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Productivity Drivers: Empirical Evidence on the Role of Digital Capital, FDI and Integration

Amat Adarov[a*], David Klenert[b], Robert Marschinski[b], Robert Stehrer[a]

Abstract

There are marked differences in productivity dynamics between countries as well as industries, often leading to substantial performance gaps, such as the gap in labour productivity between the EU and the US. In this article, we use the 2019 release of the EU KLEMS database to look into the drivers of productivity. In particular, we analyse how different types of capital (including intangible capital), foreign direct investment, integration into global value chains and EU integration affect labour productivity. Key findings are that intangible Information and Communication Technology (ICT) capital is a strong driver of productivity both at sectoral and aggregate levels, even more so than tangible ICT capital. Furthermore, backward global value chain integration and EU integration are positively associated with labour productivity. Contrary to expectations, we do not find evidence of a productivity-enhancing effect of foreign direct investment. Finally, we estimate by how much the productivity gap between the EU and the US could be reduced through different ICT investment policies.

Keywords: productivity, digitalisation, ICT, intangible capital, software capital, FDI, capital accumulation, productivity gap, global value chains.

JEL Classification Numbers: F14, F15, F21, E22

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1. Introduction

While EU-15 countries were catching up to the US in terms of productivity until the mid-1990s, this trend reversed around the year 1995 (van Ark, O'Mahony and Timmer, 2008). Since then, the productivity gap continuously widened between the EU-15 Member States and the US – an effect even more pronounced during the economic crisis of 2008-2009 (Timmer et al., 2011). Within the EU, despite a convergence process of new EU members toward the EU average, there are still large differences in absolute productivity levels of eastern and Mediterranean countries and core countries such as Austria, Belgium, Denmark, France and Germany. Both the US and the EU were affected by a slowdown in productivity growth after 2005, albeit the US to a lesser extent (Inklaar et al., 2020; OECD, 2019). Drivers of both, productivity itself, and the slowdown in productivity are still not well understood (Bauer et al., 2020).

In this paper, we perform an econometric analysis of the drivers of labour productivity, focusing in particular on the accumulation of different types of capital (including intangible capital), foreign direct investment, integration into global value chains (GVCs) and EU integration. Our analysis covers the years 2000 to 2017 and a majority of EU countries, as well as Japan and the US.[1] Furthermore, we perform two back-of-the envelope calculations to illustrate the magnitude of these effects, by estimating the change in average EU labour productivity levels and in the EU-US productivity gap, induced by different ICT investment policies.

We come to five main conclusions: First, we find ICT capital, both tangible and intangible, to be a strong driver of productivity growth across the sample. According to our estimates, a 1-percentage point (pp) increase in the growth of the real tangible ICT capital stock increases real labour productivity growth by 0.06 pp. A 1-pp increase in the growth of intangible ICT capital (i.e. software and databases) increases labour productivity growth by 0.09 pp. Results regarding other types of capital are too ambiguous to make general statements. There is, however, a marked difference between the manufacturing and agricultural sector groups, in which some sectors are affected by some types of capital, and the service sectors for which no significant effect at all could be found. Second, further drivers of productivity growth, but to a lesser extent, are backward GVC participation as well as EU integration. Third, contrary to our expectations, FDI does not have a significant effect on labour productivity growth, after controlling for capital composition, special purpose entities and low-tax outlier countries. This is consistent with the hypothesis that, in the European case, FDI targets countries with already high levels of productivity, and hence would not contribute per se to further productivity growth (Hale and Xu, 2016). Fourth, building on the previous three results, we infer that at least a part of the productivity gap between the EU and its peer economies (USA, Japan) can be explained by relatively lower intensity of investment in tangible and intangible ICT capital in many EU countries.[2] Fifth, we estimate that average labour productivity in the EU could be increased by 7.1% if lagging EU countries increased their levels of tangible ICT capital per person employed to US-levels and by 7.3% in the case of intangible ICT capital. This would reduce the EU-US productivity gap by 25.2% for the case of tangible and 28.3% for the case of intangible ICT capital. A further estimate shows that an EU-wide investment of 100bn EUR into tangible ICT capital would increase labour productivity by 1.7% (2.7% for intangible ICT capital) and would reduce the EU-US productivity gap by 6.1% (9.5% for intangible capital).

[1] The sample of countries is determined by the availability of the data in the EU KLEMS database. EU KLEMS allows to differentiate between different types of tangible and intangible capital, which is central to our analysis (for more details see Adarov and Stehrer, 2019a).

[2] This result supports the earlier empirical findings reported in Timmer et al., 2010 and Van Ark et al., 2002.

There is a large literature on the relationship between capital investment and productivity, suggesting that capital structure matters for economic performance and that ICT capital is particularly conducive for productivity (see, for example, Jorgenson and Stiroh, 2000; Oliner and Sichel, 2000; Stiroh 2002, 2005; Oliner et al. 2007; Strauss and Samkharadze, 2011; Spiezia, 2013; Wilson, 2009, but also Acemoglu et al. 2014 for more mixed results). ICT capital, being a general-purpose technology, has multiple channels through which it may influence broad-based productivity at the country level, including faster and more efficient communication, better data management practices and enhanced data flow, thereby also reducing information inefficiencies and fostering knowledge creation and transfer. Taking a comparative perspective, a number of scholars also attributed lower productivity in the EU in comparison with the USA to the lack of ICT investments in the former (Timmer et al., 2010; Van Ark et al., 2002). The importance of intangible capital in driving productivity growth has been studied in Corrado et al. (2006) and Corrado et al. (2017). However, measuring the role of intangible capital has been a challenge due to prevailing data constraints. One of the main novelties of this paper is to include previously unavailable data on intangible capital in the analysis.

The EU-internal heterogeneity of productivity has traditionally been discussed as the gap between core (i.e. central northern export-oriented) countries with high productivity levels and periphery countries (see e.g. Iversen et al. 2016). Recent literature further distinguishes eastern European countries, which exhibit relatively high levels of productivity growth and which appear to be on a catch-up trajectory towards the core group (Bohle, 2017) and financial hubs, which includes countries such as Ireland, Luxemburg, Malta and the Netherlands (Gräbner et al., 2019). The literature suggests a wide range of causes for these productivity gaps, such as low levels of investment in ICT capital (Biagi, 2013, Timmer et al., 2010) and R&D (Castellani et al., 2018). We add to this literature by including the latest data on ICT capital and by specifically analysing the role of FDI, GVC integration and intangible capital.

The ways through which foreign direct investment (FDI) might positively influence productivity in the host countries, perhaps to a greater extent than domestic capital, include the transfer of technology, improvements in management efficiency, as well as by generally increasing competition. At the same time, investments made by multinational corporations (MNEs) may not necessarily lead to a positive and significant effect per se, as this might depend on the absorptive capacity of the host countries and their industries. Borensztein et al. (1998), for instance, report that FDI facilitates productivity only when the host country reaches a certain threshold level of human capital. Having surveyed 30 papers, Hale and Xu (2016), suggest that the effects differ in advanced and developing countries: While the impact on productivity is more profound in developing countries, in advanced countries it is mixed. A related issue is the effect of GVC participation on productivity. In theory, participation in global value chains should provide an opportunity for productivity gains due to knowledge spillovers, greater specialisation in certain tasks, interaction with international frontier firms and increased competition from foreign firms (Criscuolo and Timmis, 2017). The positive link between GVC participation and labour productivity is confirmed by the empirical literature, see for instance Kummritz (2016), Jona-Lasinio and Meliciani (2019) and Pahl and Timmer (2019).

Our main contribution to the literature is as follows: We analyse different drivers of productivity based on a sample of EU countries, Japan and the USA, spanning the period 2000-2017. We thus also take into account the post-crisis years characterised by a major productivity slowdown. Besides looking into the role of FDI, GVC participation and EU integration, we also focus explicitly on the role of digital capital (i.e. intangible ICT capital).

To our knowledge, the latter has not yet been empirically assessed – apart from very few exceptions (e.g. Corrado et al., 2006, 2017) – due to data constraints. For this purpose, we take advantage of the new EU KLEMS 2019 data (see Adarov and Stehrer, 2019a) and analyse the productivity impacts based on fourteen different capital asset classes, also grouping them into tangible and intangible assets. This approach allows to simultaneously distinguish between ICT and non-ICT capital on the one hand and intangible and tangible capital assets on the other hand, which is particularly instrumental to understanding the impact of digital capital. We derive our main results at the aggregate country level, but also study the sectoral level to avoid possible aggregation biases. Apart from the manufacturing sectors, we also analyse the primary and the services sectors, while the literature has focused largely on manufacturing.

The paper is structured as follows: In Section 2 we describe the data used for the econometric analysis. Section 3 contains descriptive statistics on productivity patterns, different capital structures, GVC integration and FDI flows in different countries. In Section 4 we carry out the econometric analysis of the drivers of productivity. In Section 5 we discuss the policy implications and conclude.

2. Data and sample

For the purposes of econometric analysis we assemble a panel dataset that includes aggregate country- and sector-level variables of labour productivity, hours worked, labour composition, FDI, capital stocks and composition by asset types and other variables employed in the econometric analysis. The sample composition is largely determined by the availability of the data in the key data sources, particularly the EU KLEMS database, which covers EU countries and, among non-EU countries, only the USA and Japan. We drop low tax-countries known to be FDI-outliers[3], as well as countries for which data for the key variables of interest is missing or too short. The resulting panel dataset covers 20 countries over the period 2000-2017 (Table 2.1).[4]

Table 2.1. Sample of countries for the econometric analysis in Section 4

Country	ISO3 code	Country	ISO3 code
Austria	AUT	Greece	GRC
Belgium	BEL	Italy	ITA
Czech Republic	CZE	Lithuania	LTU
Germany	DEU	Latvia	LVA
Denmark	DNK	Portugal	PRT
Spain	ESP	Slovak Republic	SVK
Estonia	EST	Slovenia	SVN
Finland	FIN	Sweden	SWE
France	FRA	United States	USA
United Kingdom	GBR	Japan	JPN

Note: This is the sample of countries used in the econometric analysis in Section 4. For the descriptive statistics in Section 3 we include additional countries.

The FDI data is compiled using the Eurostat and the OECD data, depending on which source offers longer series for a given country and bridging to the extent possible the gaps in the data. The OECD and Eurostat use a common framework for reporting FDI statistics and thus the resulting data are internally consistent across the country-sector and time dimensions. In general, we follow the conventions and methods used by the Eurostat/OECD framework described in the 4th edition of the OECD Benchmark Definition of Foreign Direct Investment, BMD4. Importantly, our dataset excludes special purpose entities (SPEs) from the FDI data. SPEs are entities that primarily engage in holding activities and facilitate internal financing of multinational enterprises, but have little or no physical presence in the host economy, which severely distorts the FDI data and adversely affects economic inference in formal analysis, particularly, for countries hosting financial centres. Together with dropping low-tax

[3] In particular, we remove Cyprus, Luxembourg, Malta, Ireland and the Netherlands from the sample, consistent with the list of low-tax countries suggested in Hines (2010).
[4] Given the change in the NACE classification during the period 2000-2017 in order to compile a dataset internally consistent across countries and sectors for the entire time period, we devised a sectoral classification (based on NACE Rev.2). More specifically, in the original Eurostat database the sectoral FDI data for the period 2000-2007 (for some countries 2009) are available according to BPM5 in NACE Rev.1; from 2008-2012 the data are available in BPM5 and according to NACE Rev.2; from 2013-2016 these data are according to BPM6 and NACE Rev.2. The resulting classification is reported in Table 2.2, listing the corresponding NACE Rev.2 codes and labelling conventions used in the paper (the detailed mapping of sectors from different NACE versions is available from the authors on request).

countries this approach allows to focus only on the FDI dynamics with real economic relevance in the context of the productivity analysis.

Table 2.2. Classification of sectors

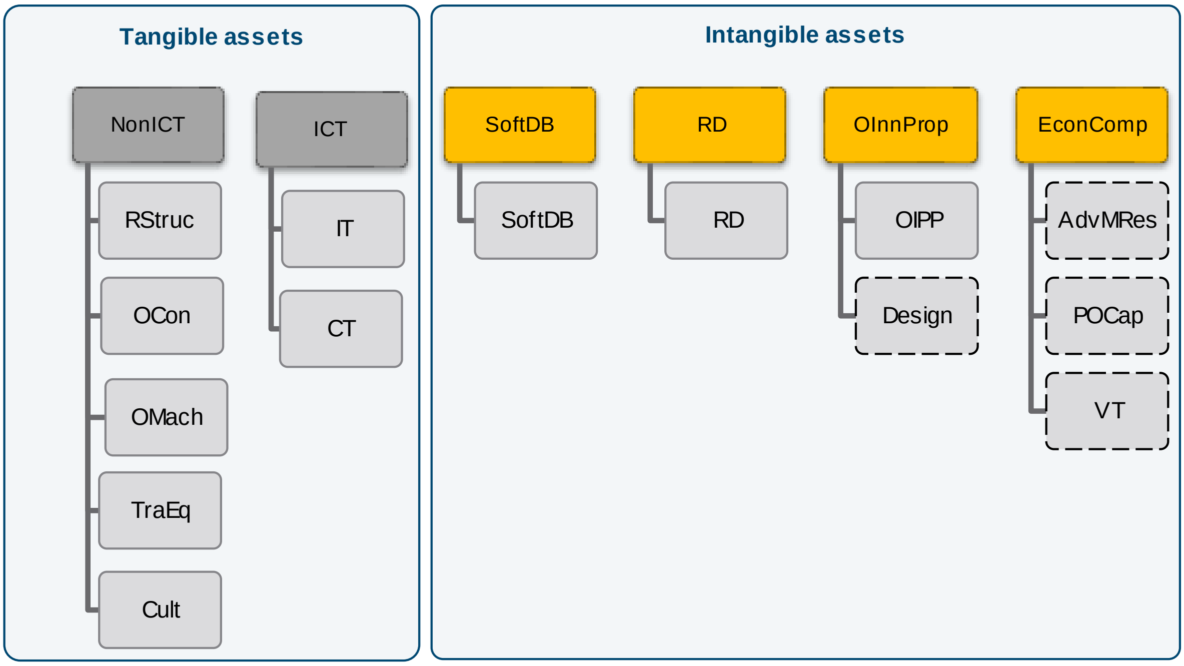
Note: the table shows the classification of sectors used in the paper with the numerical codes (SEC), corresponding NACE Rev. 2 codes, full sector name (based on NACE Rev.2) and short labels used for the brevity of exposition when discussing sectoral estimation results.

