and robotics. This enables us to highlight whether the use of new technologies increases the competitiveness of firms through improvements of their productivity, leading potentially to improved possibilities to engage in international markets.

B. From productivity to export

The second requirement for an indirect effect of ICT on export via productivity, is a significant impact of productivity on export. Since the seminal work of Bernard, Jensen, and Lawrence (1995), a burgeoning literature developed that establishes the positive link at the firm-level, both empirically and theoretically. With firm-level data revealing substantial and persistent heterogeneity in productivity (Syverson (2011); Bartelsman and Doms (2000)), these productivity differences are also systematically linked to exporting (Melitz and Redding (2014)). A stylized fact from the empirical literature is that exporters are on average more productive than non-exporters, even after controlling for additional firm characteristics such as size and industry (Bernard et al. (2003); Bernard and Jensen (2004)). While high-productivity firms may self-select into exporting, exporting also has the potential to have a positive feedback effect on productivity, for example because of learning from foreign market customers and suppliers, or a large scale of production that increases the returns to innovation. There is empirical support for effects in both directions, which we also explore in our empirical specification. We discuss the related existing evidence in turn.[1]

Firstly, highly productive firms may self-select into exporting. An often cited paper is Melitz (2003) that presents a theoretical model in which firms incur a fixed costs when they become an exporter. This fixed costs implies a threshold above which exporting becomes viable, and this threshold is easier met by firms that are more productive. Cost of exporting (Wagner (2007)) surveys the literature, and concludes that there is substantial evidence for this self-selection hypothesis (i.e. exporting firms are more productive ex ante), while the learning-by-exporting hypothesis has only weak support.

This conclusion however should be interpreted in light of the subsequent literature taking into account the endogeneity of the export decision for the productivity process. More recently, there has been a new interest in testing the learning-by-exporting hypothesis (e.g. De Loecker (2013)). That is, exports may increase productivity through a learning effect associated with the engaging in selling abroad. This so-called learning-by-exporting (LBE) effect may arise for example due to engaging with foreign customers or competitors. De Loecker (2013) argues that the weak evidence for this meachanism could be due to that common productivity measures do not take into account the (endogenous) export effect. With an alternative approach that endogenizes export status in the production function estimation, he finds that Slovenian firms become more productive by exporting, taking into account that these companies may already have been more productive before they crossed the border. These results are corroborated by Manjón et al. (2013) and Camino-Mogro, Bermúdez-Barrezueta, and Armijos (2023), for Spain and Ecuador respectively.

Silva, Afonso, and Africano (2012) note an alternative reason why the LBE hypothesis might lack broad empirical support, namely that studies have frequently overlooked that the learning effects actually often runs through innovation, with firms implementing innovations which raise productivity. As pointed out in De Loecker and Goldberg (2014) this links the LBE literature to papers which explicitly model export and innovation behavior in the productivity process. The basic intuition is that exporting increases the scale of production. Consequently, the returns to investment in productivity improvements also increase. Various studies have found evidence for the role of exporting for innovation and technology adoption. Lileeva and Trefler (2010) examine the response of Canadian plants to the elimination of U.S. tariffs, and find that those that were induced by the tariff cuts to start exporting or to export more increased their (labor) productivity, through higher engagement in product and/or process innovation. Bustos (2011) finds that Argentinean

[1] The literature also covers other aspects of internationalization such as importing and foreign direct investment, for which other mechanisms are at play compared to exporting.

firms increase their investments in technology due to trade liberalization stimulated engagement in export. For Taiwanese firms, Aw, Roberts, and Xu (2011) show that R&D investment and exporting have complementary effects on productivity.The mechanism of productivity increases through innovation and export, with subsequent feedback effects, motivates considering the simultaneous relation in our current research between productivity, export and digitalization (as an instance of process innovation and investing in advanced technology).

Finally, as De Loecker and Goldberg (2014) also point out, most research linking internationalization to productivity is based on revenue productivity measures, that is productivity measured by deflated output over deflated inputs. Failing to take into account price variations across firms, it is unclear whether the productivity differences reflect heterogeneity in the efficiency of the production process, or differences in profitability caused by variation in markups and market power across firms (Foster, Haltiwanger, and Syverson (2008)). The same holds when comparing the productivity of exporters and non-exporters. De Loecker and Warzynski (2012) indeed confirm that markups are higher for exporters than for non-exporters. De Loecker et al. (2016) show that a large part of productivity heterogeneity is in fact explained by demand and price variation.

C. From ICT to export

Digitalization can have both a direct and indirect effect on exports. In a direct sense, the general idea is that digitalization facilitates certain things that are necessary for trading internationally and making an international trade transaction possible. For example, a company with a website is easier to find, especially if it is multilingual. Digital developments also provide companies with new opportunities for selling and marketing their products. Implementing digitalization can help a company reduce the transaction costs of exporting (Goldfarb and Tucker (2019)). This includes, for example, finding buyers, distributors and meeting local product requirements. Increasingly better software also makes it easier to monitor and manage complex projects, including across borders (Bessen (2022)). Digital developments have also made it possible to organize production processes and supporting services across borders, which has resulted in an increase in world trade, especially in intermediate products, the outsourcing of supporting business processes and further integration of global value chains (Baldwin, 2016). Finally, more and more products are being traded using e-commerce and digital products are making up an increasing share of exports. If a company wants to participate in these developments, it will also have to be equipped for this in terms of ICT. For example, Kneller and Timmis (2016) find that the rise of broadband internet has been instrumental in the growth of trade in business services in the United Kingdom.

Not many studies have investigated empirically the relation between ICT use and exports. Exceptions are Hagsten and Kotnik (2017) and Añon-Higon and Bonvin (2022, 2023). Wagner (2024) considers the impact on export from the use of cloud computing. The papers by Añon-Higon and Bonvin are closest to our research as they also consider both the direct effect and the indirect effect through productivity, in their case based on data for Spanish manufacturing firms. Añón Higón and Bonvin (2022) look at export participation and intensity. Using the approach by De Loecker (2013), they endogenize past export experience and digitalization in the production function. Añón Higón and Bonvin (2024) focus on trade participation of SMEs (both export and import). Both papers show the importance of a direct and potential indirect effect, but the results suggests that the strength of the impact depends on whether one looks at export participation or intensity, as well as on firm size (large firms versus SMEs) and the industry-level of digitalization. In a more recent working paper Higón and Bournakis (2024) focus on GVC traders and intensity of GVC related trade, defined respectively as firm importing intermediates and exporting intermediates and/or final goods, and a vertical specialization measure based on the combined share of intermediate imports and share of total exports. Their results suggest that the digitalization-export relation is also mediated by the degree of GVC integration.

Broadly speaking, one can hypothesize that ICT usage reduces marginal costs, whereas vice versa exporting increases market size, thereby also increasing the return to ICT. This mechanism is similar to that considered in research discussed above on the triangle between innovation/R&D, exports, and productivity (e.g. Aw, Roberts, and Xu (2011)). Haller and Siedschlag (2011) find that export-intensive manufacturing firms in Ireland are more likely to adopt ICT. For a sample of Brazilian firms, Cirera et al. (2023) show that exporting has positive effects on firms' likelihood of adopting advanced technologies in various business functions associated to export activities. However, to our knowledge, there are no papers that consider a simultaneous relationship between export and digitalization.

2.2 Digitalization activities - A country comparison

To assess the institutional and policy differences between the three countries, we make use of the OECD Going Digital toolkit, which collects country information on different policy dimensions and subindicators. In the appendix, Box 17 lists the 7 policy dimensions that are distinguished. We can also list the indicators by dimension. Figure 16 shows averages across the indicators by policy dimension, and compares the values across the countries to the overall OECD average. Reported figures are based on the distance of each of the countries to the OECD country with the highest score, which is set to 100 (that is, a score of 60 means that a country scores 60% on an indicator compared to the maximum score observed across OECD countries). Then for each country the figure shows the percentage point difference with the OECD average.

Although it is not straightforward to derive any concrete predictions from these aggregate composite indicators, they are informative about the general state of play around digitalization and the business environment in countries. As such these indicators could provide indications to explain any country differences in econometric results later in the paper, and help to guide policymakers to undertake action in specific areas if needed. The Netherlands score relatively well on various indicators, especially Jobs, Market Openness, Use, Access and Society. Only on Trust the Netherlands are under par compared to their OECD peers. For Belgium, the picture is a bit mixed. In terms of the Innovation dimension, Belgium is under par compared to the OECD as a whole, and also compared to France and the Netherlands. In terms of Use and Access, however, it outperforms the average country, and in terms of Trust it scores highest among the trio in our sample. Finally, France scores highest on the Innovation dimension, but is under par concerning Jobs, Market Openness and Use.

An alternative grouping of the indicators is presented around the theme Productivity. In the Appendix Figures 17 and 18 provide the corresponding visualization for the three countries. The figures provide information about the spread across OECD countries and highlight the position of each country with respect to the OECD average. For Belgium, these indicators are in general quite close to the OECD average, the exception being a relatively low share of start-ups in the information industries. For France, most of the indicators are close to the OECD average as well, although ICT investment and labour productivity in the information industries are both relatively high. The Netherlands also show above average ICT investment, as well as a relatively high share of patents in ICT technologies, but business R&D expenditure is relatively low.

3 Data

The primary objective of our analysis is to examine the direct and indirect impact of ICT on export. While most firm-level studies are restricted to single countries, using data from Belgium, France and the Netherlands allows us to compare across countries and put the results in the context of institutional and policy differences. For each country, we construct a panel dataset of firms by merging data from different sources. To ensure that our results reflect underlying economic differences, and not differences in the underlying data and measures, we build three highly comparable micro-datasets that span the period

2014-2021 for all three countries. Firms in manufacturing (NACE 10-33) and services (NACE 45-47) are included in the analysis, given our focus on the export in goods.

3.1 Productivity

In all three countries, the unbalanced panel datasets to derive productivity (TFP) are sourced from firm annual accounts and VAT declarations. The observational unit is the enterprise, which can be thought of as the economic actor in the production process. For Belgium, the data are sourced from annual accounts collected by STATBEL and the National Bank of Belgium. For the Netherlands, the data are drawn from the Production Statistics survey together with combined sources of tax information, mainly profit tax and VAT, from compulsory reporting of firms and income statements available in the Dutch Business Register collected by Statistics Netherlands and data from Profit and VAT tax information referred to as Baseline. For France, to estimate the firm productivity, we use firm-level balance-sheet data from the DGFiP-Insee's FARE database. The database combines administrative data (obtained from the annual profit declarations that firms make to the tax authorities and from annual social data that provides information on employees) and data obtained from a sample of firms surveyed by a specific questionnaire to produce structural business statistics.

We retrieve data on sales (PQ), value added (VA), employment (N) - defined as the average number of employees in full-time equivalents over the year-, the wage bill (W), intermediate input consumption (M) and the capital stock (K) measured as the stock of fixed tangible assets. For Belgium, intermediate input consumption (M) is computed using firm data on value added and nominal sales.