SEC	NACE Rev.2 codes	Sector description (based on NACE 2 classification)	Label
1	A	Agriculture, forestry and fishing	1_AGRI
2	B	Mining and quarrying	2_MING
3	10-12	Food products, beverages and tobacco	3_FOOD
4	13-15	Textiles, wearing apparel, leather and related products	4_TXTL
5	16-18	Wood and paper products; printing and reproduction of recorded media	5_WOOD
6	19	Coke and refined petroleum products	6_COKE
7	20-21	Chemicals and chemical products	7_CHEM
8	22-23	Rubber and plastics products, and other non-metallic mineral products	8_RUBB
9	24-25	Basic metals and fabricated metal products, except machinery and equipment	9_METL
10	26-27	Electrical and optical equipment	10_ELEC
11	28	Machinery and equipment n.e.c.	11_MACH
12	29-30	Transport equipment	12_TRAN
13	31-33	Other manufacturing; repair and installation of machinery and equipment	13_OMAN
14	D-E	Electricity, gas and water supply	14_GASW
15	F	Construction	15_CONS
16	45	Wholesale and retail trade and repair of motor vehicles and motorcycles	16_TRMO
17	46	Wholesale trade, except of motor vehicles and motorcycles	17_WHTR
18	47	Retail trade, except of motor vehicles and motorcycles	18_RETR
19	49-52	Transport and storage	19_TRSR
20	53	Postal and courier activities	20_POST
21	I	Accommodation and food service activities	21_ACCO
22	J	Information and communication	22_INFO
23	K	Financial and insurance activities	23_FINA
24	L	Real estate activities	24_REAL
25	M-N	Professional, scientific, technical, administrative and support service activities	25_PROF
26	O-U	Community social and personal services	26_SOCI
100	TOT	Country total	100_TOTL

Source: own elaboration

The data for capital stocks, their composition by asset types, labour productivity, hours worked and labour composition variables are obtained from the new EU KLEMS 2019 Release (see Adarov and Stehrer, 2019a for additional details on the database). The new EU KLEMS release, besides additional time coverage, introduces an expanded capital asset type classification. First, it includes the ten asset types available from national accounts capital data, which have already been included in previous EU KLEMS editions (the taxonomy is presented in the Appendix Figure A1): Cultivated assets (Cult), Dwellings (RStruc), Other buildings and structures (OCon), Transport equipment (TraEq), Other machinery equipment (OMach), Computer hardware (IT), Telecommunications equipment (CT), Computer software and databases (SoftDB), Research and development (RD), Other intellectual property products (OIPP). Second, the database introduces four new 'supplementary' intangible asset types, including Advertising and Market Research (AdvMRes), Design (Design), Purchased Organisational Capital (POCap) and Vocational Training (VT).

Figure 2.1. Capital asset aggregates



Note: Dashed lines indicate asset types outside the boundaries of National Accounts.

Source: own elaboration based on Haskel and Westlake (2018).

Therefore, we distinguish fourteen capital asset types. In order to make the list of asset types more manageable and focused on the role of tangibles/intangibles and ICT/non-ICT capital, as well as to gain efficiency in the estimations given the relatively small sample size, the baseline econometric analysis follows Haskel and Westlake (2018) and groups the 14 asset types into 6 broader aggregates, as outlined in Figure 2.1.

The data for GDP, institutional development and educational attainment are obtained from the World Bank's World Development Indicators and Penn World Tables 9.1. In some empirical exercises we also employ measures for backward and forward global value chain participation (GVC participation), which are computed following the approach of Koopman et al. (2014), using the WIOD database (for additional technical details see Adarov and Stehrer, 2019b).

3 Productivity, capital and GVC dynamics: review of recent trends

This section reviews recent trends in productivity, capital and GVC integration. Key takeaways regarding productivity dynamics are as follows: First, productivity growth has been slowing on a global scale between 2000 and 2017, although comparatively less in the US than in Europe. This slowdown is more pronounced after the 2007/2008 recession. Second, EU countries with lower absolute levels of productivity tend to have higher growth rates, suggesting a certain degree of convergence between EU countries. Despite this trend, there are still substantial gaps in absolute productivity levels and some countries stay behind comparable EU economies regarding both absolute levels and growth of productivity (Croatia, Greece, Portugal and to a lesser extent Italy and Spain). Third, a majority of EU countries exhibits lower levels of productivity as well as productivity growth than the US (and, in many cases, also Japan), with the only exceptions being Austria, Belgium, Denmark, France and Germany.

Given these trends, analysing the drivers of productivity has been high on the agenda of both economists and policy makers. Prior to an econometric analysis focusing on productivity drivers, in this section, we also describe the most important trends regarding the key conjectured drivers of productivity, including capital dynamics and its composition, GVC participation and FDI.

With respect to the latter, European countries show much higher levels of FDI as a percentage of GDP compared with non-EU peer economies, but there also is significant within-EU heterogeneity. When looking at aggregate capital intensity, there are large differences between countries and EU countries generally lag behind Japan and the US. Zooming in on the composition of the capital stock demonstrates that most of the capital stock value (90%) is in non-ICT capital, with the only outlier being Japan, with particularly high shares of ICT and Software. While there have been only marginal changes in the shares of ICT and Software in total capital, there has been a notable increase in the employment intensities of these types of capital (i.e. the stock of real capital per person employed).

3.1 Productivity dynamics in Europe: a comparative perspective

This section reviews the labour productivity dynamics in Europe over time and relative to peer economies. As a measure of labour productivity we use real value added *per hour worked* (at the annual frequency), which better reflects the productivity concept in comparison with the alternative measure of labour productivity *per person employed*, as it is not prone to the bias associated with the full-time versus part-time workers.

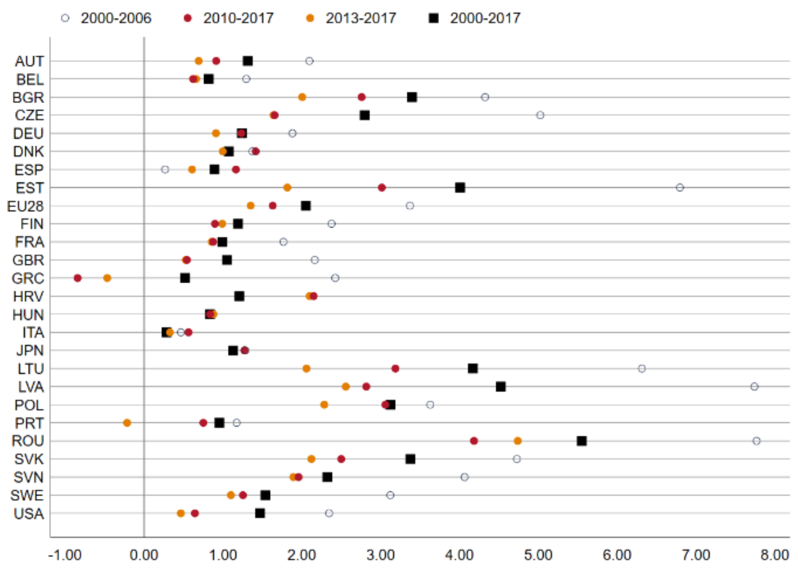
Sluggish productivity growth has been a major challenge for many economies worldwide, particularly in the post-crisis period. As can be seen in Figure 3.1, most European countries suffered a major slowdown in labour productivity growth in the aftermath of the Great Recession, followed by a double-dip recession. This dynamic did not improve in the post-

2013 period either, but, quite on the contrary, in most countries, the slowdown persisted and productivity is still hardly seen on the recovery path. With the exception of Ireland, Spain, Italy and Denmark, labour productivity growth has further decelerated in the post-crisis period. Especially strong productivity slowdowns were incurred by the Baltic countries and Romania, where the average productivity growth declined by more than 3 percentage points after the crisis.

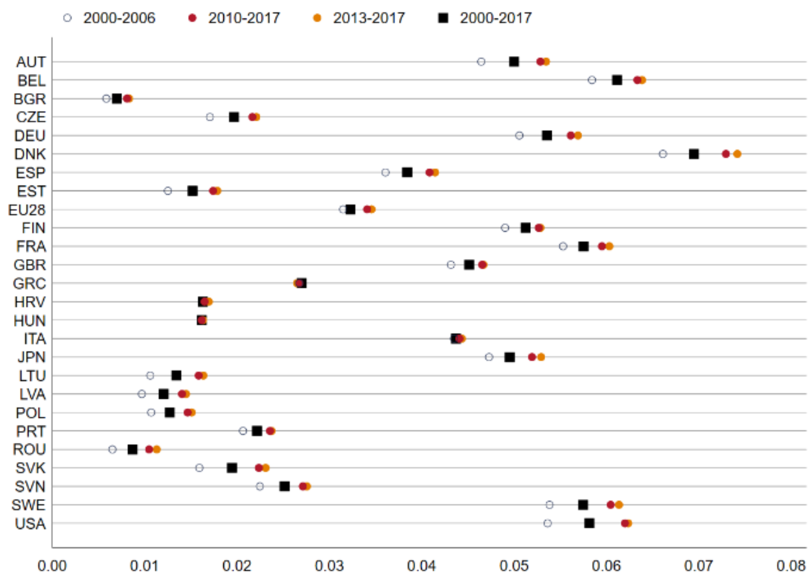
Figure 3.1. Productivity dynamics

Note: The figure shows real labour productivity (per hour worked) growth and real labour productivity level (in mn 2010 USD). The figures indicate 2000-2017 averages along with the pre-crisis and post-crisis period averages (with and without the double-dip recession period). Countries are sorted by ISO3 in alphabetic order. EU28 indicates EU-28 average values.

Labour productivity growth, year-on-year % change



Labour productivity level (th 2010 USD)



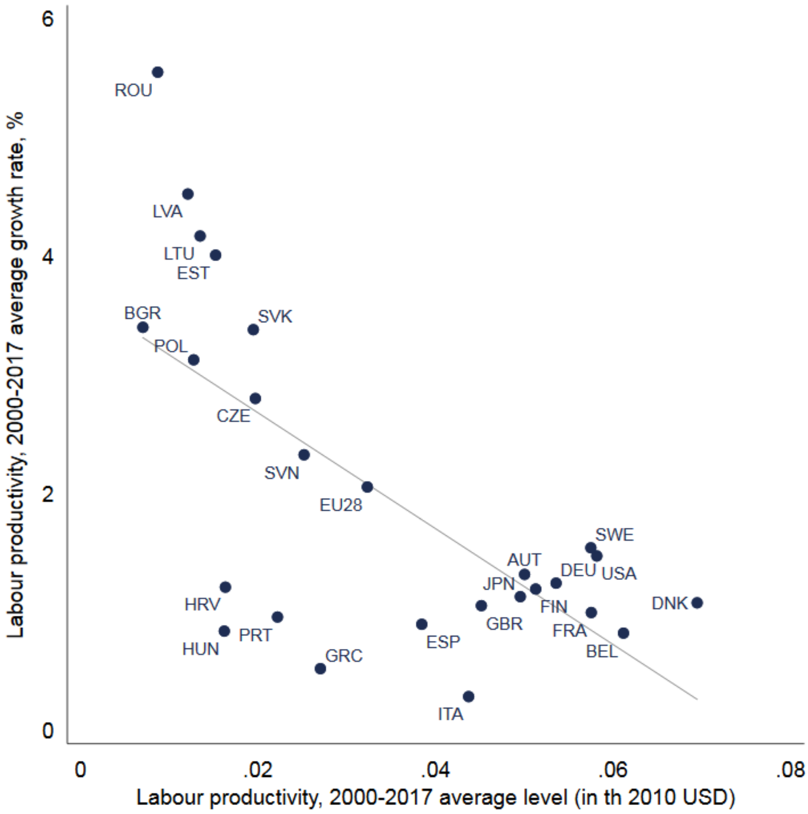
Source: own computations based on EU KLEMS 2019.

While the recent years were characterised by particularly lasting and sizeable productivity losses, it should also be noted that the productivity slowdown is not a phenomenon observed in the recent post-crisis years only; rather, many countries of Europe, both advanced and developing, suffered from productivity decelerations also in the pre-crisis period.

In case of the EU, productivity dynamics are also driven by economic convergence processes related to the EU enlargement process, as countries with lower absolute productivity levels generally tend to enjoy a faster productivity growth rates relative to high-productivity economies (Figure 3.2). This has been a particularly important factor for Europe as multi-speed EU integration facilitates institutional and infrastructural upgrading of the countries lagging behind — the transition economies and the Western Balkan countries. At the same time, a group of countries (often referred to as Mediterranean countries) comprising Portugal, Greece, Croatia, Cyprus, and, to a lesser extent, Italy and Spain, still lag behind comparable peer economies. These countries exhibit lower productivity growth than expected based on the general statistical association between the productivity levels and productivity growth rates as can be inferred from the scatterplot in Figure 3.2.

Figure 3.2. Long-run productivity convergence

Note: The figure shows the scatterplot of long-run labour productivity levels and growth rates along with the fitted linear regression line. EU28 indicates the EU sample average.



Source: own calculations based on EU KLEMS 2019.

While most EU countries tend to lag behind the US, a few of them are at or near the global ‘productivity frontier’ — Germany, France, Austria, Belgium, Denmark. These countries are also characterised by lower productivity growth rates as it is a general pattern that high-productivity countries have lower productivity growth rates.[5]

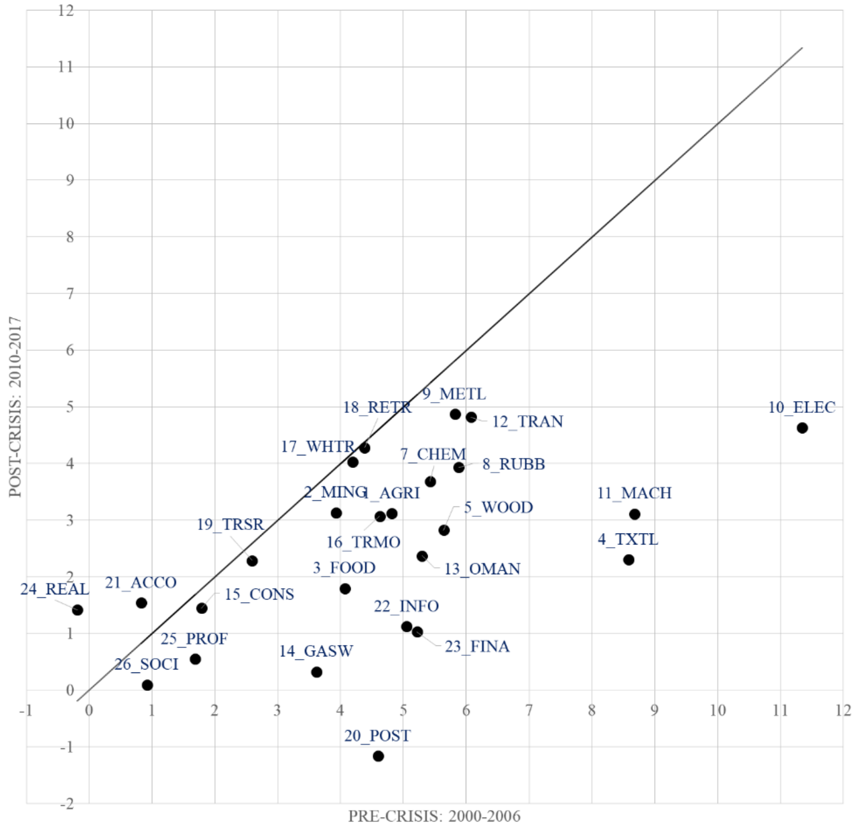
With the exception of selected high-performance economies, many EU countries lag behind the USA in terms of aggregate labour productivity, and in many cases are also behind the productivity levels of Japan. US labour productivity *levels* are in fact almost twice the EU average, and this is the case both before and after the recent crisis (see Figure 3.1). The EU suffered a major setback in productivity growth rates as a result of the crisis and, although it exhibits a productivity *growth rate* moderately above that of the USA in the post-crisis period, bridging this gap appears to be an uphill battle.

A comparative overview of sectoral labour productivity dynamics is reported in Adarov and Stehrer (2020, Figure 2.2.5.) for each of the 26 sectors outlined in Section 2 (real labour productivity growth rates in those sectors are also reported in Figure A3 in the Appendix). The sectoral labour productivity dynamics reveal a similar pattern, with most EU countries lagging behind the USA with the exception of selected frontier economies — mainly Austria, Germany, Finland, Belgium, Denmark (the relative standing of countries differs across sectors, however). Inter alia, the productivity gap is particularly pronounced in the high-tech manufacturing cluster (sectors 10_ELEC, 11_MACH, 12_TRAN). Both Japan and the USA significantly surpass average EU productivity in these sectors with the gap widening in the post-crisis period. In the post-crisis period, the EU suffered from a significant slowdown in the productivity growth dynamics in these sectors, especially in 10_ELEC and 11_MACH sectors which previously were the motor of productivity growth in the EU (see Figure 3.3 for a comparative review of the average EU productivity by sectors before and after the crisis). As productivity growth is slowing across multiple sectors, it appears that the decline in *aggregate national* productivity is associated to a greater extent with common nation-wide structural and cyclical challenges, rather than with a structural shift of the economy of European countries towards sectors with lower productivity growth rates (although the latter might still contribute to some extent).

[5] We do not include Ireland in the sample as the country is an outlier in terms of its tax regime, FDI flows and productivity. It is however worth mentioning that among the European countries and globally, Ireland has demonstrated an especially high level of labour productivity coupled with high productivity growth rates, which also proved to be resilient to the post-crisis growth malaise. Its particularly high productivity level is attributed to the heavy presence of multinational corporations in the economy (particularly, pharmaceuticals, ICT and food sectors -- see the Irish National Competitiveness Council, 2019). Notably, while the multinational companies in Ireland are highly productive, the productivity of domestic enterprises is much lower (also below the OECD average).

Figure 3.3 Labour productivity by sectors: EU-28 average before and after crisis

Note: The figure shows real labour productivity growth rates (%) before and after the crisis (the period 2000-2006 and 2007-2017, respectively) along with the 45-degree line. Sector 6_COKE is omitted (outlier, see Appendix Figure A2 for its values).



Source: own computations based on EU KLEMS 2019.

3.2. FDI and capital dynamics

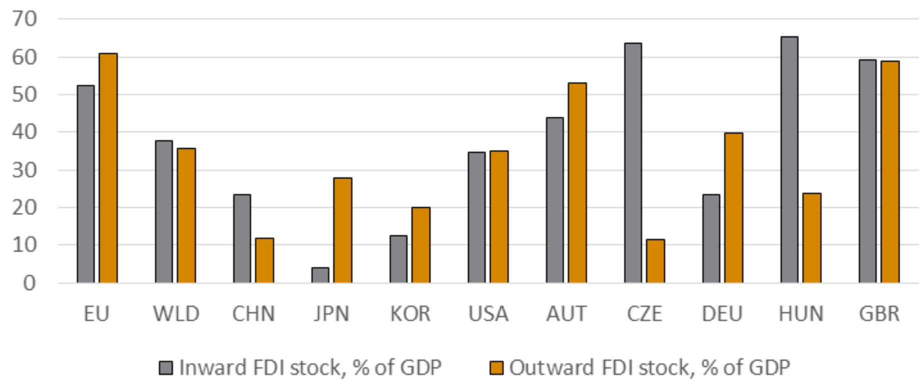
As discussed in the data section, our analysis employs the FDI data compiled using the Eurostat and OECD datasets netting out investment associated with SPEs. We also exclude countries that are commonly acknowledged by experts as low-tax countries (Hines, 2010). This allows focussing on the real economic implications pertinent to FDI, in the sense of conveying a lasting interest by an investor in one economy in having an enterprise resident in another economy.

Figure 3.4 shows the dynamics of FDI for the EU in comparison with the global FDI intensity and selected economies. The EU is characterised by a much higher FDI intensity relative to its peer economies — the USA, China, Japan, South Korea – in terms of both inward and outward FDI-to-GDP ratios. Despite a decline in the volume of FDI in the EU relative to 2017 (inward FDI stock decreased by 0.2% and outward FDI stock by 5.3%), FDI intensity in 2018 stands high at 54.8 percent of GDP for inward FDI stock and 60.3 percent of GDP in the case of outward FDI stock. Overall, the post-crisis period has been characterised by a decline in FDI inflows for European countries (Figure 3.5, top panel).

While aggregate capital intensities vary significantly across European countries (Figure 3.5, bottom panel), in terms of the absolute levels of real capital stock and capital-to-labour ratios European countries generally lag behind the peers (e.g. USA and Japan).

Figure 3.4 Inward and outward FDI stocks, 2014-2018 average

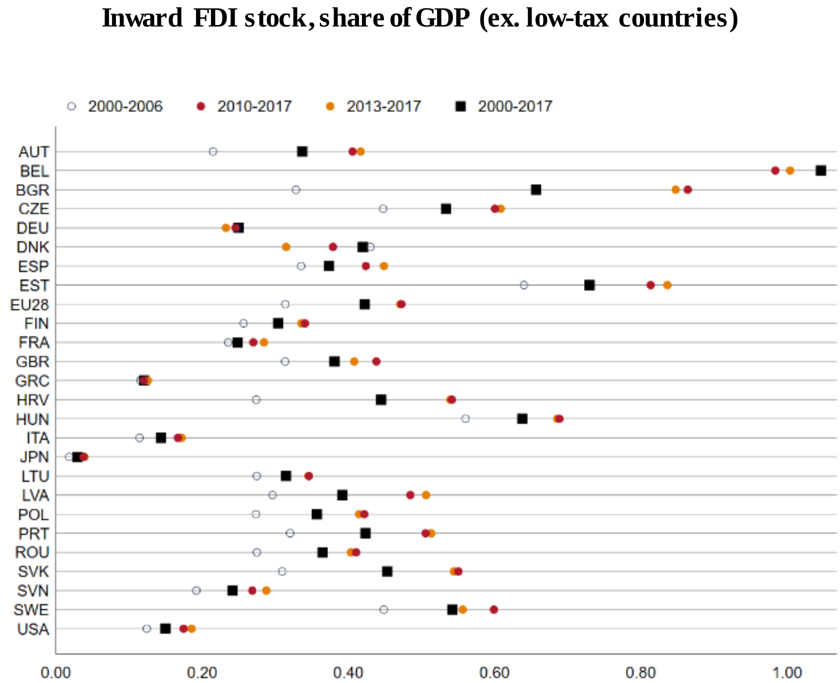
Note: the figure shows 2014-2018 average inward and outward FDI stocks as a percentage of GDP for the EU, the world economy (WLD) and selected economies. 2014-2017 average for South Korea.

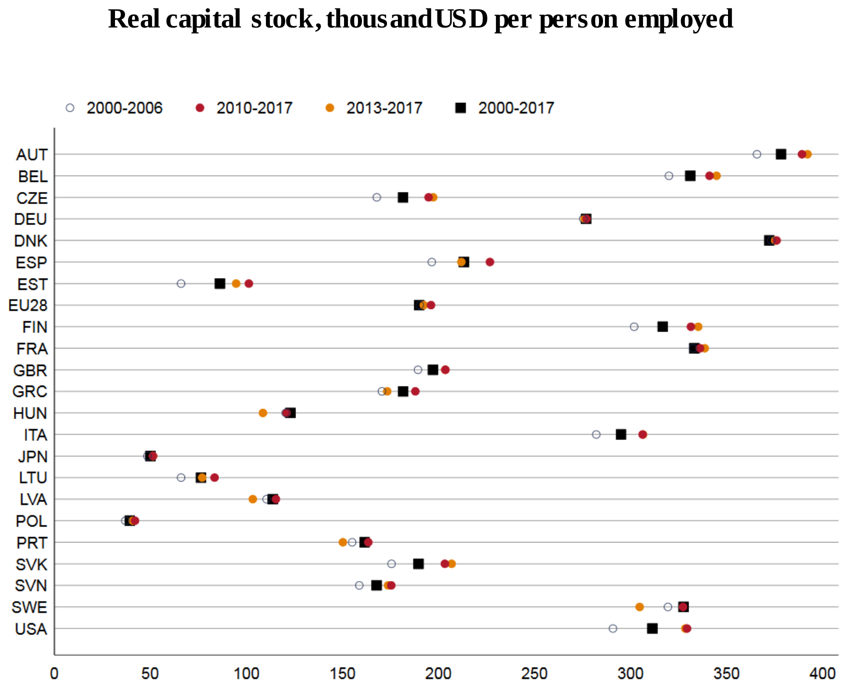


Source: own computations based on the OECD FDI database, 2019

Figure 3.5 FDI and capital accumulation before and after the Great Recession

Note: The figure shows inward FDI stocks and real capital stocks. Numbers are given as 2000-2017 averages along with the pre-crisis and post-crisis period averages (with and without the double-dip recession period). Countries are sorted by ISO3 in alphabetic order.





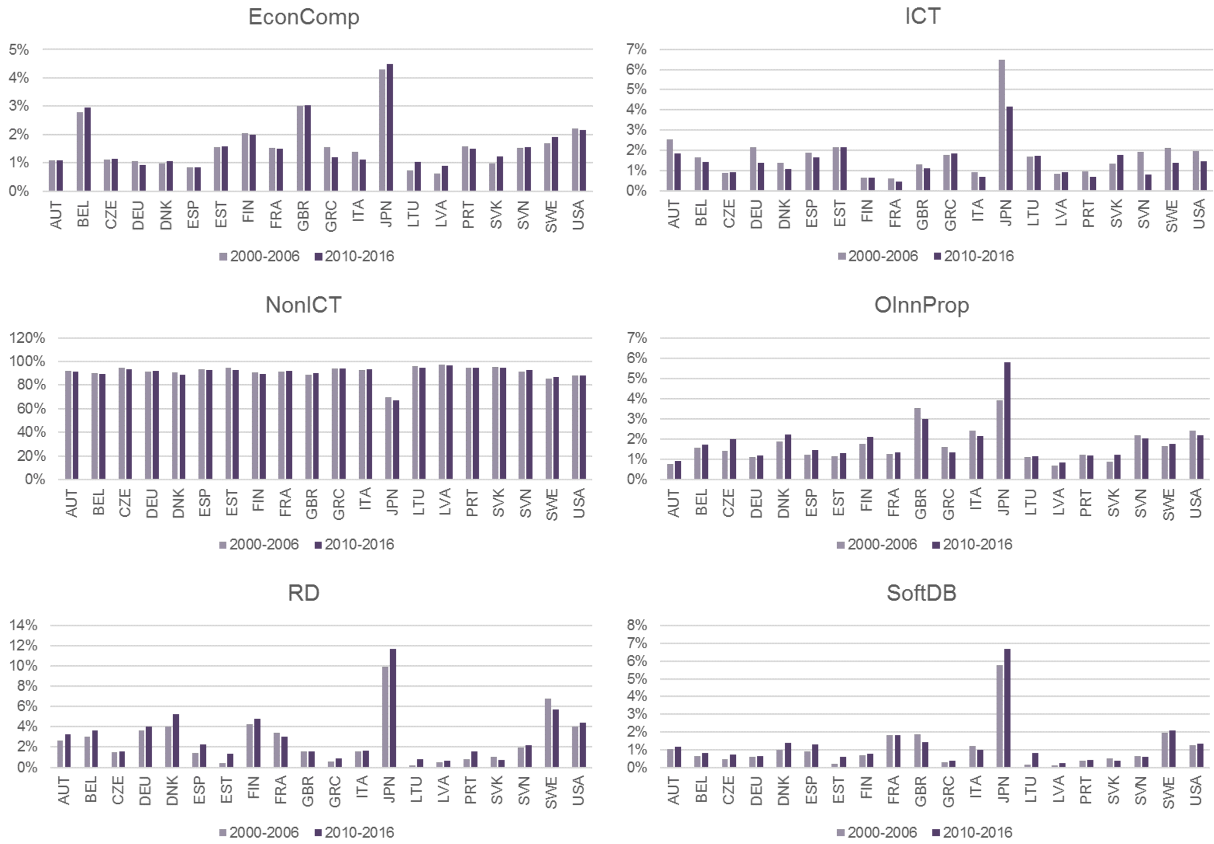
Source: own computations based on EU KLEMS 2019, Eurostat and OECD data

Of equal importance is the composition of capital stocks, in particular, the share of ICT capital and intangible assets, which recently have come to be seen as important new factors of economic growth and productivity. Based on the capital asset taxonomy introduced in Section 2, in Figure 3.6 we present the share of individual capital asset aggregates in total capital stocks, also examining the changes between the pre- and post-crisis periods (for the countries for which the detailed capital asset composition is available in the EU KLEMS 2019).

Most of the capital stock value (about 90%) is attributed nonICT capital. In this regard, Japan prominently stands out from the rest of the sample with a smaller share of nonICT capital and particularly high shares of ICT, SoftDB and RD capital in the total capital stock; however, as a share of employment these capital asset aggregates are in line with other countries. European countries exhibit significant heterogeneity in terms of capital composition. While no significant changes are observed in the shares of tangible and intangible ICT capital in total capital stocks (there is a marginal increase in share of SoftDB along with a slight decrease in the share of tangible ICT in total capital stock), their per-person-employed intensities have increased notably despite the decline in the real capital stock growth (see Fig. C.1 in Appendix C). Among the European countries, Austria, Sweden and Denmark appear to be the leaders at the digital capital frontier as measured by the importance of ICT and SoftDB relative to both total capital stock and the persons employed (France is also included in this group for SoftDB, but not for tangible ICT).

Figure 3.6 Composition of capital stocks by asset groups

Note: The figure shows the share of an asset group in the total capital stock, averages over the period 2000-2006 and 2010-2016. Countries are listed by ISO3 in alphabetic order.