To convert nominal into real values, we use two-digit industry price deflators for output, intermediate inputs and capital from the OECD STAN database for Belgium and France and from the National Accounts Statistics supplied by Statistics Netherlands for the Netherlands.

3.2 Export data

We use the French data on export from the French customs office (Direction Générale des Douanes et des Droits Indirects, DGDDI). This dataset contains for each firm all export flows, in value and quantities, by destination and by product category. For Belgium and the Netherlands, data comes also from the Customs Transaction Trade Databases that report values (and volumes) of exports at the firm-level and by product category and source/destination countries. We focus on the export in goods. For all three countries, the firm-level data contain the population of exporting firms, obtained from survey and/or customs data (in the case of the Netherlands supplemented by VAT data). All firms must report their export sales according to the following criteria: exports to each EU destination whenever within-EU exports exceeds 100,000 Euros; and exports to non-EU country whenever exports to that destination exceeds 1,000 Euros or a ton in volume. Despite these thresholds, the database is nearly comprehensive. For Dutch and French data, a breakdown by production and destination is available, but not for the Belgian data.

3.3 Data on skills

An important aspect of our paper is also to control for the role of human capital when addressing the ICT-productivity-export link. We hypothesize that firms with more human capital are associated with more innovation, as well as with technology adoption, better management, and other technology-related activities. For Belgium, the workers' skill type is sourced from the Social Balance Statistics which reports employment (number of employees in FTE) by education level, distinguishing between primary education (*Shprim*), secondary education (*Shsec*), upper non-university education and university degree. We aggregate the last two categories to construct the share of workers with upper education (*Shupuniv*).

To define the skill type of each employee in Dutch firms, we use their education type reported in the Education database which (mainly) comes from the Polis Administration, and the Labour Force Survey ("Enquete BeroepsBevolking, EBB"). The Education database provides the highest level of education attained by an individual on October 1 of the year and. For the remaining individuals, the education type comes from the EBB. The combined information covers around 70% of the Dutch population (2018). Aggregating to the firm-level, however, results in a share of workers (mainly higher-aged or migrants) for which the education level is unknown. We also aggregate the upper non-university and university degree individuals to construct the share of workers with upper education, making the conservative assumption that where the education level is missing a worker does not have upper education. The education type is based on a 2-digit SOI-code (Dutch education classification, "Standaard Onderwijsindeling") and is converted to the ISCED classification (International Standard Classification of Education).

For France, educational data on workers does not exist. Instead, we measure human capital assuming that STEM related backgrounds are associated with higher education. Harrigan, Reshef, and Farid (2023) observe from their data that around 63% of technology workers have a higher level of STEM degree. For France, we consider workers with a STEM related occupation according to the same data definition as in Harrigan, Reshef, and Farid (2023) on their classification of workers in three categories: R&D, ICT and other "techies" (based on 4-digit level occupational classification codes. The data is available from the DADS Poste, which is based on mandatory annual reports filed by all firms with employees. The DADS Poste reports for each worker their wages, hours paid, occupation, tenure, gender and age.

3.4 Data on firm-level ICT

The data on ICT is based on firm-level survey data available from the Community Survey on ICT Usage between 2014 and 2021 for each of the three countries. These surveys are harmonized across countries as part of the Eurostat statistical program. The ICT data provide rich information on digital and intangible variables including three categories: ICT infrastructure (e.g., high-speed broadband, mobile internet); intangibles including skills (computer use, ICT personnel); digital technologies (CRM/ERP, e-commerce, AI/Robots). In the surveys, adoption of different types of ICT is measured by a binary indicator Yes/No (1/0). In some cases also intensity is available, such as share in sales (e.g. e-sales) or workers (e.g. share of PC-users). The sampling frame of the ICT survey is restricted to firms with more than 10 employees, which also implies that our ultimate estimation sample where all sources are combined are subject to this lower threshold.

We construct a firm-level index of digitalization for the period 2014-2021. The use of an index is motivated by the fact that digitalization is a broad concept that covers a wide variety of technologies and applications.[2] Moreover, ICT and digital technologies are interrelated, where the impact of one technology being influenced by the use of another technology (Añón Higón and Bonvin (2024)). For instance, the adoption and efficiency of certain digital technologies may depend on the skill level and training of existing ICT personnel. Hence, ICT types are interrelated and any type of ICT construct should be assessed considering them as a whole (Calvino et al. (2018)). Finally, information about which ICT applications are used appears to be more relevant for determining the relationship with firm performance, then information about only investments in ICT resources, where no a distinction can be made, for example, between more and less advanced applications (Biagi and Falk (2017); Kneller and Timmis (2016); Fernandes et al. (2019)). In this paper, we therefore also look at several types of ICT use, each of which is used in a business process in its own way. The differences in application of these technologies can

[2]In Appendix B we address the most important technologies including on *digital infrastructure* such as ICT hardware, high-speed broadband connections, on *digital technologies* including artificial intelligence, software for Customer Relations Management and on *digital skills* including the share of ICT workforce, software specialists. It should be noted that in addition to ICT skills, we also consider a broader definition than ICT skills alone, based on level of education (BE, NL) or STEM related workers (FR).

also have an impact on the relationship with productivity and export.

We use the so-called Digital Intensity Index (DII). which is a composite indicator, derived from the annual surveys on ICT usage, which measures the use of different digital technologies at the firm-level (such as using any AI technology, having e-commerce sales, etc.) that cover the three domains: digital infrastructure, digital technologies and digital skills. The DII score (0-12) of a firm is determined by how many of the selected digital technologies over the three domains. Important to note is that the composition varies between different survey years, depending on the questions included in the survey, however comparability over time is ascertained because there is consistent coverage of itemized questions per domain included. We reduce the number of categories of the ordered DII score scale which we rescale into four categories, where Low category=1 if the DII score is between 0 and 3, Medium low=2 if the DII score lies between 4 and 6, Medium high=3 if the DII score is between 7 and 9 and High=4 if it is above 9.[3] Tables 3, 4 and 5 in the Appendix show the correlations among the different ICT measures for all three countries. The different ICT dimensions are found to be positively correlated among each other (with the exception of ICT personnel) and there does not seem to be large heterogeneity across all indicators, though these correlations seem to be very low. For practical purposes, these low correlations imply that working with composite indicators seems appropriate; in addition, low correlations also imply that using ICT types jointly in regressions is possible.

Cleaning the data. We first delete firm-year observations with labor and intermediate consumption shares in sales smaller than or equal to zero and greater than or equal to one. We also disregard firm-year observations with cost shares in the bottom 1% and top 1% of the respective industry-year distributions. The estimation sample consists of firms that are observed for at least three consecutive years because lagged inputs are needed to construct moment conditions in our estimation framework. For Belgium; the Netherlands and France, we obtain an unbalanced estimation sample consisting of 7,365; 9,125 and 37,235 observations over the years 2014-2021.

Tables 6, 7 and 8 in the Appendix report the means of our productivity and ICT related variables for the Netherlands, Belgium and France. In all three countries, real firm output, labor, capital and material measures are similar. Labor productivity calculated as the log of real value added per worker, is on average higher in the Netherlands and France compared to Belgium. However, this seems to be due to higher skewness of the productivity distribution. In the Netherlands and Belgium, the export share (($EXPsh$), defined as the exports-to-sales ratio) is higher (respectively, 29% and 32%) as compared

[3]The main problem is with too many categories in the ordered logit estimation

to 15% in France. The number of exporting firms are also higher in the Netherlands and Belgium compared to France (respectively, 85% and 76% as compared to 59% in France). This confirms the small open economy nature of the Belgian and Dutch economies, where French firms rely relatively more on the (larger) domestic market.

Turning to the ICT variables, the descriptive statistics of the ICT index across all three countries are about the same. When it comes to specific ICT activities, the number of firms engaged in e-commerce differs across countries. In particular, about firms 73.4% of Belgian firms are engaged in e-commerce activities, 45.5% in the Netherlands, whereas in France, only 13.8% of the firms are engaged in e-commerce activities. On the other hand, in Belgium and Netherlands, only 37.5% and 35.1% of the firms employ ICT specialists, while this is the case for about 62.5% of firms located in France. The percentage of firms using mobile internet is 82.3% the Netherlands, 56.6% in Belgium and only 35.8% in France.

4 Empirical Model

The main goal of this paper is to analyse the effect of ICT expansion on export and how productivity drives this relationship. For this purpose, this section present an empirical structural model where first, we add the ICT as an explanatory factor in each equation of the model, suggesting that ICT affects productivity and export differently. Second, our structural model takes into account different types of variables, continuous, binary and categorical, while considering a simultaneous equations framework in a dynamic panel data setting. More specifically, our model allows for correlation among unobserved effects and errors across equations.

4.1 Identification issues

As previously mentioned, a concern of ours is the set up of a causal mechanism to represent the process through which ICT causally affects firm productivity (Ω) and export (E). A starting point for identifying the causal mechanisms of interests is the *sequential ignorability assumption* –SIA– of Imai, Keele, and Yamamoto (2010). Let X_i be a vector of the observed pretreatment confounders for firm i. We'll come back later to the variables included in the vector X_i. Given these observed pretreatment confounders, SIA can be formally written as:

$$\{\epsilon_E, \epsilon_\Omega\} \perp\!\!\!\perp \epsilon_{ICT} | X_i = x \tag{SI.1}$$

$$\epsilon_E \perp\!\!\!\perp \epsilon_\Omega | ICT_i = ict, X_i = x \tag{SI.2}$$

where $0 < \Pr(ICT_i = ict|X_i = x) < 1$. Imai, Keele, and Yamamoto (2010) show that under SIA, the averages of the quantities of interest are identified. The main advantage of this assumption over other alternatives, (see for instance, Pearl, 2001; Robins, 2003; Petersen et al., 2006), is its ease of interpretation. SI.1 states that, given the observed confounders, the treatment assignment is independent of the potential outcome and the potential mediators. In our context, SI.1 rules out the possible existence of unmeasured confounders between ICT, productivity and export. This seems to be unrealistic, since productive firms (self-selection hypothesis, see for instance Melitz, 2003) and/or exporting firms (conscious learning by exporting, see for instance Roberts and Tybout, 1997) are more likely to start ICT. Therefore, a simultaneity bias emerges.

SI.2 states that once the observed confounders and observed ICT status are controlled for, i.e., among firms who share the same ICT status and the same characteristics, the productivity and export variable are independent of each other. However, we know that firms can anticipate the growth of their productivity and their export and their ICT-innovative efforts are driven by these future prospects. Hence, SI.2 holds only if X_i includes confounders that cause these endogeneity issues.