Source: own computations based on EU KLEMS 2019

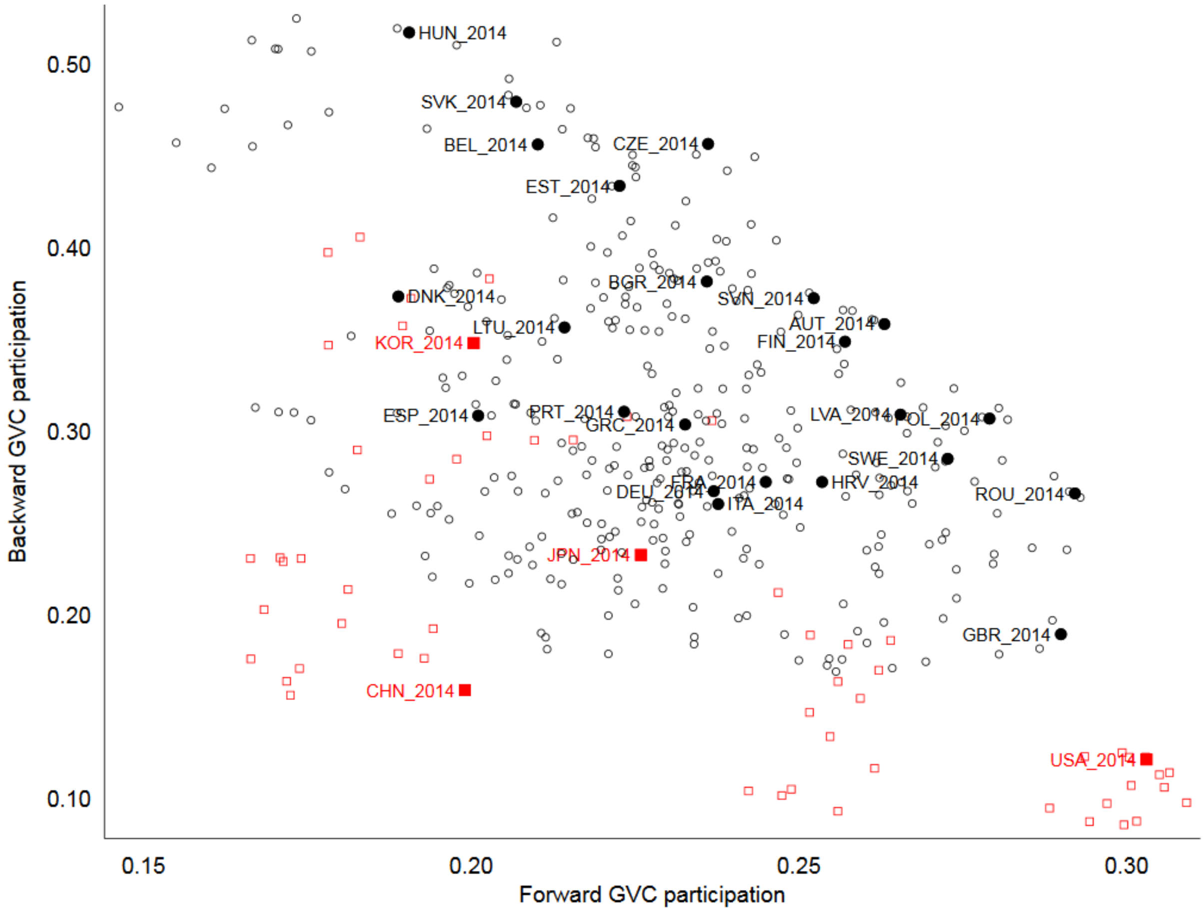
3.3 GVC integration

Based on the WIOD 2016 release (the most recent WIOD vintage to date, see Timmer et al., 2013, 2014) we compute GVC participation at an aggregate national and at sectoral levels, following the framework of Koopman et al. (2014) and identify forward and backward linkages in gross exports (see Adarov and Stehrer, 2020 for additional details).

Backward GVC participation is measured as the share of the imported value added from foreign suppliers upstream in the country's gross exports. Forward GVC participation is measured as the domestic value added entering the exports of other countries. A combination of backward and forward integration yields a measure of a country's total GVC participation.

Figure 3.7 Backward and forward GVC participation

Note: the figure shows the scatterplot of backward GVC participation against forward GVC participation (excluding low-tax countries) for the period 2000-2014. Non-EU countries are marked in red. The data for 2014 is labelled.



Source: own elaboration based on WIOD 2016 release

Observing the international production sharing patterns within Europe (Figure 3.7), it appears that countries tend to "specialize" in either backward or forward linkages. Over time, most countries have been moving in the direction of increasing both backward and forward linkages, and therefore the perceived negative relationship between $\mathrm{GVC}_{\mathrm{ct}}^{\mathrm{BWI}}$ and $\mathrm{GVC}_{\mathrm{ct}}^{\mathrm{FWI}}$ does not actually imply a trade-off between joining upstream or downstream production processes.[6]

Comparing Europe with selected peer economies – China, Japan, South Korea and the USA – suggests that European countries generally have a higher degree of GVC integration (see Figure 3.7). One notable exception is the USA, which has a higher degree of forward GVC participation than all analysed countries and, at the same time, the lowest degree of backward GVC participation. In this respect, it is on the other end of the GVC spectrum in comparison with Hungary, which, on the contrary, has the highest level of backward GVC integration, while its forward GVC participation is among the lowest in the sample. European countries also exhibit higher levels of GVC integration than China and Japan, both upstream and downstream.[7]

The relative GVC position of countries is rather stable and does not change dramatically relative to other countries (Adarov and Stehrer, 2019b). While countries did drift gradually over the observed period 2000-2014 in the GVC "space" spanning backward and forward GVC integration, relative to other countries they tend to remain localized in a certain area.

[6] Looking at the sectoral variation of value chain integration also yields interesting insights, but goes beyond the scope of this article. A detailed analysis also accounting for sectoral variation can be found in Adarov and Stehrer (2019b). For such an analysis, GVC participation measures are based on sectoral output instead of value added.

[7] Regarding GVC integration by sector, Adarov and Stehrer (2019b) show that European countries tend to be better embedded in global value chains both in terms of upstream and downstream integration in the manufacturing sectors. Only in Electronic equipment manufacturing, Japan, South Korea and the USA exhibit average forward GVC participation at relatively high levels (above 0.07), which is however still significantly lower than the forward GVC participation by frontier European countries (e.g., forward GVC participation of Austria, Lithuania and Romania exceeds 0.14).

4. The drivers of productivity: Econometric analysis

In this section, we use panel data techniques to examine the impact of capital accumulation and structure on productivity at aggregate country and sectoral levels, controlling for the impact of other relevant factors, including global value chain participation and economic integration. The model setup is briefly described in Section 4.1. In Section 4.2, we focus on the impact of different types of capital assets (including FDI) on productivity growth. Section 4.3 analyses other potential drivers of productivity, such GVC integration and EU integration, and also controls for FDI and alternative FDI measures. In Section 4.4, instead of using sector aggregates, we look at individual sectors and sector groups to check for possible aggregation biases. Finally, in Section 4.5, we use the econometric results from previous sections to estimate by how much labour productivity in the EU would increase for different ICT/Software investment policies.

4.1. Model setup

Based on a standard production function explaining output as a function of capital and labour inputs, as well as total factor productivity, we use the following specification as the baseline model:

$$\Delta \mathrm{lnPROD}_{\mathrm{ct}} = \alpha_1 \mathrm{lnPROD}_{\mathrm{ct-1}} + \alpha_2 \mathrm{lnL}_{\mathrm{ct}} + \sum_{\mathrm{q \in Q}} \beta_q \, \Delta \mathrm{lnK}_{\mathrm{qct}} + \sigma \Delta \mathrm{lnFDI}_{\mathrm{ct-1}} + \boldsymbol{\xi} \mathbf{X}_{\mathbf{ct}} + \boldsymbol{\mu} + \varepsilon_{\mathrm{ct}}$$

where $\Delta \mathrm{lnPROD}_{\mathrm{ct}}$ is the measure of productivity in country c (real value added per hour worked), in log-differenced form (thus conveying its growth rate). The term $\mathrm{lnPROD}_{\mathrm{ct-1}}$ is the lagged level of real labour productivity capturing the convergence effect. $\Delta \mathrm{lnL}_{\mathrm{ct}}$ is the labour input: the growth of the labour services, which is used for baseline estimations, or a combination of the hours worked and the change in the labour composition, i.e. $\Delta \ln \mathrm{L}_{\mathrm{ct}} = \Delta \ln \mathrm{LC}_{\mathrm{ct}} + \Delta \ln \mathrm{H}_{\mathrm{ct}}$.

The term $\Delta \mathrm{lnK}_{\mathrm{qct}}$ denotes the measure of capital inputs. The baseline model uses real capital stocks in log-differences distinguishing between several capital asset types (alternative specifications include capital services growth and the change in real capital stocks as a share of employed persons). In the baseline analysis we distinguish the six broader capital asset groups as defined in Section 2, i.e. the set Q = {SoftDB; NonICT; ICT; RD; OInnProp; EconComp}. As a robustness check, we also analyse the fourteen detailed capital asset types instead of the aggregate groups.

The variable $\Delta \mathrm{lnFDI}_{\mathrm{ct-1}}$ denotes a measure of foreign direct investment; the baseline model employs inward FDI growth (real inward FDI stock in log-differences[8]), alternative specifications use the change in the inward FDI stock as a share of GDP and the ratio of (real)

[8] GDP deflators are used to compute FDI in constant prices.

inward FDI stock to the persons employed in log-differences. In order to address possible endogeneity issues the FDI variable is lagged by one or more years.

In additional empirical exercises the model is further augmented by other explanatory variables of interest $\mathbf{X_{ct}}$, including interaction terms of FDI with various variables conveying 'absorptive capacity': institutional variables (World Bank's Worldwide Governance Indicators measuring government effectiveness and control of corruption), educational attainment, quality of infrastructure, financial development measured as private credit-to-GDP ratio and others. Further estimations also incorporate GVC participation measures and EU integration variables — discussed in more detail in Section 4.3. Finally, $\boldsymbol{\mu}$ denotes the vector of country (time-invariant) and year fixed effects, capturing unobserved country heterogeneity and common year-specific shocks.

4.2. The impact of digital capital and other capital asset types

In this section, we assess the effects of different capital asset types and FDI on labour productivity (all variables are given in log-differences). The model is estimated first via fixed effects with standard errors clustered by country ("FE") as the baseline estimator — the results are reported in Table 4.1 with the baseline specification listed in column 1. We also report pooled OLS ("POLS") and the Arellano-Bover / Blundell-Bond system GMM ("System GMM") estimates for comparison. The results are consistent across all specifications and estimators in terms of statistical significance and magnitudes.

Although we remove the effects of SPEs from the FDI data and drop low-tax countries (see Section 2), the panel dataset still suffers from outliers associated with some countries (the issue is worse for the sector-level analysis) that may bias the results. The main results are thus based on the threshold of 2 standard deviations from the mean imposed on the key variables of interest (labour productivity growth, growth of real capital stock by asset types and growth of real FDI stock). This allows to focus on the robust average marginal effects (effectively, based on 87-90% of the data).[9]

The analysis strongly suggests that higher investment in ICT capital is associated with an increase in labour productivity growth, consistent with the idea that advanced technology embodied in ICT effectively complements workers' skills leading to productive efficiency gains. More generally, ICT capital, being a general-purpose technology, has multiple channels through which it may influence broad-based productivity at the country level, including faster and more efficient communication, better data management practices and enhanced data flow, thereby also reducing information inefficiencies and fostering knowledge creation and transfer. Notably, both tangible ICT (ICT) and intangible ICT (SoftDB) variables are statistically significant and imply sizeable economic effects: a 1-pp increase in the growth of

[9] The use of the cut-off thresholds to control for outliers was motivated by a series of additional specification tests, including partial-regression leverage plots, added-variable plots and the Cook's distance measures. Estimation results with alternative outlier thresholds, along with the estimates without any outlier control, are reported in the Appendix in Table B3 accompanied by Table B4 which contains related summary statistics for each exercise.

real capital stock induces an increase in real labour productivity growth of about 0.06 pp in the case of the tangible ICT capital and 0.09 pp in the case of the intangible SoftDB capital. In fact, the impact of SoftDB is more profound relative to the ICT aggregate in terms of the magnitude and manifests itself more strongly across multiple specification and robustness checks, including alternative samples and models.[10]

Contrary to our expectations, we do not find an impact of FDI growth on productivity growth. In fact, neither does an effect manifest at deeper lags of the FDI variable, nor after adjusting for each country's absorption capacity as proxied by institutional development, human capital and financial development measures. This implies that, after imposing a strict control over the sample, that is, removing the impact of strong outliers like Ireland, removing the bias associated with SPEs and controlling for other factors, the role of FDI as a booster of labour productivity may not be significant at least in the relatively short time spans of several years. This is however consistent with the idea that in the present case FDI is targeting countries (or sectors) with already high levels of productivity, and thus does not necessarily contribute to further productivity growth at aggregate country levels.

The variable lagged labour productivity level is negative and significant throughout specifications, indicating strong convergence effects as countries with lower productivity levels generally exhibit faster productivity growth. Introducing deeper lags of the real labour productivity variable as a robustness check yields very similar results (available upon request). The growth of labour services is overwhelmingly associated with a declining rate of labour productivity. The decomposition of labour services into its components – the hours worked and the labour composition (Column 2) – reveals that this effect is entirely attributable to the negative impact of the growth in the hours worked, which confirms the conjecture of diminishing marginal returns to labour inputs.

[10] We also included an interaction term between SoftDB and ICT capital to account for possible mutually reinforcing effects. The interaction term however does not enter statistically significantly and also does not change the results qualitatively (the results are available on request). Further, we additionally estimate the model using the fourteen detailed capital asset types, which confirms our baseline results and otherwise does not yield additional insights (results available upon request).

Table 4.1. Aggregate country-level estimation results

Note: The table shows the estimation results using fixed effects ('FE') with standard errors clustered by country (in parentheses), as well as pooled OLS ('POLS') and system GMM ('GMM') based on 3-year non-c averages. The dependent variable is Δln (labour productivity). *, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively. The GMM model is reported merely for reference as it is based on 3-year non-overlapping averages, which ensures that N > T (in this case N=20 and T=6), which significantly reduces the sample size.

	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) POLS	(7) GMM
ln (Labour productivity), lag	-0.122***	-0.119***		-0.135***	-0.106***	-0.010***	-0.117**
	(0.021)	(0.019)		(0.022)	(0.020)	(0.002)	(0.047)
Δln (Labour services)	-0.333***		-0.397***	-0.327***	-0.356***	-0.325***	-0.282*
	(0.073)		(0.079)	(0.079)	(0.068)	(0.059)	(0.166)
Labour composition growth		-0.028					
		(0.151)					
Δln (Hours worked)		-0.378***					
		(0.072)					
Δln (Inward FDI stock), lag	-0.012	-0.011	-0.012	-0.013		-0.004	-0.011
	(0.007)	(0.008)	(0.008)	(0.008)		(0.007)	(0.035)
ΔLn (EconComp, real capital stock)	-0.039*	-0.031	-0.040		-0.029	-0.012	-0.099
	(0.020)	(0.021)	(0.024)		(0.020)	(0.025)	(0.073)
ΔLn (ICT, real capital stock)	0.055**	0.061***	0.045**		0.040**	0.031**	0.030
	(0.021)	(0.021)	(0.021)		(0.017)	(0.013)	(0.059)
ΔLn (NonICT, real capital stock)	-0.037	0.018	-0.063		-0.006	-0.002	0.119
	(0.122)	(0.103)	(0.120)		(0.114)	(0.096)	(0.323)
ΔLn (OInnProp, real capital stock)	-0.002	-0.003	-0.021		0.013	0.008	0.026
	(0.050)	(0.047)	(0.054)		(0.049)	(0.054)	(0.098)
ΔLn (RD, real capital stock)	0.046	0.041	0.057		0.041	0.020	0.014
	(0.039)	(0.039)	(0.044)		(0.033)	(0.035)	(0.084)
ΔLn (SoftDB, real capital stock)	0.085**	0.085***	0.091**		0.083***	0.091**	0.105*
	(0.031)	(0.029)	(0.035)		(0.027)	(0.036)	(0.060)
ΔLn (Labour productivity), lag							-0.043
							(0.185)
Country FE	Yes	Yes	Yes	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216	216	216	248	262	216	76
Adj. R-squared	0.581	0.593	0.521	0.495	0.589	0.468	

We also run estimations separately for the pre-crisis and post-crisis periods, as well as the full period, excluding the crisis years (for the purpose of the analysis the crisis years are defined as the period of 2007-2009, which covers the periods of real economic growth decline and post-crisis recovery). The results are reported in Table 4.2. The exclusion of the crisis years has virtually no effect on the estimates. At the same time, examining separately the pre-crisis and the post-crisis periods, while the tangible ICT capital variable does not result statistically significant in both periods, the impact of intangible ICT (SoftDB) remains significant, albeit with a somewhat lower coefficient before than after the crisis (0.06 vs. 0.11). One should however note that the number of observations available for the pre-crisis period is not high (59) and thus the results are less robust.