4.2 Model

Following this logic the basic set-up of our empirical model incorporates a system of three equations characterizing the ICT status, the level of TFP and the export status. We specify the following equations:

$$\begin{cases} ICT_{it} &= \eta_{1,t} + \beta_1' x_{1,it} + u_{1,i} + \varepsilon_{1,it} \\ \omega_{it} &= \eta_{2,t} + \gamma_1 ICT_{it} + \beta_2' x_{2,it} + u_{2,i} + \varepsilon_{2,it} \\ E_{it} &= \eta_{3,t} + \kappa_1 \omega_{it} + \gamma_2 ICT_{it} + +\beta_3' x_{3,it} + u_{3,i} + \varepsilon_{3,it} \end{cases} \tag{1}$$

where $t = 1, \ldots, T_i$, $i = 1, \ldots, N$; where ICT_{it} can be either a linear outcome or it can be considered as a categorical variable (e.g., binary, ordered logit). In the second equation ω_{it} is total factor productivity and E_{it} is defined as export measured either as a binary indicator or continuous. In Appendix A, we provide details for the measurement of ω_{it} where we apply the estimation procedure proposed by Ackerberg, Caves, and Frazer (2015) using the insight that observed input decisions depend on unobserved productivity. In the vector x, for the variables that are considered the same for all three equations, we include firms' characteristics of size measured by the number of skilled labor by firm and export in $t-1$. We also include equation-specific covariates which we further explain in 4.2.2. Equation 1 also contain industry and year effects denoted as $\eta_{1,t}$,$\eta_{2,t}$ and $\eta_{3,t}$. The identically and independently distributed errors of the equations

$\varepsilon_{1,i}, \varepsilon_{2,i}, \varepsilon_{3,i}$ are assumed to follow a joint normal distribution. We allow for contemporaneous correlations between the ε's. If these correlations are not considered, we lose in efficiency and potentially inconsistent parameter estimates (Greene (2012) due to the relationship between the different types of firm outcomes (export, ICT activities and TFP). The random variables, u's, include unobserved firm heterogeneity components, we also allow for contemporaneous correlations among these three random variables.

In this framework, there is a major issue of endogeneity of ICT in the productivity equation ($u_{1,i} \not\perp u_{2,i}$), of the productivity in the export equation ($u_{2,i} \not\perp u_{3,i}$), and of ICT in the export equation ($u_{1,i} \not\perp u_{3,i}$). The endogeneity of ICT, export and productivity can come from at least two different sources. First, there is the problem of joint correlation with a third variable since some variables (e.g., entrepreneurship, skills) that may explain ICT-innovation may also explain productivity and export. A second source of endogeneity, is the problem of anticipation in the decision to invest in ICT. Indeed, these decisions may influence future profits, and hence, for instance, productivity and export. [4] In particular, the identification of γ_1 and γ_2 is important for the direct effect of ICT on export and the indirect one through productivity. For instance, in the export equation, the assumption is that given the observed confounders, x_{it}, and the observed productivity level (ω), the firm ICT is independent of its export level. This assumption makes it possible to identify the parameter γ_2, but it is rather strong, since the relationship between export and ICT has another endogeneity problem: self-selection into export activities. Moreover there is learning by exporting, i.e. entering new markets allows firms to acquire new knowledge which affects ICT. This makes ICT endogenous in the export equation. Assumption is that u can be considered as a measured confounding factor between the export and the ICT equation: *i.e.*, $\epsilon_{1,it}$ is orthogonal to $\epsilon_{3,it}$. However, through the self-selection, the ICT parameters would be biased: in such case, $\epsilon_{1,it}$ will be correlated with $\epsilon_{3,it}$; that is, the assumption SI.2 does not hold.

Asymptotic least squares (e.g., Crepon, Duguet, and Mairesse (1998)), structural equation modelling (e.g., Chemo Dzukou and Vancauteren (2024)) and sequential instrumental variables (e.g., Janz, Lööf, and Peters (2003)) are generally used in the literature so to identify the parameters of interest in a structural model.

[4]For instance, Caldera (2010) and Doraszelski and Jaumandreu (2013) show that the relationship between innovation and productivity has a simultaneity problem through self-selection into innovation activities which makes innovation, in our case ICT, endogenous in the productivity equation. Similarly, recent work of Bai et al. (2024) study optimal dynamic trade policies in an Eaton-Kortum model with technology diffusion through trade. The process of innovation and diffusion is one in which new ideas are combined with insights from others patterns that affect the degree and quality of diffusion.

4.2.1 Estimation and identification strategies

For the estimation of our multi-equations model in the case of endogenous treatments on diverse types of outcomes (including continuous and count outcomes), Roodman (2011) has formulated multistage procedures for fitting mixed models using a Full Information maximum likelihood estimator. However, this procedure does not explicitly take into account the panel dimension of the data. Instead, Adeline and Moussa (2020) offer an extension of Roodman's framework to a panel data dimension, as well as, linear and non-linear outcomes.[5]. Explicitly taking into account individual effects across equations and allowing for correlations (in addition to the remaining idiosyncratic errors), controls for endogeneity issues and unobserved heterogeneity.

For the estimation purposes, we consider an error-components approach, such as $\epsilon_{j,it} = \varepsilon_{j,it} + u_{j,i}$; where j = 1,2,3, where $u_{j,i}$ are the time-invariant unobserved confounders and $\varepsilon_{j,it}$ denotes the idiosyncratic errors encompassing other time-varying unobserved confounders. More formally, we assume that the vectors $u = (u_{1,i}, u_{2,i}, u_{3,i})'$ and $\varepsilon = (\varepsilon_{1,it}, \varepsilon_{2,it}, \varepsilon_{3,it})'$ are independently and identically (over time and across individuals) normally distributed with means 0 and covariance matrices $\mathbf{\Sigma}_{\boldsymbol{\varepsilon}}$ and $\mathbf{\Sigma}_{\boldsymbol{u}}$ respectively, and independent of each other.

$$\mathbf{\Sigma}_{\boldsymbol{\varepsilon}} = \begin{pmatrix} 1 & & \\ \tau_{12} & \sigma_2^2 & \\ \tau_{13} & \tau_{23} & \sigma_3^2 \end{pmatrix} \text{ and } \mathbf{\Sigma}_{\boldsymbol{u}} = \begin{pmatrix} \sigma_{u_1}^2 & & \\ \rho_{12}\sigma_{u_1}\sigma_{u_2} & \sigma_{u_2}^2 & \\ \rho_{13}\sigma_{u_1}\sigma_{u_3} & \rho_{23}\sigma_{u_2}\sigma_{u_3} & \sigma_{u_3}^2 \end{pmatrix}.$$

The scalars $\{\rho_{jk}\}_{j\neq k}$ and $\{\tau_{jk}\}_{j\neq k}$ with k,j = 1,2,3, govern the correlations between the unobserved firm heterogeneities, u_j and u_k, and the correlation between idiosyncratic errors, $\varepsilon_{j,it}$ and $\varepsilon_{k,it}$, respectively. These correlation parameters tells us whether the sequential ignorability assumption holds or not.

The likelihood function of one firm, starting from $t = 1$ is written as

$$L_i = \int_{\Re^3} \prod_{0_i+1}^{T_i} \ell_{it|u}(ICT_{it},\omega_{it},E_{it}) \times \phi(u_{1,i}, u_{2,i}, u_{3,i})\, \mathrm{d}u_{1,i}\mathrm{d}u_{2,i}\mathrm{d}u_{3,i} \tag{2}$$

where $\ell_{it|u}(\omega_{it},ICTit,E_{it})$ is the joint density function of the model, $\phi(\cdot)$ is the trivariate normal density function of $(u_{1,i}, u_{2,i}, u_{3,i})'$.[6] The 3-dimensional integral of normal densities

[5]We note that using a three-stage least squares estimator is not feasible because it can only be applied to linearly dependent variables.

[6]In this section we write the likelihood function for a FIML estimator in a general setting while in the empirical setting we consider specific cases. More specifically, we consider a general case where the ICT variable is an ordered variable, TFP is continuous and export is a binary variable. In addition, we also consider the case where the three dependent variables are linear outcomes.

renders standard Maximum likelihood infeasible. We use simulated maximum likelihood techniques (SML) to solve the computational problem of evaluating 3-dimensional integrals (see for instance, Train, 2003). More precisely, three uncorrelated Halton sequences of dimension R are first obtained. Then, random draws from density $\phi(\cdot)$ are simulated using the Halton sequences, a Cholesky decomposition, and the inverse cumulative normal distribution. Next, for each draw (which is a three-dimensional vector), the conditional likelihood of the i-th firm is evaluated. Finally, an average of the R simulated conditional likelihoods is taken. This average is the contribution of the i-th firm to the overall simulated likelihood – an approximation of the trilpe integral in Eq.2. Halton sequences have been shown to achieve high precision with fewer draws than uniform pseudo-random sequences because they have a better coverage of the [0,1] interval (for more on this topic see Train, 2003). Furthermore, Maximum simulated likelihood is asymptotically equivalent to maximum likelihood as long as R grows faster than $\sqrt{N}$ (Gourieroux and Monfort, 1993).

4.2.2 Equation-specific control variables and exclusion restrictions

Technically, the model is identified through functional form (see Heckman, 1978). However, in spite of this formal identification even in the absence of exclusion restrictions, our estimation procedure, like others, may suffer from "tenuous identification" and including equation-specific covariates may be important to ensure the empirical identification of the parameters of interest when real data are used (Bratti and Miranda, 2011; Miranda, 2011). Hence, specifying exclusion restrictions to help identification is a good practice.

We begin by the ICT variable. For this endogenous variable, we include past ICT activities (ICT measured in the period $t-1$). Over the past two decades, a large body of literature has analysed innovation persistence at the micro level both empirically as well as from a theoretical perspective (see, for example, Holl, Peters, and Rammer (2023), Peters (2009), Raymond et al. (2010), amongst others). Innovation persistence can result from true state dependence when there is a causal relationship between the decision to engage in innovation activity in one period and the propensity to conduct innovation activities in subsequent periods and can be explained by the potential existence of sunk costs and knowledge effects (Holl, Peters, and Rammer (2023)).

Furthermore, since we are using $ICT_{i,t-1}$ as an instrument for ICT_{it}, this could create an initial condition problem; *i.e.,* $ICT_{i,t-1}$ could be correlated with $\epsilon_{1,it}$ through $u_{1,i}$. To solve the initial conditions problem here the strategy suggested by Wooldridge (2005) is used. This approach consists of using the first observation that is available in the sample, ICT_{0_i}, as an additional covariate in equation 1. This approach is a guarantee of the exogeneity of the variables $ICT_{i,t-1}$. We follow this form of dynamics in each of the equations. In the export decision equation, we follow a similar approach in terms of capturing dynamics, that is adding lagged exports and controlling for the initial condition. In the TFP equation, we capture productivity persistence by adding the initial level of TFP and lagged TFP.

An important aspect of our paper is also to control for the extent of technology employed by firms by looking at technology- related human capital. The idea that technically-proficient workers are important for productivity is at the center of endogenous growth theory (e.g., Romer (1991)) and has received empirical support. The motivation of this literature is that the ability to successfully use a technology depends on the technical skills and know-how of the workforce (Harrigan, Reshef, and Farid (2023), Tambe and Hitt (2014), Teece, Pisano, and Shuen (1997)). For instance, Harrigan, Reshef, and Farid (2023) show that so-called "techies" who work with ICT and other technical tasks strongly correlate with firm-level innovation (R&D, patents, process and product innovation). In another related paper, Castillo and Vonortas (2024) show that realized absorptive capacities such as R&D cooperation and e-communication (signaling firms' ability to exploit and transform available information) are found to have a positive impact on TFP growth if used jointly.

For France, data enables us to identify STEM workers while in the Netherlands and Belgium, we identify workers by their educational background. Overall, we assume in the model that higher STEM intensive workers or higher educated workers lead to more ICT, TFP and EXP.

5 Empirical Evidence

This section present our main results. As a starting point, Tables 9, 10 and 11 show the results of the system estimation (1) using a random-effect ordered probit model for the ICT equation, a random-effects linear model for the TFP equation and a random-effect logit model for the EXP probabilities. Overall, it is shown that concerning the direct and indirect effects of ICT on exports, there is some difference between the three countries. In Belgium and in the Netherlands we don't find any significant direct effect of ICT on export. Only in France, the direct effect is strongly significant. In all three countries, we find a very significant positive effect of TFP on export. This corresponds to the selecion effect, that more productive firms self-select into exporting. This effect is more important in Belgium than in the Netherlands and the least important in France. We also find in the three countries a positive indirect effect of ICT on export, which increases monotonically with the level of the Digital Innovation Index. The effect is very strong and significant for Belgium, less significant for the Netherlands and less sizable for France.

In conclusion, ICT increases the propensity to export everywhere, but the transmission mechanism differs across the three countries. In Belgium and in the Netherlands it is to a large extent due to ICT-driven improved productivity whereas in France, although the indirect effect also exists, ICT affects exporting mainly through other unidentified (that is, non-TFP related) channels.

Turning to the other results, in all three countries, there is a persistence in the use of ICT: the higher the past use of ICT, the higher the present use of ICT. Controlling for the initial conditions (with beginning-of-observation-period values by firm) assures that this persistence is not merely spurious. Moreover, except for Belgium and the medium-high level of the Digital Intensity Index, the persistence increases exponentially with the past level of ICT. Concerning the other controls, we also find that lagged skill level and export are positively and significantly related to all three endogenous variables: ICT, TFP and export. Thereby, confirming the importance of key workers within innovative and trade-oriented firms; for exporting and TFP, this is the so-called learning-by-exporting effect, which is only significant in the Netherlands. We find a high persistence in productivity in all three countries. However, ICT use is negatively correlated to past TFP in Belgium, positively in France and not significantly in the Netherlands. This suggests different dynamic effects across the three countries. For instance, in France we find the lowest magnitudes for the effect of ICT use on productivity, but it is the only country where we find a feedback effect of productivity on future ICT use. In turn, this increase in ICT use positively affects future TFP, and so on. A full quantification of the effect of ICT on productivity (and hence, the indirect effect on export) requires to take into account these dynamics effects as well. For now, we leave this for future version of this paper.

The correlations between the time-invariant individual effects are generally insignificant. Only in the Netherlands we find a significant correlation between the individual effects in the TFP and export equations. A few of the correlations between the idiosyncratic effects are significant. There is no particular pattern in these effects. Most of them though are negatively correlated suggesting that unobserved time-variant individual forces have opposite effects in different equations.

5.1 Robustness - Using export shares

In the following subsections, we run some robustness checks. As a first robustness check, we model exports at the intensive margin (as a share in sales). Trade models based on firms' heterogeneity consider both the intensive and extensive margin of trade (Melitz (2003); Chaney (2008)). This distinction has some theoretical underpinnings with specific reference to innovation. The product cycle models of trade (Vernon (1966)) predict that product innovation, rather than process innovation, expand the range of goods that a country exports. Hence, product innovation is positively associated with the extensive margin of export. Another strand of literature (Grossman and Helpman (1991)) emphasizes the role of innovation in product quality and hence increases the value of the exports - intensive margin. Similarly, some studies argue that cost reducing process innovation increases the export competitiveness of firms and increases domestic as well as foreign sales - intensive margin of exports (Becker and Egger (2013)). With specific reference to the role of ICT, Añón Higón and Bonvin (2022) find that the use of ICT plays an direct role in explaining export participation (only for SMEs), not the export intensity. Export intensity only increases with ICT only through TFP. The authors argue that this is because for the average firm, ICT only has a proportionally impact on domestic sales. Table 13 in the Appendix shows the results of our estimations where we replace the export decision with the log of export shares (log EXPSh). We find that using export levels does not result in any changes on our main conclusion: that is, a direct effect of ICT on export is only significant for French firms. However, the productivity effect on export is now much more comparable between Belgium and France, and remains strong in the Netherlands.

5.2 Robustness - Markup adjustment

The TFP mechanism that may explain the indirect role of ICT on export may also reflect markups (price-cost margins) adjustments that capture market power in the output market (due to e.g., higher investments, higher quality that may result into higher prices, lower marginal costs). Recent evidence suggests that markups have risen in recent years (e.g., De Loecker, Eeckhout, and Unger (2020); Ganapati and McKibbin (2023)). Autor et al. (2020) argue that higher market power is related to technological change and the rise of superstar firms which have high profits and productivity. Other research points out that the rise of ICT and other intangible capital lead to higher market power (Bessen (2022); Crouzet and Eberly (2019)). Using data on ICT use of firms in Ecuador, Rodríguez-Moreno and Rochina-Barrachina (2019) find that ICT use affects positively firms' productivity and markups and there is also evidence that the effect of ICT on markups operates through TFP and not prices.

In order to estimate the markups at the firm-level, we follow the setup developed by De Loecker and Warzynski (2012). Their approach relies on two assumptions. The first is standard cost minimisation and the second is at least one variable input that is free of adjustment costs. The method relates output elasticity, which is recovered from the production function estimation, to adjusted revenue shares. We refer to Appendix A for details on the estimation of firm-level markups. If the effect of ICT on TFP reflect markup adjustments (due to higher investments), we expect that the ICT variable affects positively and significantly the markups of the firm. To test this, we re-estimate our equation estimation where we replace the TFP variable by the firm markups. Table 13 shows the results of these estimations. Interestingly, we find that the indirect effect of ICT on export is not significant for the three countries. This strongly suggests that markups do not mediate the effect of ICT on export. Thus, the ICT mechanism highlighted above does not reflect any changes in prices (or quality upgrading) but is due to an actual productivity effect. In addition, we now also find a direct effect of ICT on export, not only for French but also for Belgian firms. This suggests that by focusing on the profitability component of TFP, ICT picks up more of the efficiency gains which were captured by TFP in our previous estimations. For the Netherlands, this direct effect turns from negative to positive, but is still insignificant. In France, the direct effect of markups on export is also positive and significant. This suggests that part of the productivity effect found above (already lowest among the three countries) runs through profitability rather than efficiency. For Belgium and the Netherlands we do not find any indication that any part of the productivity effect is due to higher markups.

5.3 Robustness - Different types of digitalization

While ICT as a composite of different technologies may be positively correlated to export and productivity, it seems plausible that the use of some types of ICT technologies may have different implications for TFP and export activities. For example, advances in automation and robotics (e.g., CRM-ERP techologies) are helping firms to reduce labour costs and to handle production-related tasks in parallel to employees, leading to a higher productivity performance. In contrast, advances in communication technologies (e..g., e-commerce sales are helping firms to increase their internationalization activities (Añón Higón and Bonvin (2024).[7] In Tables 14 and 15, we turn to the estimation results where we replace the ICT index by either e-commerce sales or CRM-ERP adoption. Results in panel 14 no longer confirm a direct positive impact of digitalization on export for all three countries, which is not line with what we expected. The productivity effect of e-commerce is positive and significant effect only for Belgium and France. Turning to the results in panel 15 on the CRM-ERP adoption, our results reveal a direct and indirect effect on export probabilities in France and Belgium while the effect on export only goes through TFP in the Netherlands. As a result, we do find some evidence of a strong CRM-ERP

[7]Non reported data on the average firm-level usage of different ICT types according to their export intensities and TFP levels intensities, for instance, show for firms that apply e-commerce sales, TFP is about 7% points higher.

effect in the production process, as expected.

6 Conclusion

Already within the Europe 2020 strategy - itself the successor of the Lisbon Agenda - European leaders have earmarked human capital, innovation, digitalization and ICT as key priorities for action and investment. Today, digital innovation, trade, and skills remain prominently in the European Commission's program for Strengthening European Competitiveness (see for instance the 2024 Letta and Draghi reports). Our paper builds from an emerging view that investments in technology in manufacturing and non-manufacturing sectors can be important drivers for explaining export activities (see e.g. Añón Higon and Bonvin, 2023). Investments in technology can be explained by ICT adoption but can also be extended to other channels of technologies based on human capital. In this paper, we provide empirical evidence on the role of TFP as an important mediator of the ICT-export link.

In order to highlight the mechanism that explains the causal effect of ICT on export, we develop an empirical model taking into account numerous endogeneity problems. The empirical model is implemented on separate panels of Belgian, French and Dutch firms, observed over the period 2014-2021 which allows us to compare the interplay between ICT, TFP and export in three countries that differ in terms of ICT and global activities.

Our core results are that ICT increases export (both at the intensive and extensive margin) everywhere, but the transmission mechanism differs across the three countries. In Belgium and in the Netherlands it is to a large extent due to ICT-driven improved productivity whereas in France ICT affects exporting mainly through other unidentified channels.

Policies aimed at promoting digitalization also aim at improving international competitiveness. Our study explicitly links firms' use of ICT to their presence in the international market via improvements in productivity (i.e., competitiveness). It is surprising that the role of ICT and digitalization for trade has been so unexplored. The policy to stimulate export directly and indirectly through ICT can be defined at the micro and macro-level. Combining firm and country-level perspectives with a focus on three EU countries, this paper allows to disentangle various economic policy drivers within a contextual framework. The policy implications of our study can be summarized as follows:

1) if exporting (at the intensive or extensive margin) is a policy goal, export performance is positively related to increased productivity. Hence any policy boosting productivity

should on average promote exports.

2) A potential policy lever to promote productivity is to provide incentives for a greater use of ICT. Our results clearly show that a higher use of ICT increases productivity.

3) Small open economies heavily involved in international trade, like Belgium and the Netherlands, probably have a lead when it comes to ICT investments necessary to increase their export performance. Firms in economies with a larger domestic market and less dependent on international trade, like France, may still have to make progress in exporting through the adoption of ICT. For instance French firms seems to be behind Dutch and Belgian firms in the adoption of mobile internet, website, e-commerce and CRM/ERP.