Table 4.2. Pre-crisis and the post-crisis periods

Note: The table shows the estimation results using fixed effects with standard errors clustered by country (in parentheses). The dependent variable is Δln (labour productivity). *, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively. Baseline specification is estimated for the full sample including all years, i.e. 2000-2017 (column 1), the period 2000-2006 (pre-crisis), the period 2010-2017 (post-crisis) and the full sample excluding the crisis years, including the post-crisis recovery period (2007-2009).

	(1) all years	(2) pre-crisis	(3) post-crisis	(4) all years, excl. crisis
Ln (Labour productivity), lag	-0.122***	-0.082	-0.198***	-0.112***
	(0.021)	(0.092)	(0.056)	(0.021)
ΔLn (Labour services)	-0.333***	-0.433**	-0.354***	-0.338***
	(0.073)	(0.176)	(0.115)	(0.078)
ΔLn (EconComp, real capital stock)	-0.039*	-0.064	-0.031	-0.082**
	(0.020)	(0.088)	(0.034)	(0.034)
ΔLn (ICT, real capital stock)	0.055**	0.004	0.073	0.058***
	(0.021)	(0.015)	(0.043)	(0.020)
ΔLn (NonICT, real capital stock)	-0.037	0.108	0.107	-0.108
	(0.122)	(0.155)	(0.165)	(0.107)
ΔLn (OInnProp, real capital stock)	-0.002	-0.084	-0.073	0.002
	(0.050)	(0.150)	(0.061)	(0.060)
ΔLn (RD, real capital stock)	0.046	0.030	-0.018	0.018
	(0.039)	(0.094)	(0.040)	(0.034)
ΔLn (SoftDB, real capital stock)	0.085**	0.108*	0.060**	0.098***
	(0.031)	(0.057)	(0.024)	(0.025)
ΔLn (Inward FDI stock), lag	-0.012	-0.010	0.003	-0.008
	(0.007)	(0.008)	(0.007)	(0.007)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	216	59	117	176
Adj. R-squared	0.581	0.368	0.594	0.574

4.3. Further inquiry into the integration effects

In this section, we present additional results focusing on the effects of GVC participation, European economic integration, as well on the implications of FDI for labour productivity, given that the baseline estimation results did not reveal any significant impact, somewhat contrary to standard intuition. The results are reported in Table 4.3.

Table 4.3. The impact of GVC participation and EU membership

Note: The table shows the estimation results using fixed effects with standard errors clustered by country (in parentheses). The dependent variable is Δln (labour productivity). *, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively. 'FDI' in the interaction terms refers to real inward FDI stock in log-differences, i.e. Δln (Inward FDI stock).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Labour productivity), lag	-0.120***	-0.120***	-0.129***	-0.121***	-0.121***	-0.148***	-0.148***
	(0.025)	(0.026)	(0.026)	(0.027)	(0.021)	(0.029)	(0.029)
ΔLn (Labour services)	-0.339***	-0.339***	-0.336***	-0.347***	-0.334***	-0.342***	-0.342***
	(0.076)	(0.075)	(0.080)	(0.075)	(0.077)	(0.076)	(0.076)
ΔLn (EconComp, real capital stock)	-0.042	-0.042	-0.042	-0.044	-0.039*	-0.027	-0.027
	(0.028)	(0.028)	(0.026)	(0.028)	(0.020)	(0.022)	(0.022)
ΔLn (ICT, real capital stock)	0.043**	0.043**	0.043**	0.039*	0.055**	0.060**	0.060**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)
ΔLn (NonICT, real capital stock)	0.036	0.036	0.015	0.048	-0.034	-0.050	-0.050
	(0.131)	(0.131)	(0.128)	(0.123)	(0.124)	(0.126)	(0.126)
ΔLn (OInnProp, real capital stock)	-0.003	-0.002	-0.005	-0.005	-0.002	-0.002	-0.002
	(0.044)	(0.043)	(0.046)	(0.044)	(0.049)	(0.049)	(0.049)
ΔLn (RD, real capital stock)	0.056	0.056	0.054	0.053	0.046	0.036	0.036
	(0.040)	(0.040)	(0.039)	(0.041)	(0.040)	(0.037)	(0.037)
ΔLn (SoftDB, real capital stock)	0.075**	0.075**	0.082**	0.070**	0.085**	0.081**	0.081**
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.029)	(0.029)
FDI = ΔLn (Inward FDI stock), lag	-0.014*	-0.014*	-0.013	-0.009	-0.012	-0.012	-0.012
	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)
Δ Backward GVC, lag	0.200**	0.204**		0.237**			
	(0.085)	(0.076)		(0.091)			
Δ Forward GVC, lag	-0.017		-0.139	-0.108			
	(0.155)		(0.146)	(0.179)			
FDI × Δ Backward GVC , lag				-0.083			
				(0.461)			
FDI × Δ Forward GVC, lag				1.664			
				(1.001)			
FDI × Transition economy DV, lag					0.003		
					(0.016)		
EU membership DV						0.015**	0.015**
						(0.006)	(0.006)
Years in the EU							0.006*
							(0.003)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193	193	193	193	216	216	216
Adj. R-squared	0.601	0.603	0.594	0.604	0.579	0.585	0.585

Across all specifications, the marginal effect of ICT and SoftDB remains significant. We first examine the impact of backward and forward GVC participation on productivity. While forward GVC integration does not reveal any impact, backward GVC participation enters significantly with the marginal impact of 0.2, which implies that an increase in backward GVC participation by 0.1 induces a 2 pp increase in the growth of aggregate labour productivity.[11] It is intuitive that participation in global value chains provides an opportunity for productivity gains due to knowledge spillovers from MNEs and efficiency gains associated with greater specialisation in certain tasks. In this respect, the results highlight the important difference in the relative gains associated with the mode of GVC participation: in the case of specialisation in relatively more downstream industries, as measured by backward GVC participation, firms are able to take advantage of imported inputs of superior quality and/or lower costs, and, in general, greater available variety of foreign inputs.

We perform a range of additional empirical exercises with alternative FDI measures, as well as interaction terms (available upon request). However, FDI effects do not manifest themselves at statistically significant levels, consistent with the baseline results.

[11] For reference, the backward GVC participation indicator by construction takes on values only in the 0-1 interval; the sample year-on-year change in the backward GVC participation varies from -0.05 to +0.04 with a mean of 0.005.

Finally, we augment the model with an EU dummy variable that takes the value of 1 if the country is an EU member and, additionally, the number of years in the EU is introduced to gauge possible non-linear effects associated with the intensity of integration.[12] Notably, both variables are statistically significant, implying that the EU membership boosts labour productivity growth by 1.5 pp, with each year in the bloc bringing an additional increase of 0.6 pp, ceteris paribus, that is in addition to the general convergence effects. Proxying EU integration only by a dummy variable and by the number of years in the EU is of course a crude measure and therefore these results have to be interpreted cautiously.

4.4. Sectoral analysis

In order to address the possible aggregation bias and investigate heterogeneous effects of digital capital and other variables of interest across sectors, we also perform separate estimations for each of the twenty-five sectors[13] as outlined in Section 2, as well as pooled estimations with the primary, manufacturing and services sector groups.

For the sector-specific analysis, we use a specification similar to the baseline aggregate country-level model:

$$\Delta\mathrm{lnPROD_{cjt}} = \alpha_1 \mathrm{lnPROD_{cjt-1}} + \alpha_2 \mathrm{lnL_{cjt}} + \sum_{\mathrm{q\in Q}} \beta_q \, \Delta\mathrm{lnK_{qcjt}} + \sigma\Delta\mathrm{lnFDI_{cjt-1}} + \boldsymbol{\xi}\mathbf{X_{cjt}} + \boldsymbol{\mu} + \varepsilon_{\mathrm{cjt}}$$

Here, j denotes the economic sector. For the pooled estimations with sector groups, as well as the all-sector pooled sample, the model is estimated with several alternative vectors of fixed effects for robustness, including country-sector and year effects, country-sector and sector-year fixed effects, country-sector and country-year fixed effects. In pooled sectoral estimations standard errors are clustered at the country-sector level.

Similarly to the aggregate country-level regression analysis, in the baseline analysis we drop observations that are outside of the two-standard deviation interval from the sector-specific sample mean for the main variables of interest (labour productivity, FDI and capital growth rates) as the marginal impact of outlier values would be even greater at the sectoral level.

We first run individual estimations for each sector in the analysis using the baseline fixed effects model regressing real labour productivity growth on real inward FDI stock growth lagged by one year, real capital stock growth (by capital asset aggregates) and control variables as described in the previous subsection.

The marginal effects for each capital asset aggregate and the FDI variable are reported in Figure D.1 in Appendix D. In addition, the 99% and 90% confidence intervals computed from the robust standard errors are plotted along with the marginal effects to gauge both the

[12] To this end we use the year of entry of each country starting from the Treaties of Rome (i.e. the year 1958) as listed by the European Commission on the EU portal: https://europa.eu/european-union/about-eu/countries_en#tab-0-1.
[13] Sector 20_POST lacks sufficient capital asset data and is therefore omitted in the sectoral analysis.

statistical and the economic significance of the estimates. The corresponding regression results are reported in Table 4.4.

In the following, we group our findings by independent variable and discuss in which sector it is significant, starting with different capital assets (tangible and intangible ICT, R&D, FDI and aggregate capital) and then discussing other independent variables and model variations.

Regarding ICT capital, the positive impact of tangible ICT capital accumulation (labelled "ICT") is found for sectors 3_FOOD and 12_TRAN. Among the services sectors, the significant effect (although only at the 10% level) is found for the sector 22_INFO, which is in line with expectations as the provision of information and communication services heavily relies on tangible and intangible ICT capital. In all three cases, the magnitude of the effect is about 0.1. At the same time, notably, the impact of intangible ICT capital ("SoftDB") is more pronounced, with especially strong positive effects in terms of both statistical and economic significance observed in sectors 4_TXTL, 16_TRMO and 6_COKE. In the latter case, the magnitude is particularly high, implying almost a one-to-one increase in labour productivity growth associated with the growth in SoftDB capital. SoftDB capital also enters positively for the sector 11_MACH, but the effect is less significant statistically and in terms of economic significance (the estimate varies in the range of 0.08-0.1 across specifications). Surprisingly, intangible ICT also has a negative impact on sector 5_WOOD. Overall, the results observed across all specifications do not reveal strong systematic patterns across sectoral groups; while the high-tech sectors and sectors involved in the provision of information and communication services tend to exhibit more consistent positive response of productivity growth to ICT and RD capital, the impact of capital composition varies significantly and is specific to each sector.

RD capital, besides the mining sector 2_MING, is found to be conducive to labour productivity growth in technologically advanced manufacturing and services sectors: 11_MACH, 13_OMAN, 22_INFO and 25_PROF. The results are particularly noteworthy for sectors 11_MACH and 25_PROF, which are characterised by relatively high average intensity of RD capital in total capital stock of the sector.[14]

We generally do not find a strong impact of inward FDI on labour productivity. The positive effects manifest themselves only for some sectors at deeper lags. At the 1-year lag, the weakly statistically significant — at the 10-percent level of statistical significance — impact of FDI is observed only for sector 1_AGRI (positive effect), and for sectors 10_ELEC and 15_CONS (negative effects). Estimations with alternative FDI measures yield similar results (available upon request).

By contrast, the impact of capital accumulation on labour productivity is much more profound, although the impact varies significantly across sectors and capital asset types. Examining first the impacts of non-ICT capital asset types, notably, in the case of the primary

[14] More generally, the RD-capital intensive sectors with the average share of RD capital in total capital stock of at least 10% are the high-tech manufacturing sectors involved in the production of machinery and electronics (SEC10, SEC11, SEC 12) and chemical/pharmaceutical products (7_CHEM), as well as SEC25 (professional services). See Table A2 in the Appendix for a review of capital composition by sectors.

sectors, 1_AGRI and 2_MING, investment in EconComp facilitates labour productivity with the estimated magnitude of about 0.3 (a 1-pp increase in the growth of capital stock induces an 0.3-pp increase in productivity growth), statistically significant at the 5-10% level.[15] For a number of manufacturing and services sectors, the impact of EconComp however is negative with magnitudes in the 0.2-0.3 range (especially for sectors 3_FOOD and 13_OMAN, as well as 7_CHEM and 24_REAL). NonICT capital enters significantly with a positive sign for 13_OMAN, 15_CONS and 25_PROF sectors.

Summarising the estimation results across various empirical exercises, consistent with aggregate country results, labour services growth is associated with lower labour productivity growth on account of the hours worked component embedded in the labour services variable. Across all sectors, the convergence effects can also be observed as picked up by the negative and in most cases statistically significant coefficients of the lagged real labour productivity level variable.[16]

Finally, we also run pooled sectoral estimations with appropriate fixed effects included to control for year, country and sector effects (see Table 4.5). We look at both, pooling across all sectors, and across sector groups (primary, manufacturing and services). In the case of the all-sector pooled estimation results SoftDB is positive, but only marginally significant (up to 5% level of statistical significance) with the marginal effect low at 0.03. For other capital assets the impacts are small in magnitude and/or statistically weakly significant or insignificant.

Splitting the sample into sector groups yields more relevant results. The primary sector reveals a positive effect of RD and EconComp capital asset groups on labour productivity with marginal effects of 0.1 and 0.3, respectively. In the manufacturing sector group both EconComp and OInnProp capital growth have a negative productivity impact, while, notably, RD and SoftDB capital asset groups enter positively with a statistical significance of 1-5%. Estimates suggest that a 1-pp increase in the growth of real capital boosts labour productivity growth by about 0.1 pp in the case of SoftDB and 0.2 pp in the case of RD. Finally, the pooled services sector group does not reveal any significant effects associated with capital accumulation. Consistent with aggregate country and sector-specific results, in all cases the FDI variable is not significant.

As a robustness check, in order to allow for the possibility of a delayed impact on productivity, we additionally explore deeper lags of the FDI variable: the results with the 3-year lags are also included in Figure F.1. Using capital services growth rates instead of real capital stock growth yields largely identical results, as well as specifications with real inward FDI and real capital stocks by asset groups taken as a share of employment. The results are available upon request.

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[15] This holds for specifications involving the real capital stock and the alternative capital-to-labour ratio variable.

[16] In both the aggregate country analysis and sector estimations deeper lags of the productivity level variables were also tried, yielding very similar results.

Table 4.4. Drivers of labour productivity: regressions with real capital and real inward FDI stock (1-year lag) growth rates

Note: The dependent variable is real labour productivity (per hour worked) in log-differences. The table shows the estimation results using fixed effects with standard errors clustered by country (in parentheses). *, **, *** indicate statistical significance at the 10, 5 and 1% levels. Sector 20_POST has an insufficient number of observations and therefore is omitted from the analysis.