4) Overall, the export performance in France is at this stage still less affected by ICT use than it is in Belgium and the Netherlands.

5) The lower effect of ICT on export in France could be due to the structure of France's economy, with a higher share of activities in low digital-intensive industries and a lower share of activities in high digital-intensive industries than in Belgium and in the Netherlands (in 2018 the proportion of low-intensive activities was 31.85% in France, 26.18% in Belgium and 25.62% in the Netherlands, whereas the proportion of high-intensive activities was 24.92% in France, 27.64% in Belgium and 28.06% in the Netherlands; source: OECD, STAN Database for Structural Analysis.)

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A Production Function Estimation

This section outlines the methodology employed to estimate firm productivity and output elasticities, leveraging the approach developed by Ackerberg, Caves, and Frazer (2015)—hereafter referred to as ACF. Due to the substantial heterogeneity inherent in production processes across various industrial sectors within a country (e.g., food, trade, pharmaceuticals), it is imperative to avoid the use of functional forms that impose overly restrictive assumptions on production technology, such as the fixed-proportion (Leontief) or Cobb-Douglas functions. Consequently, this study adopts a translog (TL) gross output production function that includes labor, capital, and material costs, owing to its flexibility.

The TL production function presents several key advantages. First, it does not impose a priori restrictions on substitution elasticities or economies of scale. Second, it accommodates nonlinear effects of input factors and their interactions on output. Moreover, the TL function allows for variation in output elasticities over time and across firms, which is particularly advantageous for the estimation of markups.

However, the use of a more flexible production technology is not without its challenges. Specifically, the TL specification necessitates a trade-off between allowing for firm-specific output elasticities and potentially introducing bias from unobserved prices (De Loecker and Warzynski, 2012). Since our dataset does not include physical quantities of output and inputs, we employ an approach that implicitly treats deflated turnover and expenditures as proxies for these quantities in the estimation of output elasticities. While this approach may be susceptible to omitted variable bias related to output and input prices—thus impacting the estimation of input coefficients and, consequently, output elasticities—we consider this bias to be minimal in our context. As noted by De Loecker et al. (2016), "input-price bias is partly offset by output-price bias when using standard firm-level data, as firms with higher input prices tend to have higher output prices."

To be specific, consider the following TL functional form:

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lm} l_{it} m_{it} + \beta_{lk} l_{it} k_{it} \\ &\quad + \beta_{mk} m_{it} k_{it} + \omega_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where y_{it}, l_{it}, m_{it}, and k_{it} denote the logarithms of revenue, labor, intermediate inputs, and capital, respectively. We distinguish between a persistent Hicks-neutral productivity term ω_{it}—modeled as a Markov process known to the firm, thereby influencing its input choices—and an idiosyncratic term ε_{it}, which is mean-independent of inputs and captures unobserved factors affecting output, such as transitory productivity shocks and measurement errors. Given that input choices are correlated with the productivity shock (ω_{it}), the estimation of the production function generally leads to inconsistent estimates of the elasticities of materials, labor, and capital.

To address the endogeneity associated with the estimation of input coefficients in the production function, we follow the two-step procedure proposed by ACF. In the first step, we estimate $\hat{\phi}_{it}$ and $\hat{\varepsilon}_{it}$ by running the following regression:

$$y_{it} = \phi_{it} + \varepsilon_{it} \tag{4}$$

where $\phi_{it} = f(k_{it}, l_{it}, m_{it}) + h(k_{it}, l_{it}, m_{it}, e_{i,t-1}, i_{it})$. Here, $f(\cdot)$ represents the TL production function, and $h(\cdot)$ serves as the inverse of the material demand function, which proxies the productivity term.[8] In the second step, the elasticities of the production parameters are estimated through generalized method of moments (GMM), using inputs orthogonal to the unexpected productivity shock as instruments. Following the first stage, we can use the estimated value $\hat{\phi}_{it}$ to compute the productivity estimate ω_{it} for each value of β_s as follows:

$$\begin{aligned} \widehat{\omega}_{it}(\beta) \;\; = \;\; & \hat{\phi}_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{kk} kit^2 - \beta_{lm} l_{it} m_{it} \\ & - \beta_{lk} l_{it} k_{it} - \beta_{mk} m_{it} k_{it} \end{aligned} \tag{5}$$

This second stage relies on the law of motion for productivity. We allow the law of motion of productivity to depend on lagged export status ($e_{i,t-1}$) and the current digitalization index (i_{it}), as described by the following $g(\cdot)$ function:[9]

$$\omega_{it} = g(\omega_{i,t-1}, e_{i,t-1}, i_{it}) + \xi_{it} \tag{6}$$

where $\xi_{it}(\beta)$ represents the innovation in productivity. To recover ξ_{it}, we non-parametrically regress ω_{it} on a third-order polynomial of its lag $\omega_{i,t-1}$ as constructed in Eq.(5). Based on our assumptions, ξ_{it} is independent of the predetermined working capital stock, k_{it}, and l_{it}, as well as the lagged variable inputs, $m_{i,t-1}$. In the case of our three-input TL production function, where labor and capital are quasi-fixed and intermediate inputs (materials) are fully flexible, we employ the following moment conditions to estimate the parameters of the production function:

$$\mathbb{E}\left[\xi_{it}(\beta) Z\right] = 0 \tag{7}$$

[8] The unknown function $h(\cdot)$ is approximated parametrically by a third-order polynomial expansion of the parameters.

[9] In this specification, we assume that the current digitalization index, i_{it}, is orthogonal to the innovation in productivity, ξ_{it}. This assumption is made because the ICT survey data for year t are used to measure the digitalization index for year $t-1$.

$$Z' = (l_{it}, m_{it-1}, k_{it}, l_{it}^2, m_{i,t-1}^2, k_{it}^2, l_{it}m_{it-1}, l_{it}k_{it}, m_{it-1}k_{it}) \tag{8}$$

Once the output elasticities have been estimated, computing markups becomes a simple task. Since the observed output $Y_{it} = Q_{it}\exp(\epsilon_{it})$ includes idiosyncratic factors including non-predictable output shocks and potential measurement error in the output and inputs (ϵ_{it}), we need to correct the observed revenue shares for labor and intermediate inputs for these factors. We can recover an estimate of (ϵ_{it}) from the production function estimates routine and obtain adjusted revenue shares as follows: Rubens (2023)

$$\widehat{\alpha}_{it}^{N} = \frac{W_{it}N_{it}}{P_{it}\frac{Y_{it}}{\exp(\epsilon_{it})}} \tag{9}$$

$$\widehat{\alpha}_{it}^{M} = \frac{J_{it}M_{it}}{P_{it}\frac{Y_{it}}{\exp(\epsilon_{it})}} \tag{10}$$

Using Eqs. (9), and (10), in combination with the output elasticity with respect to intermediate inputs from our translog productivity model, we obtain estimates of the price-cost markup μ_{it}, as follows:

$$\widehat{\mu}_{it} = \frac{(\widehat{\varepsilon}_{M}^{Q})_{it}}{\widehat{\alpha}_{it}^{M}} \tag{11}$$

where $(\widehat{\varepsilon}_{M}^{Q})_{it}$ is calculated from the translog production function estimation (3).

B Different forms of digitalization

Digitalization is a broad concept that covers a wide variety of technologies and applications. It is therefore a complex phenomenon that is difficult to capture in a single indicator (Zand, 2011). Moreover, information about which ICT applications are used appears to be more relevant for determining the relationship with productivity than information about only investments in ICT resources, where no distinction can be made between, for example, more and less advanced applications (Biagi and Falk, 2017). Another important issue is that differences in the application of these technologies can also have an impact on the relationship with productivity and exports. Table refx provides an overview and description of all ICT applications included in the analyses. This selection of ICT applications is based, among other things, on scientific literature and available information from the ICT survey.

Using a computer is the most basic form of digitization. In general, the use of many other ICT applications will be associated with a higher share of PC use. This is because its presence is a prerequisite, such as when using software systems such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM). CRM and ERP aim to integrate and streamline different business processes (Aral et al. 2006), which can reduce lead times and sales costs (Engelstätter, 2011).

The use of broadband and mobile internet relates to the connectivity of a company and therefore to the flexibility and speed of internal and external communication. Fast internet is also a necessary prerequisite for other applications, such as cloud services, AI and teleworking. Hagsten and Kotnik (2017) further argue that fast internet is complementary to digital knowledge and skills. Other network-based technologies such as ERP and e-commerce systems also depend on fast internet. Mobile internet gives employees flexibility to work on the go and be digitally accessible, which can improve the speed of communication and productivity. Something similar applies to teleworking, which goes a little further and provides remote access to company systems. Teleworking has boomed in recent years as a result of the corona measures and has also been linked to the emergence of facilities such as video-conferencing software, which can to a certain extent replace face-to-face communication.

Websites, e-commerce and the use of social media are more directly linked to the sales channel and marketing of companies. It gives companies the opportunity to reach a larger market. These can also be foreign markets. For example, companies that have an English-language website on which customers can place orders or that promote their product in other countries via social media can benefit from this in terms of exports.

These types of digitization can therefore have a direct effect on exports, while a larger sales market can also have a positive impact on employment. On the other hand, it is not obvious that this will necessarily make companies produce more efficiently, although economies of scale as a result of a larger sales market also lead to higher productivity.

The use of robotics and AI mainly relates to the automation of processes within the company. One reason for using robotics is to save on labor costs or simply because of the difficulty of finding personnel, but it can also be related to the desire to increase the quality and variety of the product. AI is also used for a wide range of applications, from administrative processes to cyber-security and from production to marketing. Both technologies can be labor-saving, but also supportive: the employment effect is therefore ambivalent. Nevertheless, higher productivity can reduce the price and increase demand for the product, with positive effects on employment and exports. In the case of robotics, more exports may occur as a result of the position in the value chain that a company with robotics occupies, for example in the assembly or as a processing party of an industrial intermediate product (see also Chapter 4 of this publication). It is also obvious that investing in robotics is easier for companies that are active in a larger, possibly international, market.

Table 1: Digital intensity Index, 2021

1	Enterprises where more than 50% of the persons employed have access to the internet for business purposes
2	Have ERP software package to share information between different functional areas
3	The maximum contracted download speed of the fastest fixed line internet connection is at least 30 Mb/s but less than 100 Mb/s
4	Enterprises where web sales were more than 1% of the total turnover and B2C web sales more than 10% of the web sales
5	Enterprises use interconnected devices or systems that can be monitored or remotely controlled via the Internet (Internet of Things)
6	Use any social media
7	Have CRM
8	Buy sophisticated or intermediate CC services (2021)
9	Enterprises use artificial intelligence
10	Buy CC services used over the internet
11	Used any computer networks for sales (at least 1%) – continuation with previous years
12	Use two or more social media

Source: Eurostat, Community suvrye on ICT usage and e-commerce enterprises.