	1_AGRI	2_MING	3_FOOD	4_TXTL	5_WOOD	6_COKE	7_CHEM	8_RUBB	9_METL	10_ELEC	11_MACH	12_TRAN	13_OMAN
Ln (Labour productivity), lag	-0.211***	-0.099***	-0.163*	-0.404***	-0.092**	-0.222*	-0.231*	-0.370***	-0.163**	-0.108*	-0.195***	-0.432***	-0.165**
	(0.050)	(0.031)	(0.085)	(0.060)	(0.040)	(0.108)	(0.115)	(0.057)	(0.061)	(0.061)	(0.039)	(0.071)	(0.060)
ΔLn (Labour services)	-0.478	-0.299***	-0.413*	-0.873***	-0.350*	0.536	-0.349*	-0.113	-0.325	-0.168	-0.386*	0.261*	-0.512***
	(0.273)	(0.060)	(0.209)	(0.194)	(0.163)	(0.744)	(0.186)	(0.155)	(0.186)	(0.189)	(0.201)	(0.133)	(0.143)
ΔLn (EconComp, real capital stock)	0.284**	0.334*	-0.246***	-0.003	0.155	-1.030	-0.223*	-0.091	-0.095	0.025	0.061	0.216	-0.264**
	(0.119)	(0.169)	(0.078)	(0.145)	(0.122)	(0.614)	(0.118)	(0.103)	(0.092)	(0.189)	(0.076)	(0.148)	(0.097)
ΔLn (ICT, real capital stock)	-0.020	0.055	0.117**	0.063	0.065	-0.061	-0.039	-0.019	0.020	0.006	0.029	0.135**	0.034
	(0.055)	(0.083)	(0.053)	(0.062)	(0.047)	(0.270)	(0.064)	(0.069)	(0.054)	(0.078)	(0.040)	(0.062)	(0.041)
ΔLn (NonICT, real capital stock)	-0.420	0.106	0.137	0.080	-0.054	-1.189	0.497	-0.003	-0.026	0.285	-0.383**	0.069	0.253*
	(0.443)	(0.223)	(0.400)	(0.497)	(0.219)	(0.702)	(0.312)	(0.189)	(0.373)	(0.278)	(0.138)	(0.419)	(0.123)
ΔLn (OInnProp, real capital stock)	-0.150	-0.201	0.061	0.006	0.022	-1.015	0.112	-0.354*	0.062	-0.293	-0.187	-0.547*	-0.366*
	(0.181)	(0.145)	(0.072)	(0.203)	(0.191)	(1.105)	(0.077)	(0.164)	(0.135)	(0.223)	(0.182)	(0.295)	(0.187)
ΔLn (RD, real capital stock)	-0.059	0.219**	-0.164*	-0.031	0.091	-0.324	0.121	-0.024	0.130	0.271	0.363*	0.209	0.207***
	(0.075)	(0.087)	(0.085)	(0.106)	(0.068)	(0.289)	(0.208)	(0.167)	(0.110)	(0.211)	(0.176)	(0.142)	(0.053)
ΔLn (SoftDB, real capital stock)	-0.050	-0.036	-0.020	0.229***	-0.156**	0.973**	-0.051	0.016	-0.032	-0.130	0.084*	-0.131	-0.093
	(0.055)	(0.051)	(0.089)	(0.062)	(0.053)	(0.361)	(0.050)	(0.036)	(0.036)	(0.096)	(0.040)	(0.107)	(0.087)
ΔLn (Inward FDI, real stock), lag	0.033*	-0.004	-0.010	0.001	0.004	0.031	0.013	-0.001	-0.020	-0.023*	-0.018	-0.003	0.005
	(0.017)	(0.010)	(0.008)	(0.018)	(0.016)	(0.061)	(0.014)	(0.019)	(0.016)	(0.012)	(0.015)	(0.011)	(0.007)
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	100	153	132	106	104	76	122	109	138	120	136	113	109
Adj. R-squared	0.268	0.270	0.308	0.517	0.222	0.347	0.130	0.464	0.350	0.389	0.567	0.565	0.642

Table 4.4 (cont.)

	14_WATR	15_CONS	16_TRMO	17_WHTR	18_RETR	19_TRSR	21_ACCO	22_INFO	23_FINA	24_REAL	25_PROF	26_SOCI
Ln (Labour productivity), lag	-0.198***	-0.144**	-0.189**	-0.124	-0.358**	-0.440***	-0.266***	-0.071*	-0.188**	-0.268**	-0.106***	-0.140**
	(0.061)	(0.052)	(0.073)	(0.101)	(0.096)	(0.097)	(0.065)	(0.034)	(0.073)	(0.092)	(0.030)	(0.057)
ΔLn (Labour services)	-0.506***	-0.321**	-0.253	0.178	-0.531**	-0.178	-0.215	-0.400***	-0.207**	-0.199	-0.398***	-0.318**
	(0.103)	(0.139)	(0.146)	(0.441)	(0.180)	(0.154)	(0.238)	(0.112)	(0.094)	(0.125)	(0.092)	(0.125)
ΔLn (EconComp, real capital stock)	-0.066	-0.122	0.115	-0.046	-0.102	0.073	0.161*	-0.082	-0.074	-0.213**	0.027	-0.003
	(0.089)	(0.085)	(0.187)	(0.151)	(0.173)	(0.129)	(0.090)	(0.066)	(0.210)	(0.085)	(0.050)	(0.046)
ΔLn (ICT, real capital stock)	-0.013	-0.057	0.077	-0.176**	-0.057	0.141	0.008	0.096*	-0.035	-0.021	0.033	0.022
	(0.043)	(0.040)	(0.073)	(0.062)	(0.116)	(0.098)	(0.046)	(0.052)	(0.048)	(0.049)	(0.028)	(0.014)
ΔLn (NonICT, real capital stock)	-0.286	0.397**	-0.723*	0.087	0.023	0.274	0.583	-0.015	-0.198	0.144	0.171**	0.107
	(0.318)	(0.154)	(0.315)	(0.333)	(0.318)	(0.344)	(0.372)	(0.100)	(0.123)	(0.468)	(0.075)	(0.090)
ΔLn (OInnProp, real capital stock)	0.111	-0.000	0.230	-0.040	-0.214	0.049	0.114	0.128	-0.026	0.050	0.060	-0.021
	(0.275)	(0.125)	(0.181)	(0.168)	(0.158)	(0.201)	(0.067)	(0.097)	(0.071)	(0.056)	(0.062)	(0.047)
ΔLn (RD, real capital stock)	0.058	0.068*	-0.031	-0.048	0.022	-0.053	-0.019	0.110*	0.021	-0.010	0.135**	-0.038
	(0.069)	(0.035)	(0.035)	(0.099)	(0.066)	(0.052)	(0.028)	(0.053)	(0.035)	(0.023)	(0.056)	(0.047)
ΔLn (SoftDB, real capital stock)	-0.133	-0.060	0.327**	-0.019	-0.011	0.042	0.024	0.005	-0.062	0.000	-0.038	0.018
	(0.076)	(0.045)	(0.108)	(0.068)	(0.030)	(0.065)	(0.028)	(0.039)	(0.084)	(0.028)	(0.049)	(0.025)
ΔLn (Inward FDI, real stock), lag	0.010	-0.016*	-0.017	0.011	0.030	0.009	0.015	-0.000	0.005	-0.005	0.002	0.000
	(0.011)	(0.008)	(0.028)	(0.032)	(0.022)	(0.010)	(0.016)	(0.005)	(0.015)	(0.011)	(0.004)	(0.001)
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	152	151	47	68	54	72	106	163	158	112	162	152
Adj. R-squared	0.268	0.270	0.308	0.517	0.222	0.347	0.130	0.464	0.350	0.389	0.567	0.565

Table 4.5. Regressions with pooled sectors

Note: The table shows the estimation results using fixed effects with standard errors clustered by country (in parentheses). The dependent variable is real labour productivity (per hour worked) in log-differences. *, **, *** indicate statistical significance at the 10, 5 and 1% levels. Sector 20_POST has an insufficient number of observations and therefore is omitted from the analysis.

	Primary sectors SEC 1-2		Manufacturing sectors SEC 3-13		Services sectors SEC 14-26		All sectors SEC 1-26	
Ln (Labour productivity), lag	-0.106***	-0.111***	-0.113	-0.095	-0.127***	-0.148***	-0.104*	-0.098*
	(0.029)	(0.030)	(0.074)	(0.070)	(0.024)	(0.022)	(0.054)	(0.051)
ΔLn (Inward FDI stock)	0.004	0.003	-0.000	-0.005	-0.003	-0.001	-0.002	-0.001
	(0.007)	(0.010)	(0.012)	(0.011)	(0.002)	(0.002)	(0.004)	(0.004)
ΔLn (EconComp, real capital stock)	0.311**	0.315**	-0.292**	-0.216***	-0.054	-0.060	-0.124*	-0.084
	(0.133)	(0.142)	(0.114)	(0.071)	(0.039)	(0.044)	(0.068)	(0.058)
ΔLn (ICT, real capital stock)	0.028	0.037	0.016	0.020	-0.010	-0.005	0.015	0.013
	(0.047)	(0.063)	(0.038)	(0.034)	(0.015)	(0.013)	(0.014)	(0.012)
ΔLn (NonICT, real capital stock)	-0.002	0.005	-0.181	-0.223	0.006	-0.008	-0.069	-0.114
	(0.204)	(0.221)	(0.178)	(0.229)	(0.052)	(0.056)	(0.094)	(0.133)
ΔLn (OInnProp, real capital stock)	-0.193	-0.201	-0.332*	-0.251**	0.048	0.062	-0.148*	-0.091
	(0.142)	(0.139)	(0.163)	(0.115)	(0.036)	(0.038)	(0.078)	(0.063)
ΔLn (RD, real capital stock)	0.121*	0.148**	0.233**	0.185***	-0.013	-0.004	0.035	0.037**
	(0.062)	(0.067)	(0.088)	(0.058)	(0.009)	(0.014)	(0.021)	(0.015)
ΔLn (Soft_DB, real capital stock)	-0.038	-0.031	0.097**	0.119***	0.006	-0.005	0.030	0.034**
	(0.049)	(0.046)	(0.035)	(0.039)	(0.023)	(0.014)	(0.018)	(0.013)
ΔLn (Labour services)	-0.291***	-0.309***	-0.143	-0.287*	-0.271***	-0.330***	-0.201***	-0.310***
	(0.075)	(0.067)	(0.155)	(0.144)	(0.070)	(0.079)	(0.056)	(0.062)
Country-sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes		yes		yes		yes	
Sector-year FE		yes		yes		yes		yes
Observations	253	253	1,265	1,265	1,414	1,414	2,932	2,932
Adj. R-squared	0.313	0.376	0.214	0.397	0.219	0.417	0.141	0.367

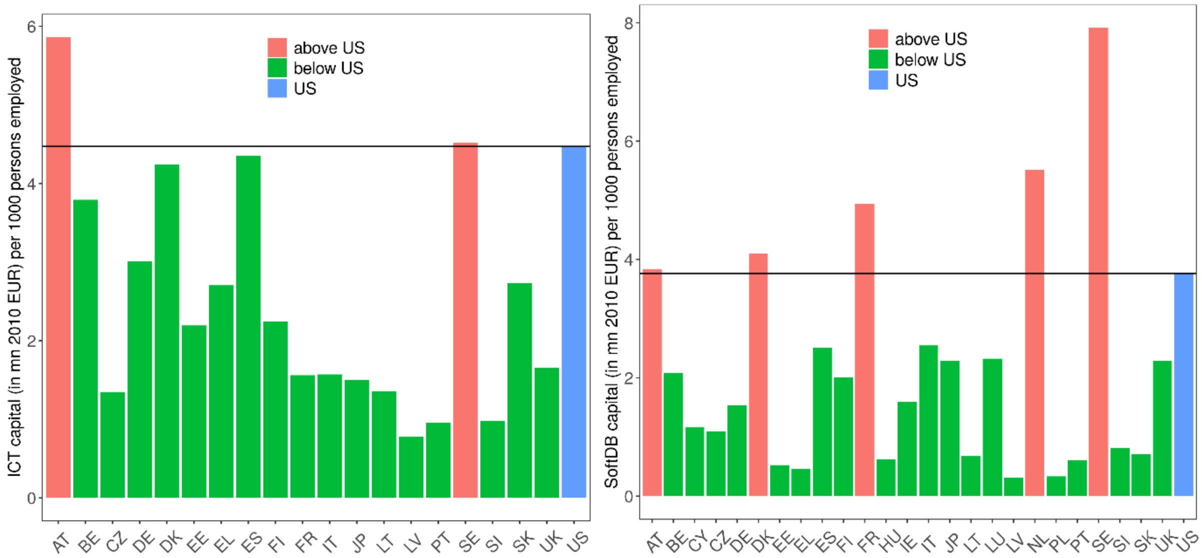
4.5 Implications for productivity gaps between countries

In this section, we illustrate the order of magnitude of the effects identified in the previous sections and their possible impact on inter-country productivity gaps by making two example calculations. First, we estimate how increasing the level of tangible (intangible) ICT capital per person employed in EU countries to US levels affects labour productivity in a given year. We assume that only countries with below-US levels of ICT capital per person employed increase their ICT investment; otherwise, their ICT investment remains unchanged. Second, we look at a hypothetical ICT investment package of 100bn EUR distributed according to population across EU countries. We further assume that everything else remains constant, which leads to a relatively rough estimate. Nevertheless, it gives an idea of the contribution of ICT capital, both tangible and intangible, to inter-country productivity gaps.

There are large differences between EU countries in the levels of both tangible and intangible ICT capital per person employed. Figure 4.1 compares (in) tangible ICT capital levels (in 2010 EUR) per 1000 persons employed across different countries. Countries with levels below those of the US are marked in green, countries above US levels are marked in red. This figure demonstrates that most EU countries are below US levels – an effect more pronounced for tangible ICT capital (left panel) than for intangible ICT capital (right panel).

Figure 4.1

Note: ICT capital (in mn 2010 EUR) per 1000 persons employed in 2015. Left panel: tangible ICT capital, right panel: intangible ICT capital.

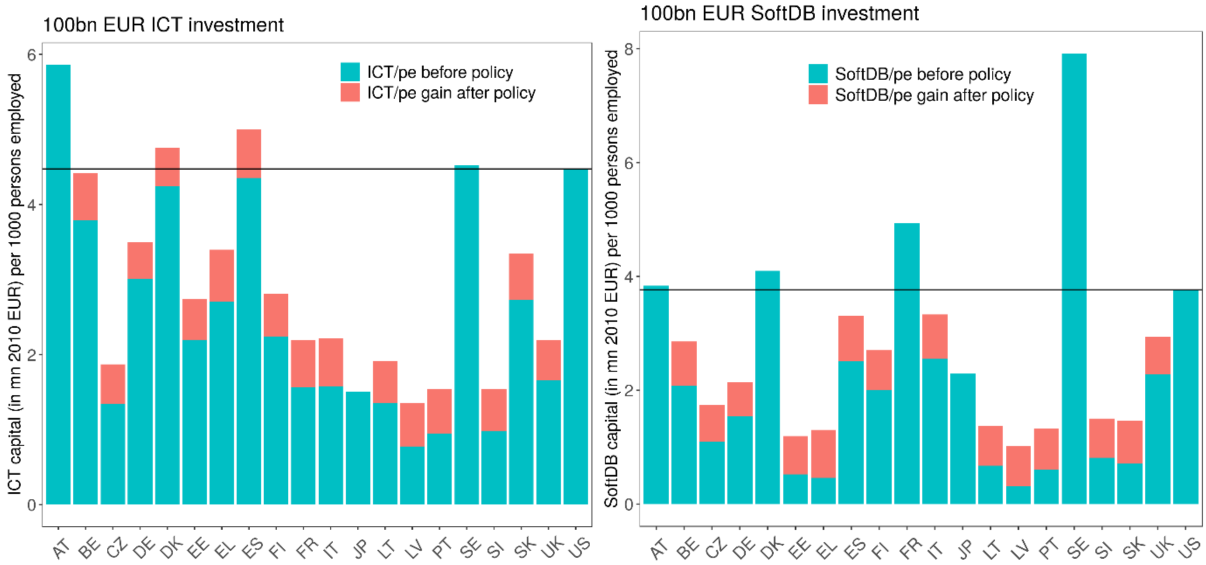


We find that increasing tangible ICT capital per 1000 persons employed in the EU to US levels leads to an increase of 7.1(±2.3)% in population-weighted labour productivity and a reduction of the EU-US productivity gap of 25.2(±8.4)%. For intangible ICT capital, EU productivity increases by 7.9(±2.6)% and the EU-US productivity gap is reduced by 28.3(±8.6)%.