C Tables

Table 2: Description of variables from the Survey ICT and e-commerce use by firms

Variables	Description
E-commerce (2012-2021)	Dummy variable=1 and share of e-commerce sales in total sales of the firm
Use PC (2012-2021)	Employees that work with computers, includes ICT users and specialists
Broadband usage (2012-2021)	Dummy variable=1 and percentage of employees who have access to a fast, fixed internet connection. For this purpose, the percentage of employees who have access to the internet was combined with whether the company has a fixed internet connection of at least 30 Mbps.
Website	Dummy variable=1 if the firm has own website
Use CRM-ERP system (2012-2015; 2017; 2019)	Dummy variable=1 if the firm has used Customer Relationship Management (CRM) or Enterprise Resource planning (ERP) software package to share information between different functional areas
Use AI/Robots (2018-2021)	Dummy variable=1 if the firm has used AI and/or Robot technologies
Use ICT personnel(2012-2021, 2016 missing)	Dummy variable=1 if the firm employs ICT specialists

Table 3: The correlation between ICT measures, the Belgium, (2014-2021)

	1	2	3	4	5	6	7
Use broadband (> 30Mb.)	1						
Use website	0.08	1					
% PC at work	0.05	0.11	1				
% Mobile Int.	0.03	0.12	0.87	1			
Use E-commerce	0.07	0.14	0.09	0.07	1		
Use CRM/ERP	0.06	0.19	0.13	0.07	0.39	1	
Use ICT personnel	0.09	0.06	0.13	-0.02	0.34	0.16	1

Table 4: The correlation between ICT measures, the Netherlands, (2014-2021)

	1	2	3	4	5	6	7
Use broadband (> 30Mb.)	1						
Use website	-0.06	1					
% PC at work	0.41	0.02	1				
% Mobile Int.	0.32	-0.00	0.45	1			
Use E-commerce	0.02	0.09	0.09	0.04	1		
Use CRM/ERP	0.05	0.15	0.16	0.18	0.06	1	
Use ICT personnel	0.04	0.06	-0.17	-0.05	0.02	-0.05	1

Table 5: The correlation between ICT measures, France, (2014-2021)

	1	2	3	4	5	6	7
Use broadband (> 30Mb.)	1						
Use website	0.11	1					
% PC at work	0.19	0.21	1				
% Mobile Int.	0.15	0.18	0.43	1			
Use E-commerce	0.11	0.15	0.09	0.01	1		
Use CRM/ERP	0.13	0.21	0.21	0.19	0.10	1	
Use ICT personnel	0.11	0.22	0.21	0.16	0.08	0.22	1

Table 6: Descriptive statistics for the Netherlands, 2014-2021

	mean	sd	p25	p50	p75	count
ln(wagebill$_{it}$)	15.402	1.257	14.457	15.394	16.211	19,367
ln(output$_{it}$)	17.079	1.508	16.009	16.998	18.018	19,367
ln(employment$_{it}$)	4.531	1.186	3.624	4.517	5.275	19,367
ln(intermediate input$_{it}$)	16.731	1.631	15.590	16.661	17.758	19,367
ln(capital$_{it}$)	13.005	1.716	11.854	12.995	14.118	19,367
ln(real output per worker$_i t$)	12.547	0.863	11.948	12.441	13.020	19,367
ln(real value added per worker$_i t$)	11.071	0.668	10.730	11.083	11.445	19,349
Capint	8.473	1.107	7.833	8.487	9.166	19,367
EXP	0.851	0.356	1.000	1.000	1.000	19,367
EXPsh	0.297	0.460	0.003	0.117	0.505	19,367
use CRM/ERP	0.528	0.499	0.000	1.000	1.000	13,187
use website	0.947	0.224	1.000	1.000	1.000	19,367
use broadband	0.432	00.383	0.000	0.400	0.800	19,271
use e-commerce	0.455	0.498	0.000	0.000	1.000	14,839
use PC	0.660	0.297	0.000	1.000	1.000	19,367
Use mobile internet	0.823	0.382	0.000	0.000	1.000	19,367
use ICT specialists	0.375	0.325	0	1	0.031	19,367
ICT Index	2.432	0.681	2	2	3	9,125
N	9,125					

Table 7: Descriptive statistics for Belgium, 2014-2021

	mean	sd	p25	p50	p75	count
ln(wagebill$_{it}$)	15.717	1.464	14.726	15.604	16.827	9,826
ln(output$_{it}$)	17.696	1.511	16.607	17.543	18.651	9,826
ln(employment$_{it}$)	4.706	1.391	3.837	4.608	5.775	9,826
ln(intermediate input$_{it}$)	17.421	1.580	16.324	17.266	18.414	9,826
ln(capital$_{it}$)	15.096	2.097	13.892	15.247	16.422	9,745
ln(real output per worker$_{it}$)	12.968	0.932	12.334	12.813	13.436	9,826
ln(real value added per worker$_{it}$)	9.668	1.512	8.764	9.760	10.662	9,826
Capint	9.123	2.071	8.293	9.481	10.399	9,753
EXP	0.766	0.423	1.000	1.000	1.000	9,826
EXPsh	0.324	0.406	0.000	0.133	0.640	9,826
use CRM/ERP	0.630	0.483	0.000	1.000	1.000	5,667
use Website	0.934	0.248	1.000	1.000	1.000	9,648
use broadband	0.606	0.489	0.000	1.000	1.000	9,826
use e-commerce	0.734	0.442	0.000	1.000	1.000	7,722
use PC	0.668	0.373	0.000	1.000	1.000	9,826
use mobile internet	0.566	0.431	0.000	0.000	1.000	7,441
use ICT specialists	0.351	0.479	0	0	1	9,648
ICT Index	2.645	0.875	2	3	3	7,365
N	7,365					

Table 8: Descriptive statistics for France, 2014-2021

	mean	sd	p25	p50	p75	count
ln(wagebill$_{it}$)	14.897	1.869	13.426	14.429	16.313	37,253
ln(output$_{it}$)	16.692	2.145	14.978	16.393	18.291	37,253
ln(employment$_{it}$)	4.050	1.765	2.639	3.610	5.464	37,253
ln(intermediate input$_{it}$)	16.346	2.258	14.603	16.102	18.016	37,253
ln(capital$_{it}$)	14.766	2.445	12.914	14.306	16.632	37,253
ln(real output per worker$_{it}$)	12.642	1.109	12.024	12.536	13.035	37,253
ln(real value added per worker$_{it}$)	11.122	0.728	10.781	11.083	11.438	36,106
Capint	10.716	1.282	10.040	10.757	11.473	37,253
EXP	0.595	0.490	0	1	1	37,253
EXPsh	0.153	0.263	0	0.006	0.179	37,253
use CRM/ERP	0.398	0.489	0.000	0.000	1.000	37,253
use website	0.777	0.415	1.000	1.000	1.000	37,253
use broadband	0.418	0.493	0.000	0.000	1.000	37,253
use e-commerce	0.138	0.345	0.000	0.000	0.000	37,253
use PC	0.556	0.496	0.000	1.000	1.000	37,253
use mobile internet	0.358	0.479	0.000	0.000	1.000	37,253
use ICT specialists	0.625	0.484	0	1	1	37,253
ICT Index	2.432	0.681	2	2	3	37,253
N	37,253					

Table 9: The direct and indirect impact of ICT index on firm exports, Belgium

Variables	ICT use (1)		Total factor Productivity (2)		Export output (3)	
Panel A. Parameters of interest						
ICT_{itML}			0.040***	(0.010)	-0.095	(0.227)
ICT_{itMH}			0.082***	(0.026)	0.040	(0.290)
ICT_{itH}			0.120***	(0.035)	0.205	(0.405)
ω_{it}					0.580***	(0.125)
Panel B. Exclusion variables						
$ICT_{i,0}$	0.640***	(0.100)				
$ICT_{i,t-1ML}$	1.010***	(0.115)				
$ICT_{i,t-1MH}$	1.950***	(0.160)				
$ICT_{i,t-1H}$	2.770***	(0.250)				
$SKILL_{i,t-1}$	0.957***	(0.240)	0.084***	(0.023)	0.112*	(0.065)
$Capint_{i,t-1}$	-0.065***	(0.017)			-0.012	(0.039)
$Emp_{i,t-1}$	0.230***	(0.030)			0.313***	(0.083)
$\omega_{i,t-1}$	-0.340***	(0.050)	0.945***	(0.007)		
$\omega_{i,0}$			0.345***	(0.044)		
$EXP_{i,0}$					2.431***	(0.542)
$EXP_{i,t-1}$	0.845***	(0.272)	0.084	(0.201)	0.245***	(0.075)
Correlations idiosyncratic errors						
$corr(\varepsilon_{1,it},\varepsilon_{2,it})$	-0.032	(0.110)				
$corr(\varepsilon_{1,it},\varepsilon_{3,it})$	-0.221***	(0.056)				
$corr(\varepsilon_{2,it},\varepsilon_{3,it})$	-0.114	(0.087)				
Correlations individual effects						
$corr(u_{1,it},u_{2,it})$	-0.067	(0.166)				
$corr(u_{1,it},u_{3,it})$	0.073	(0.074)				
$corr(u_{2,it},u_{3,it})$	-0.151	(0.100)				

Notes: The coefficients on $ICT_{i,0}$ by ICT category (medium-low, medium-high and high) are reported as an average coefficient for space saving. All equations includes year and sector dummies and an intercept. We report the estimated coefficients rather than the average partial effects. For the export decision equation, we report average partial effects instead of coefficients. Standard Error are in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 10: The direct and indirect impact of ICT index on firm exports, the Netherlands

	ICT use		Total factor Productivity		Export output	
Variables	(1)		(2)		(3)	
Panel A. Parameters of interest						
ICT_{itML}			0.044	(0.040)	-0.469	(0.627)
ICT_{itMH}			0.103^{**}	(0.055)	-0.645	(0.765)
ICT_{itH}			0.125^{*}	(0.075)	-0.434	(1.112)
ω_{it}					0.334^{**}	(0.122)
Panel B. Exclusion variables						
$ICT_{i,0}$	0.635^{***}	(0.058)				
$ICT_{i,t-1ML}$	0.915^{***}	(0.162)				
$ICT_{i,t-1MH}$	1.295^{***}	(0.176)				
$ICT_{i,t-1H}$	1.955^{***}	(0.215)				
$SKILL_{i,t-1}$	1.300^{***}	(0.252)	1.007^{***}	(0.192)	0.122	(0.301)
$Capint_{i,t-1}$	0.035	(0.028)			0.201^{**}	(0.071)
$Emp_{i,t-1}$	0.100	(0.075)			0.009	(0.085)
$\omega_{i,t-1}$	-0.019	(0.010)	0.760^{*}	(0.431)		
$\omega_{i,0}$			0.295^{***}	(0.022)		
$EXP_{i,0}$					1.377^{***}	(0.229)
$EXP_{i,t-1}$	1.600^{***}	(0.215)	0.057^{***}	(0.019)	0.940^{*}	(0.561)
Correlations idiosyncratic errors						
$corr(\varepsilon_{1,it},\varepsilon_{2,it})$	-0.471^{**}	(0.221)				
$corr(\varepsilon_{1,it},\varepsilon_{3,it})$	0.070	(0.183)				
$corr(\varepsilon_{2,it},\varepsilon_{3,it})$	-0.115	(0.876)				
Correlations individual effects						
$corr(u_{1,it},u_{2,it})$	0.016	(0.096)				
$corr(u_{1,it},u_{3,it})$	0.051	(0.081)				
$corr(u_{2,it},u_{3,it})$	0.255^{***}	(0.100)				

Notes: The coefficients on $ICT_{i,0}$ by ICT category (medium-low, medium-high and high) are reported as an average coefficient for space saving. All equations includes year and sector dummies and an intercept. We report the estimated coefficients rather than the average partial effects. For the export decision equation, we report average partial effects instead of coefficients. Standard Error are in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 11: The direct and indirect impact of ICT index on firm exports, France

Variables	ICT use (1)	Total factor Productivity (2)	Export decision (3)
Panel A. Parameters of interest			
ICT_{itML}		0.023***(0.005)	0.028***(0.008)
ICT_{itMH}		0.037***(0.006)	0.062***(0.012)
ICT_{itH}		0.058***(0.010)	0.120***(0.019)
ω_{it}			0.050***(0.007)
Panel B. Other variables			
$ICT_{i,0}$	0.637***(0.009)		
$ICT_{i,t-1ML}$	0.542***(0.048)		
$ICT_{i,t-1MH}$	0.947***(0.057)		
$ICT_{i,t-1H}$	1.248***(0.075)		
$SKILL_{i,t-1}$	0.914***(0.090)	0.050***(0.010)	0.037***(0.013)
$Capint_{i,t-1}$	0.026***(0.009)		0.002 (0.001)
$Emp_{i,t-1}$	0.246***(0.009)		0.005***(0.001)
$\omega_{i,t-1}$	0.130***(0.048)	0.637***(0.004)	
$\omega_{i,0}$		0.289***(0.005)	
$EXP_{i,0}$			0.159***(0.006)
$EXP_{i,t-1}$	0.344***(0.028)	-0.002 (0.004)	0.087***(0.012)
Correlations idiosyncratic errors			
$corr(\varepsilon_{1,it},\varepsilon_{2,it})$	0.025 (0.033)		
$corr(\varepsilon_{1,it},\varepsilon_{3,it})$	-0.201***(0.044)		
$corr(\varepsilon_{2,it},\varepsilon_{3,it})$	-0.106***(0.018)		
Correlations individual effects			
$corr(u_{1,it},u_{2,it})$	0.033 (0.068)		
$corr(u_{1,it},u_{3,it})$	-0.080 (0.055)		
$corr(u_{2,it},u_{3,it})$	-0.064 (0.041)		

Notes: The coefficients on $ICT_{i,0}$ by ICT category (medium-low, medium-high and high) are reported as an average coefficient for space saving. All equations includes year and sector dummies and an intercept. We report the estimated coefficients rather than the average partial effects. For the export decision equation, we report average partial effects instead of coefficients. Standard Error are in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 12: Robustness. Using export shares

Variables	Total factor Productivity (1)	Export output (2)
A. Main parameters of the model, Belgium		
ICT_{itML}	0.064^{***} (0.018)	0.012 (0.010)
ICT_{itMH}	0.106^{***} (0.026)	0.015 (0.016)
ICT_{itH}	0.157^{***} (0.036)	0.019 (0.024)
ω_{it}		0.015^{**} (0.007)
B. Main parameters of the model, the Netherlands		
ICT_{itML}	0.281 (0.312)	0.532 (0.497)
ICT_{itMH}	0.108^{**} (0.049)	0.775 (0.612)
ICT_{itH}	0.154^{**} (0.066)	0.784 (0.776)
ω_{it}		0.185^{**} (0.101)
C. Main parameters of the model, France		
ICT_{itML}	0.023^{***} (0.005)	0.011^{***} (0.002)
ICT_{itMH}	0.037^{***} (0.006)	0.021^{***} (0.002)
ICT_{itH}	0.050^{***} (0.010)	0.031^{***} (0.003)
ω_{it}		0.023^{***} (0.004)

Notes: To obtain results in columns (1) and (2), we regress equations 1 using a random-effects mixed model (ordered logit for the ICT (not reported) and linear models for TFP and export). All the estimated equations include variables in the vector x_{it} as observed confounders. We also include variables used as excluded instruments in their respective equation. The values reported in the Table are the estimated coefficients and values in parentheses are the standard error. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 13: Robustness. Using markups

	Log of markups		Export output	
Variables	(1)		(2)	
A. Main parameters of the model, Belgium				
ICT_{itML}	0.019	(0.028)	0.947***	(0.213)
ICT_{itMH}	0.053	(0.026)	1.361***	(0.345)
ICT_{itH}	0.102*	(0.058)	1.185***	(0.024)
μ_{it}			0.861	(1.3001)
B. Main parameters of the model, the Netherlands				
ICT_{itML}	0.281	(0.312)	0.119	(0.144)
ICT_{itMH}	0.177	(0.190)	0.775	(0.612)
ICT_{itH}	0.112	(0.260)	1.049	(1.082)
μ_{it}			0.861	(1.300)
C. Main parameters of the model, France				
ICT_{itML}	0.024	(0.082)	0.028***	(0.008)
ICT_{itMH}	0.033	(0.073)	0.063***	(0.012)
ICT_{itH}	0.047	(0.123)	0.120***	(0.019)
μ_{it}			0.021**	(0.011)

Notes: To obtain results in columns (1) and (2), we regress equations 1 using a random-effects mixed model (ordered logit for the ICT (not reported) and linear models for markups and export). All the estimated equations include variables in the vector x_{it} as observed confounders. We also include variables used as excluded instruments in their respective equation. The values reported in the Table are the estimated coefficients and values in parentheses are the standard error. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 14: Robustness. Using e-commerce shares

	Total factor productivity	Export output
Variables	(1)	(2)
A. Main parameters of the model, Belgium		
$ECom_{it}$	0.276***(0.045)	-0.081 (0.349)
ω_{it}		0.260***(0.088)
B. Main parameters of the model, the Netherlands		
$ECom_{it}$	-0.044***(0.011)	0.004 (0.255)
ω_{it}		0.875***(0.083)
C. Main parameters of the model, France		
$ECom_{it}$	0.011***(0.003)	0.191***(0.060)
ω_{it}		0.752***(0.101)

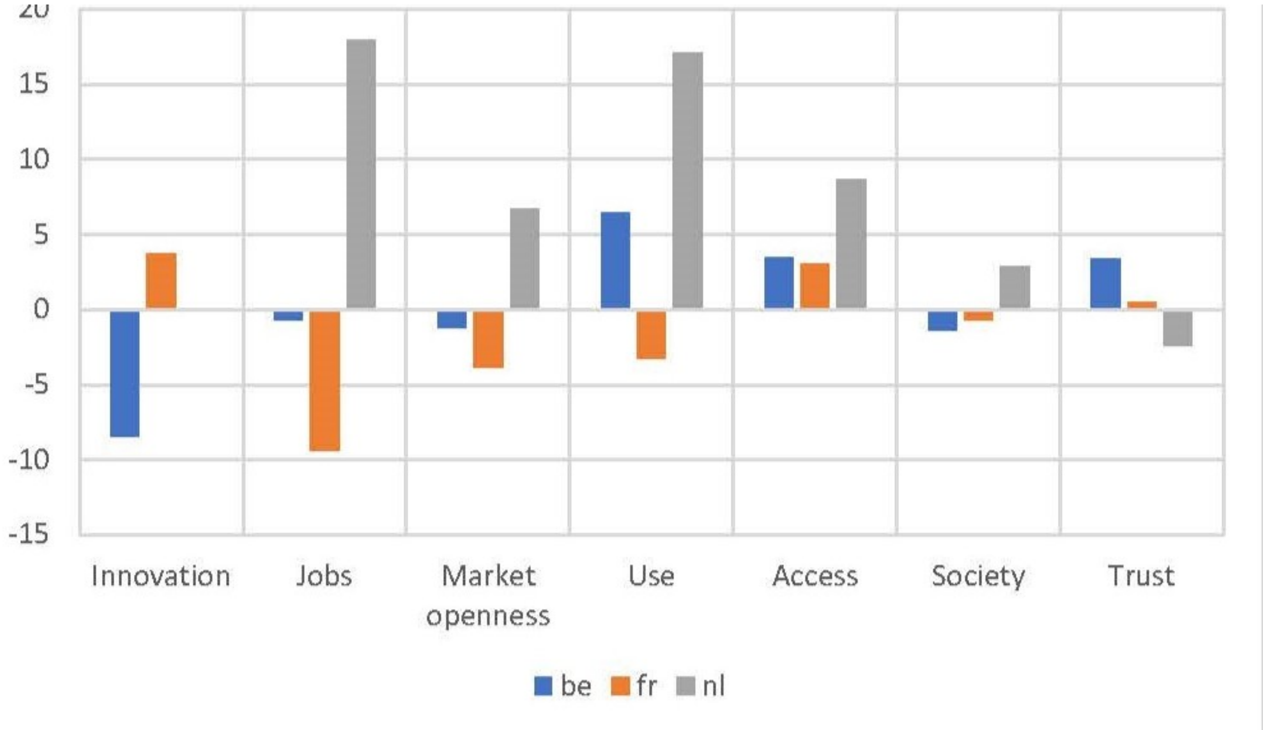
Notes: To obtain results in columns (1) and (2), we regress equations 1 using arandom-effects mixed model (ordered logit and linear models). All the estimated equations include variables in the vector x_{it} as observed confounders. We also include variables used as excluded instruments in their respective equation. The values reported in the Table are the estimated coefficients and values in parentheses are the standard error. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 15: Robustness. Using CRM-ERP

	Total factor productivity	Export output
Variables	(1)	(2)
A. Main parameters of the model, Belgium		
$CrmErp_{it}$	0.204***(0.050)	0.723** (0.346)
ω_{it}		0.317* (0.186)
B. Main parameters of the model, the Netherlands		
$CrmErp_{it}$	0.089***(0.023)	1.060 (0.686)
ω_{it}		0.611** (0.248)
C. Main parameters of the model, France		
$CrmErp_{it}$	0.019***(0.002)	0.089** (0.042)
ω_{it}		0.739***(0.101)

Notes: To obtain results in columns (1) and (2), we regress equations 1 using a random-effects mixed model (ordered logit for the ICT (not reported) and linear models for TFP and export). All the estimated equations include variables in the vector x_{it} as observed confounders. We also include variables used as excluded instruments in their respective equation. The values reported in the Table are the estimated coefficients and values in parentheses are the standard error. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 16: Average score on OECD Going Digital policy dimension indicators (relative to average OECD country)



Note: Source: OECD. Figure note: derived from goingdigital.oecd.org (access on September 3 2024). Indicators might refer to different years, ranging in general from 2020-2023, but exceptionally to earlier years back to 2015. The score is defined relative to the maximum across countries; the figure reports the deviation by country from the average OECD score.