In this paragraph, we analyse the effect of a hypothetical 100bn EUR investment in tangible/intangible capital in 2014 on labour productivity in 2015. We assume that the share each EU country receives is proportional to its population, and that only countries with a lower ICT per person employed level than the USA receive funding. We find that such a policy would increase population-weighted average labour productivity in the EU by 1.7(±0.6)% for tangible ICT capital, and 2.7(±0.9)% for intangible ICT capital. The productivity gap between the US and the EU would be reduced by 6.1(±2.0)% and 9.5(±3.1)%, respectively. The corresponding change in ICT capital per person employed is illustrated in Figure 4.2 below.

Figure 4.2

Note: Change in ICT capital (in mn 2010 EUR) per 1000 persons employed corresponding to 100bn EUR investment in 2015. Left panel: tangible ICT capital, right panel: intangible ICT capital.



5. Policy implications and concluding remarks

Low productivity growth has been a major challenge in the post-crisis period in a large number of EU countries. Some countries have been affected comparatively more than others, which has led to pronounced productivity gaps, both within the EU and between EU countries and economies such as the US and Japan. The aim of this paper is to measure the impact of different drivers of productivity growth, such as to enhance our understanding of recent productivity dynamics. For that purpose, we perform an econometric analysis of the drivers of productivity, looking in particular at the accumulation of different types of capital (including intangible capital), foreign direct investment, integration into global value chains and EU integration.

We find that ICT capital, both tangible and intangible, has a significant positive impact on productivity. The effect of intangible ICT capital even exceeds that of tangible capital: a 1-pp increase in the intangible ICT capital growth rate is associated with a 0.09 pp increase in real labour productivity growth, while this number is 0.06 pp for a 1-pp increase in the growth rate of tangible ICT capital. In fact, intangible ICT capital is the only capital asset type that robustly emerged as a driver of productivity across multiple model specifications at the sectoral and aggregate levels.

Furthermore, we find that higher levels of integration in value chains and in particular backward GVC integration is associated with productivity growth: Increasing backward GVC participation by 0.01 induces a 0.2 pp increase in the growth of aggregate labour productivity (the mean year-to-year change in backward GVC participation is 0.005).[17] Our results also suggest that EU integration has been essential for productivity growth, confirming earlier studies (see e.g. Kutan and Yigit, 2007, 2009). There may be multiple channels through which this happens, including regulatory convergence and upgrading of institutions, co-funding of infrastructure and efficiency gains due to a more efficient cross-border reallocation of productive resources. Finally, we did not find evidence for a productivity-enhancing effect of FDI, which is in line with the hypothesis that EU inward FDI is targeted at countries with already high levels of productivity, reducing its potential to further advance productivity growth (Hale and Xu, 2016).

Europe has all the necessary ingredients to boost innovation and innovation-driven productivity, including a skilled workforce, strong institutions and research infrastructure. However, more efforts are needed to mobilise them and to channel them into the real economy in order to narrow productivity gaps within the EU and not fall behind peer economies outside the EU.

Our estimates suggest that, ceteris paribus, if all lagging EU countries increased their levels of tangible ICT capital per person employed US levels, population-weighted mean productivity

[17] This is intuitive, as participation in global value chains provides an opportunity for productivity gains due to knowledge spillovers from MNEs and efficiency gains associated with greater specialisation in certain tasks. This result also confirms earlier studies on GVC participation and productivity (Kummritz, 2016, Jona-Lasinio and Meliciani, 2019 and Pahl and Timmer, 2019).

levels in the EU would increase by 7.1%. For intangible ICT capital, productivity growth in the EU would increase by 7.9%. This would imply a decrease of 25.2% and 28.3%, respectively, in the gap in labour productivity levels between the EU and the US. Despite their approximate nature, these estimates give a rough idea of the order of magnitude of the effects of ICT capital on labour productivity. Looking instead at a 100bn EUR EU-wide investment plan for countries with below-US levels of (in)tangible ICT capital per person employed, would yield a 1.7% (2.7%) increase in average EU labour productivity levels and a corresponding reduction in the EU-US productivity gap of 6.1% (9.5%). These findings are in line with earlier literature that stresses the importance of different levels of tangible ICT capital in explaining the labour productivity gap between the EU and the US (Timmer and van Ark, 2005; Cette et al., 2015). We add to this literature by using more recent data and by analysing the role of intangible ICT capital.

Our results demonstrate that policies promoting a more efficient allocation of investment in both tangible and intangible ICT capital might be highly conducive for labour productivity and might reduce the productivity gap to the US significantly. This outcome is even more relevant, as ICT capital affects the entire economy through various channels and thus constitutes a general purpose technology. Discussing policies to facilitate the accumulation of ICT capital such as creating tax incentives, infrastructure investment and fostering learning of ICT skills, goes beyond the scope of this paper, but is treated at length in Adarov and Stehrer (2020).

Further, our results refute Solow's computer paradox, which states "[y]ou can see the computer age everywhere but in the productivity statistics" (Solow, 1987). This statement has been receiving renewed interest recently, for example in Acemoglu et al. (2014). On the contrary, our findings highlight the important roles ICT capital and especially intangible ICT play in boosting productivity. The lack of visible productivity accelerations in Europe may thus in part be attributed to underinvestment in digital capital. Our findings provide further empirical support for the necessity of additional policy efforts targeted at the efficient adoption of ICT capital, both tangible and intangible, which is especially vital for the EU in light of its relatively weak post-crisis productivity and growth performance. Moving the digital transformation forward via ICT capital investment may further enhance convergence between EU Member States and thereby improve its internal cohesion and resilience. Finally, the COVID-19 crisis has demonstrated that digital infrastructure is not only at the forefront of tracking and combatting the virus, but that it is also crucial in mitigating the effects of the ensuing economic crisis.

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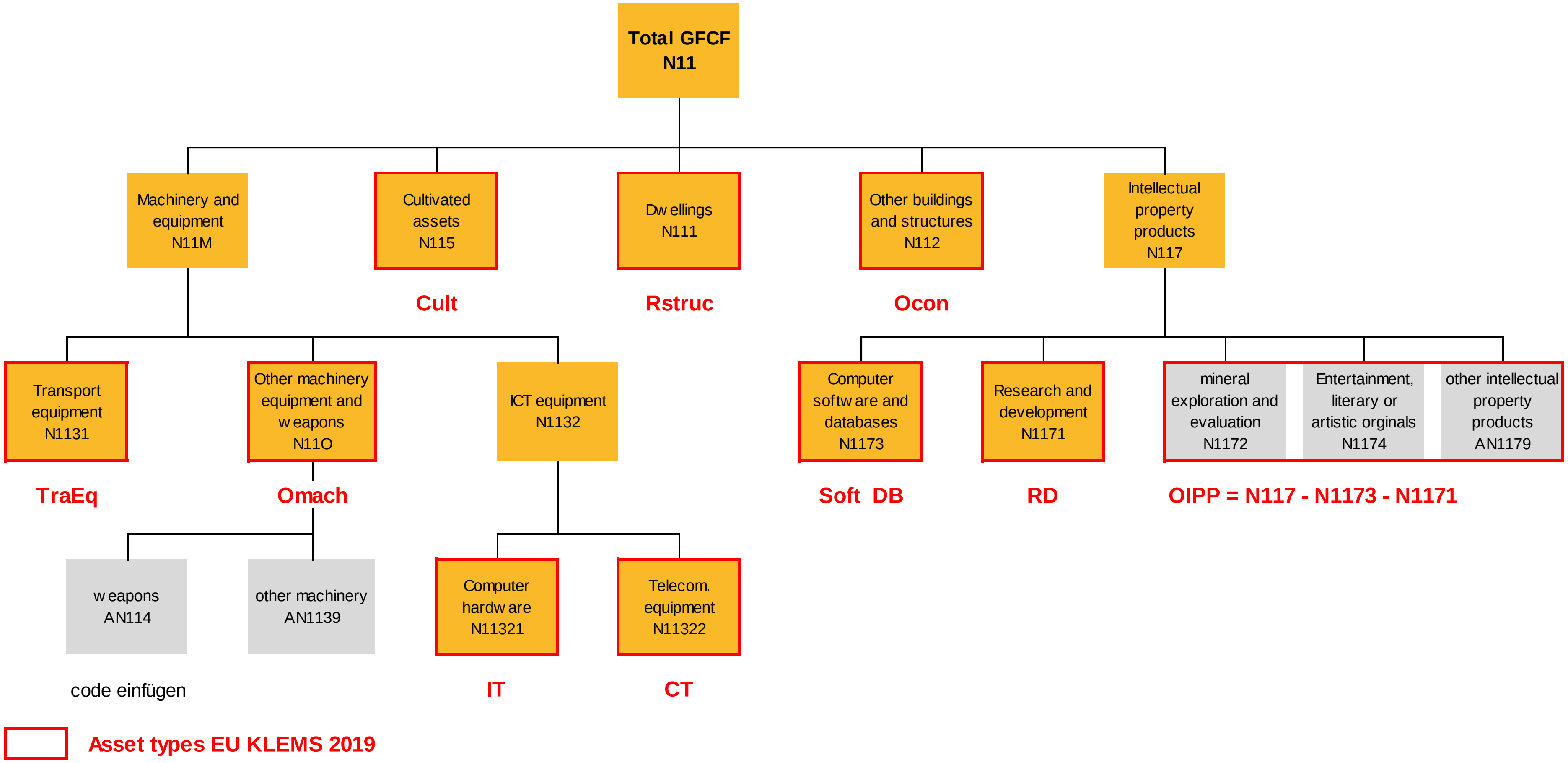
Appendix A. Summary statistics

Table A1. Summary statistics for aggregate country-level variables

Variable	Variable description	N	mean	median	std. dev.	min	max
ΔLn (Labour productivity)	Growth of value added per hour worked, chain-linked 2010 USD	216	0.012	0.010	0.017	-0.032	0.068
Ln (Labour productivity)	Value added per hour worked, chain-linked 2010 USD	216	-3.215	-3.033	0.461	-4.438	-2.625
ΔLn (Inward FDI stock)	Growth of inward FDI stock, chain-linked 2010 USD	211	0.051	0.046	0.121	-0.272	0.319
ΔLn (Labour services)	Growth of labour services	216	0.008	0.010	0.022	-0.182	0.062
ΔLn (EconComp, real capital stock)	EconComp, chain-linked 2010 USD	216	0.030	0.026	0.047	-0.111	0.206
ΔLn (ICT, real capital stock)	ICT, chain-linked 2010 USD	216	0.041	0.042	0.056	-0.107	0.186
ΔLn (NonICT, real capital stock)	NonICT, chain-linked 2010 USD	216	0.011	0.010	0.013	-0.018	0.048
ΔLn (OInnProp, real capital stock)	OInnProp, chain-linked 2010 USD	216	0.020	0.027	0.035	-0.106	0.133
ΔLn (RD, real capital stock)	RD, chain-linked 2010 USD	216	0.025	0.022	0.032	-0.069	0.148
ΔLn (SoftDB, real capital stock)	SoftDB, chain-linked 2010 USD	216	0.037	0.036	0.045	-0.141	0.199
Labour composition growth	Labour composition growth	216	0.006	0.005	0.007	-0.021	0.032
ΔLn (Hours worked)	Growth of hours worked	216	0.002	0.005	0.022	-0.180	0.035
ΔLn (Inward FDI stock, share of employed)	Growth of inward FDI stock, chain-linked 2010 USD, as a share of employed	211	0.070	0.055	0.132	-0.263	0.414
Δ GVC_BWI	Change in backward GVC participation	179	0.005	0.003	0.016	-0.049	0.044
Δ GVC_FWI	Change in forward GVC participation	179	0.002	0.002	0.008	-0.030	0.022
Δ Control of corruption	Change in the WB WGI Control of corruption estimate	204	-0.008	-0.002	0.086	-0.287	0.242
Δ Government effectiveness	Change in the WB WGI Government effectiveness estimate	204	-0.011	-0.007	0.120	-0.670	0.299
Labour force with advanced education	Labor force with advanced educ. (% of working-age population with adv. educ.)	207	79.038	78.243	3.791	73.250	89.974
Labour force with basic education	Labor force with basic educ. (% of total working-age population with basic ed.)	205	38.729	37.631	11.679	13.960	68.337
Δ Private credit-to-GDP	Change in private credit by deposit money banks, % of GDP	205	0.480	0.135	6.525	-18.350	26.370
Δ Human capital index	Change in the human capital index	216	0.015	0.016	0.007	0.002	0.050

Source: own computations

Figure A1. National Accounts asset breakdown



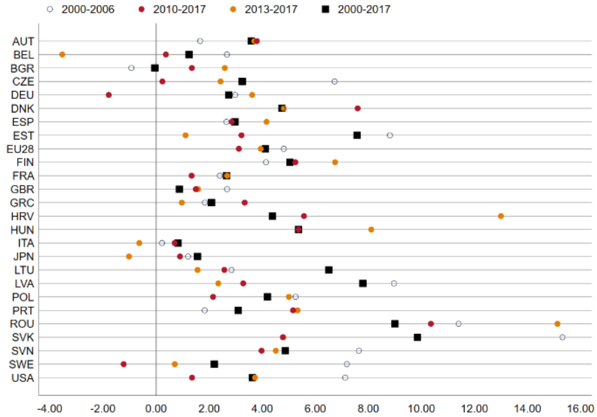
Note: Asset types are based on ESA'2010 definition. Those with a code are available at Eurostat (yellow/orange), others not (grey).

Source: *Adarov and Stehrer (2019a)*

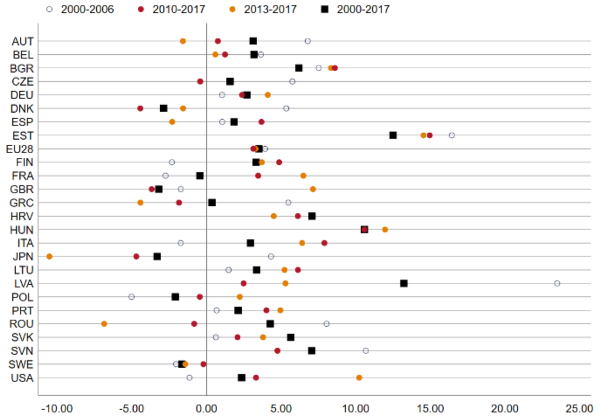
Figure A2. Productivity dynamics by sectors (growth rates)

Note: The figure shows real labour productivity growth rates for the 26 sectors as outlined in Table 2.2. The figures indicate 2000-2017 averages along with the pre-crisis and post-crisis period averages (with and without the double-dip recession period). Countries are sorted by ISO3 in alphabetic order. EU28 indicates average EU-28 values.