Table 17: OECD Going Digital toolkit, which collects country information on different policy dimensions and subindicators

Access

Access to communications infrastructures, services and data underpin digital transformation.

Use

The power and potential of digital technologies and data for people, firms and governments depends on their effective use.

Innovation

Innovation pushes out the frontier of what is possible in the digital age, driving job creation, productivity and sustainable growth.

Jobs

As labour markets evolve, digital transformation should lead to more and better jobs and facilitate just transitions from one job to the next.

Society

Digital technologies affect society in complex and interrelated ways, which challenges stakeholders to work together to balance benefits and risks.

Trust

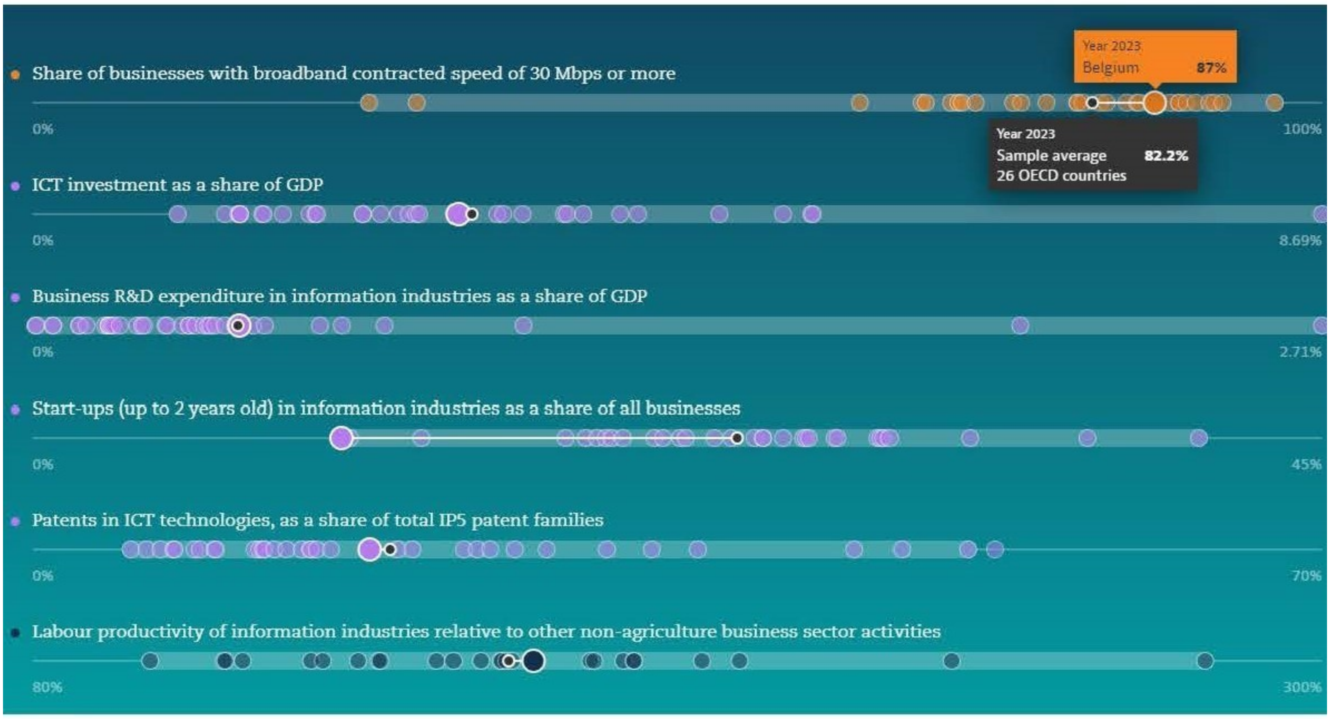
Trust in digital environments is essential for economic and social progress.

Market openness

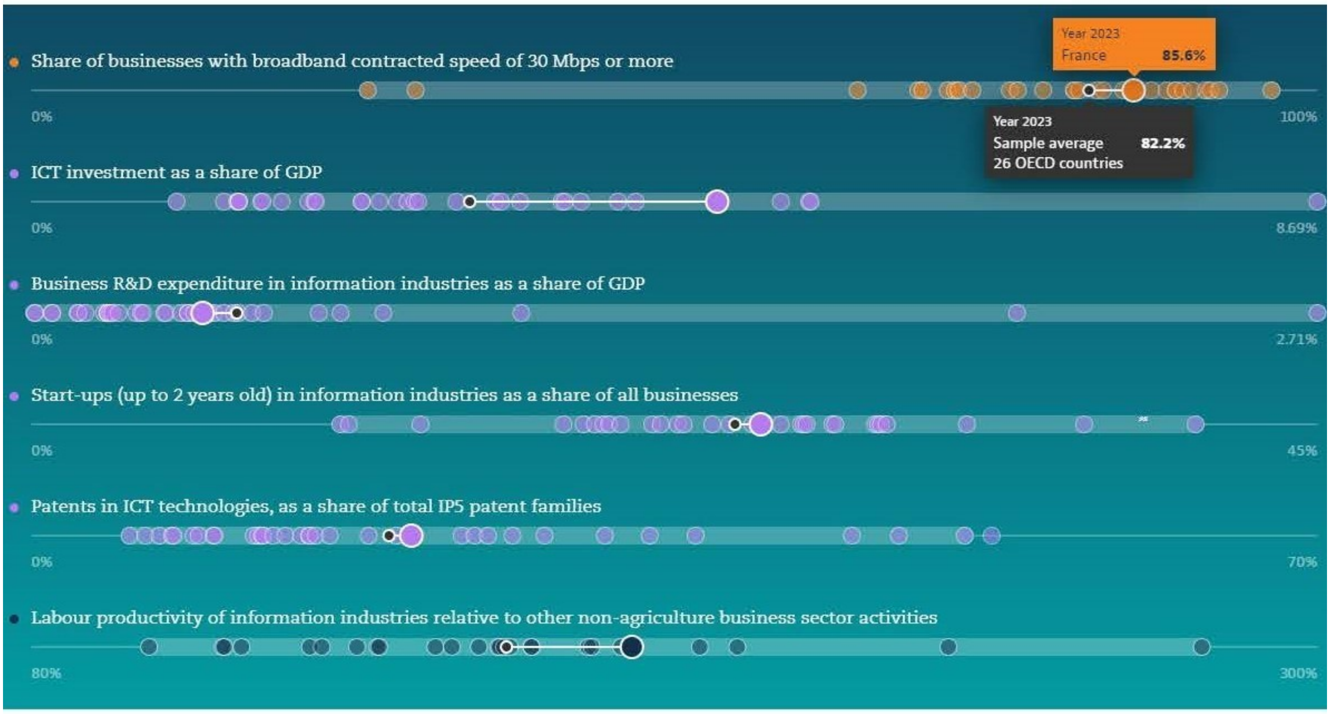
Digital technologies change the way firms compete, trade and invest; market openness creates an enabling environment for digital transformation.

Note: Source: OECD. Figure note: derived from goingdigital.oecd.org (access on September 3 2024).

Table 18: Going Digital visualization of productivity related indicators



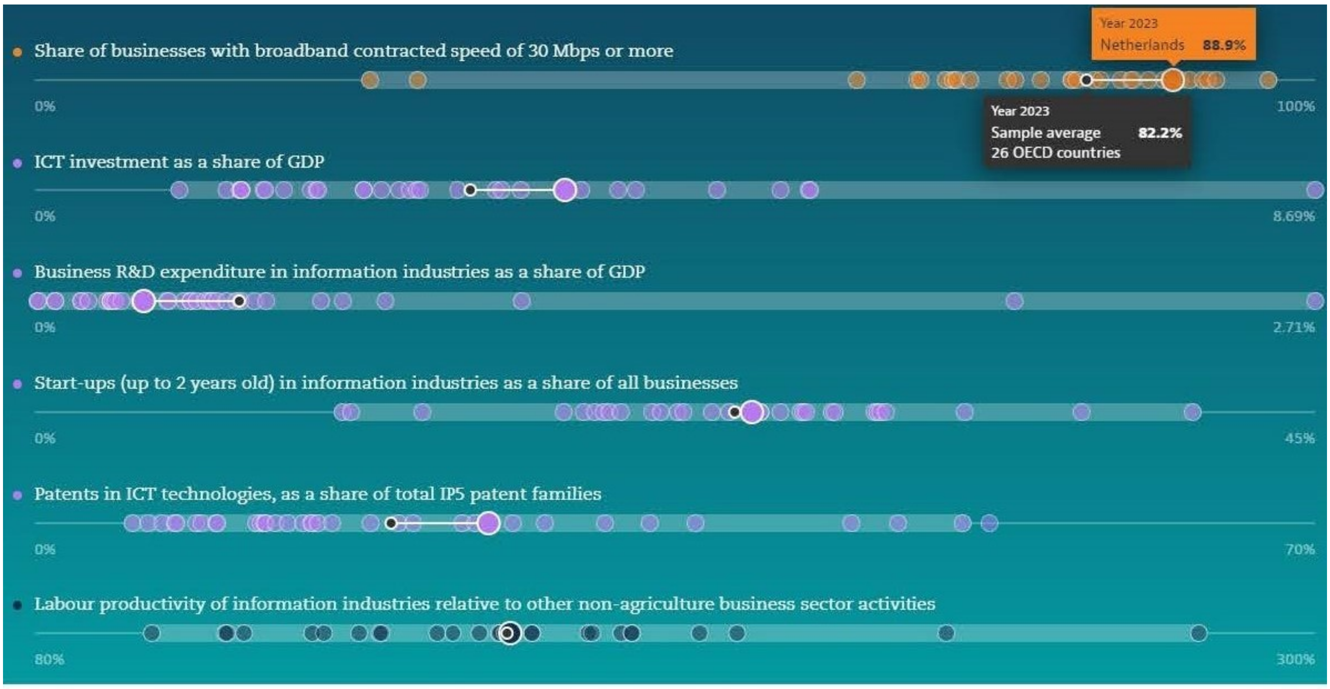
Belgium



France

Note: Source: OECD. Figure note: derived from goingdigital.oecd.org (access on September 3 2024).

Table 19: Going Digital visualization of productivity related indicators, the Netherlands



Note: Source: OECD. Figure note: derived from goingdigital.oecd.org (access on September 3 2024).

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