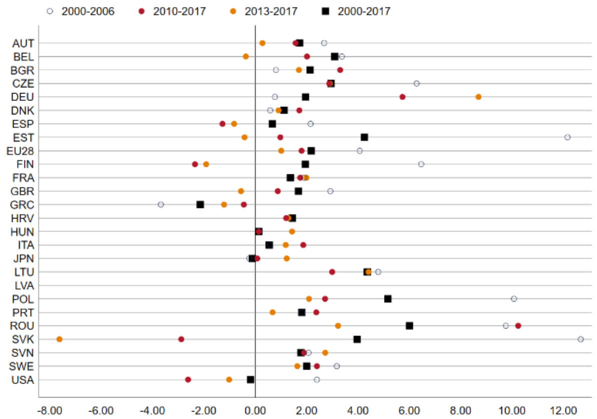
1_AGRI



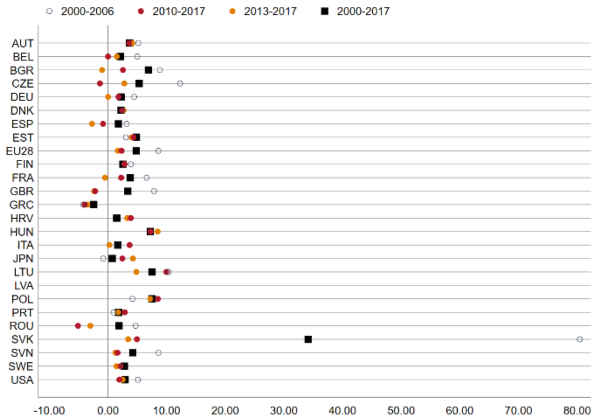
2_MING



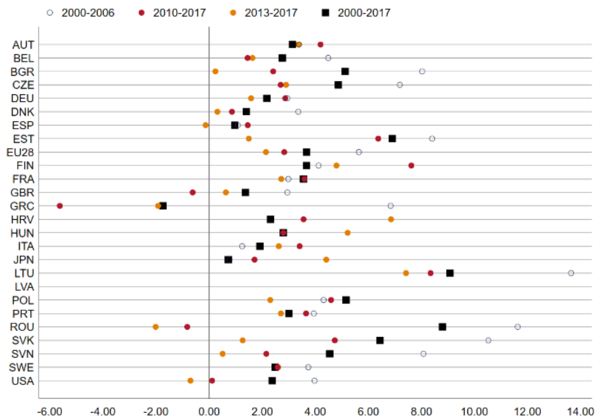
3_FOOD



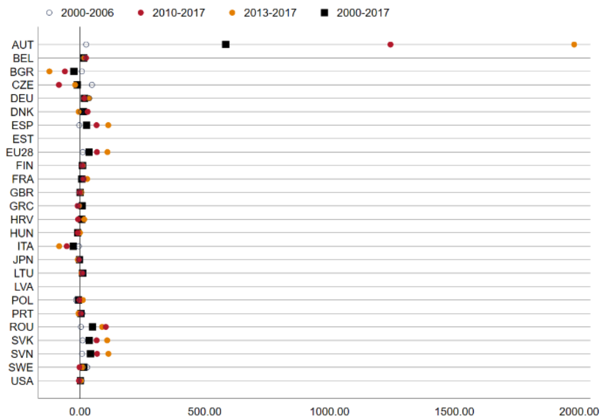
4_TXTL



5_WOOD

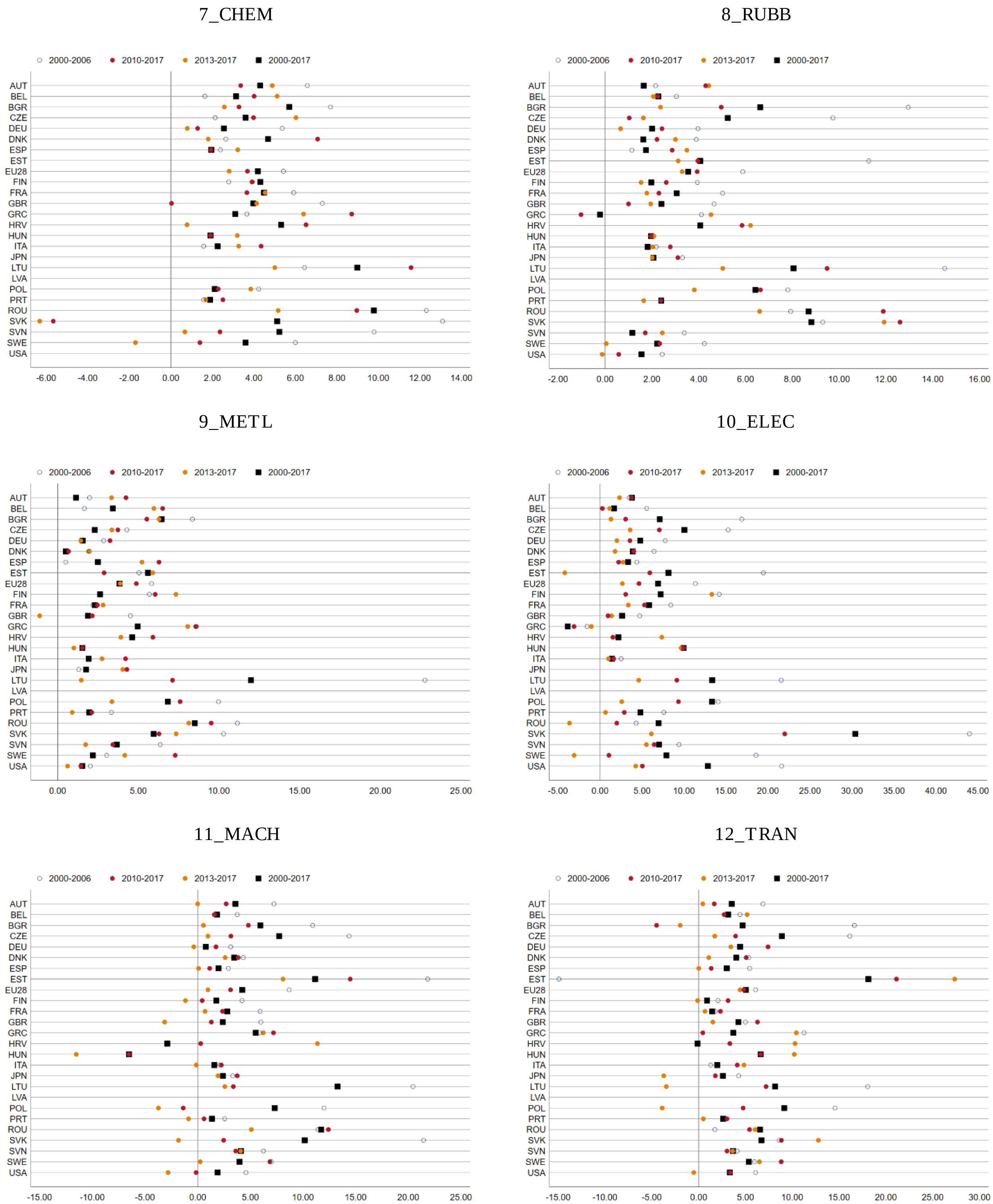


6_COKE



Source: own computations based on the EU KLEMS 2019 data.

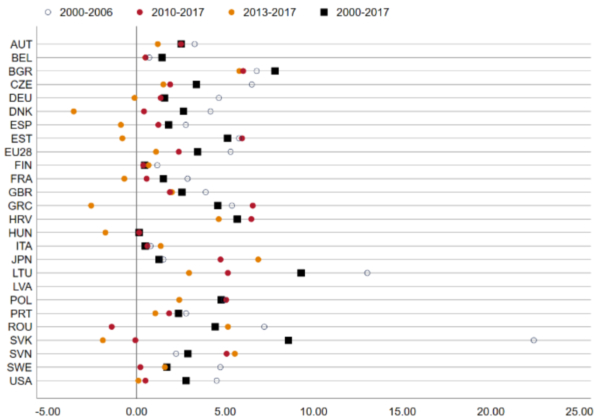
Figure A2 (cont.)



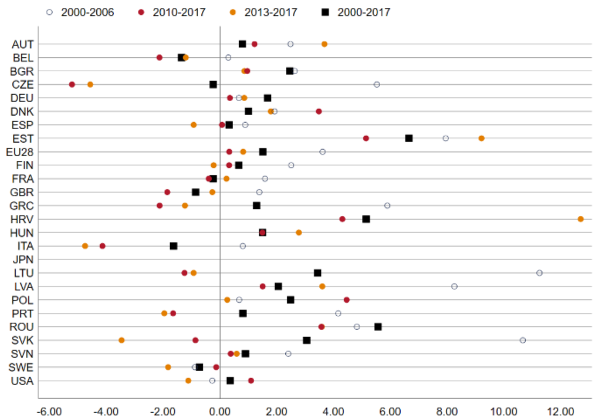
Source: own computations based on the EU KLEMS 2019 data.

Figure A2 (cont.)

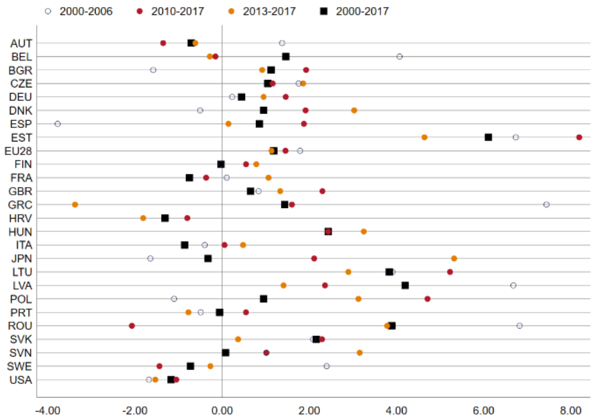
13_OMAN



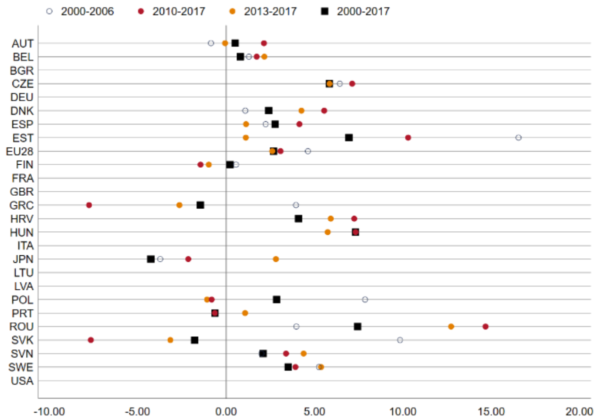
14_GASW



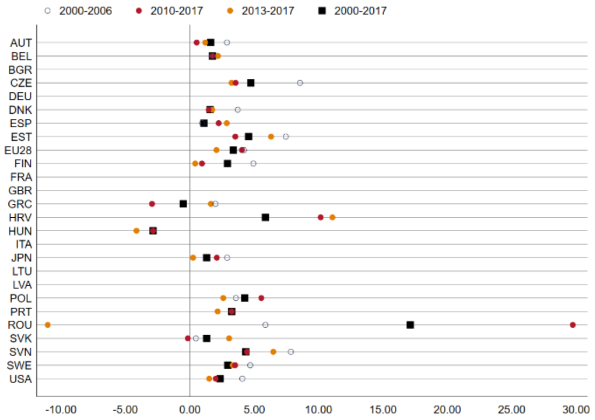
15_CONS



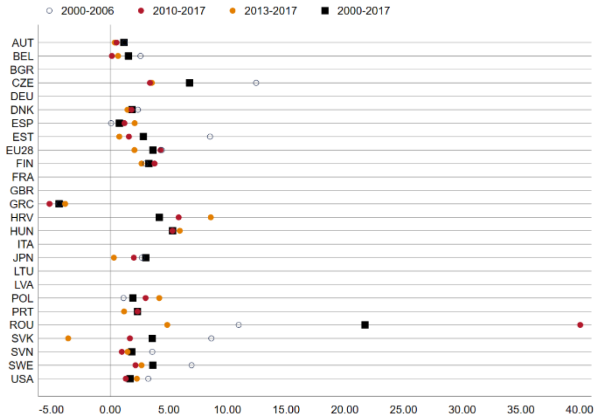
16_TRMO



17_WHTR



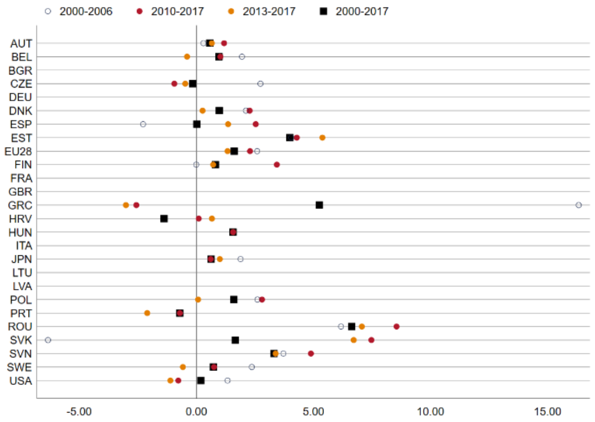
18_RETR



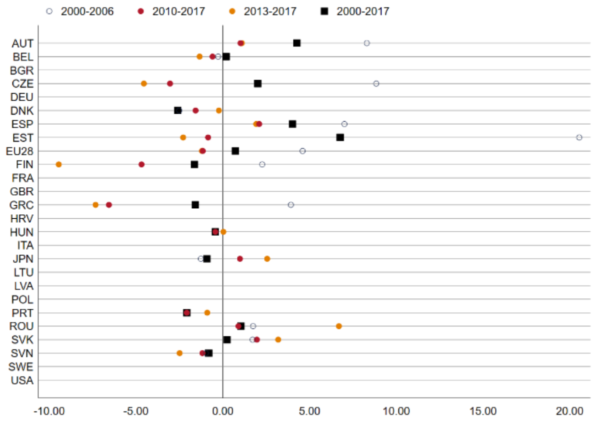
Source: own computations based on the EU KLEMS 2019 data.

Figure A2 (cont.)

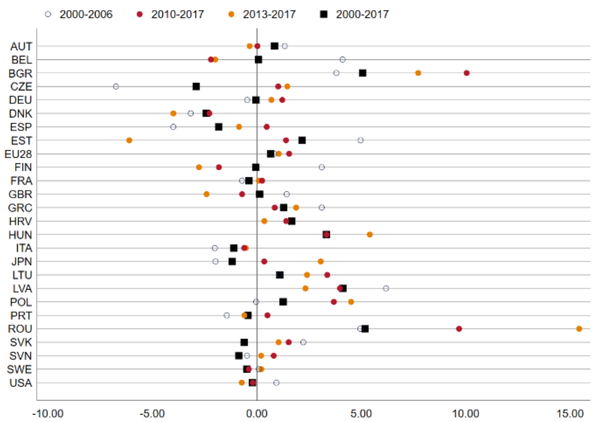
19_TRSR



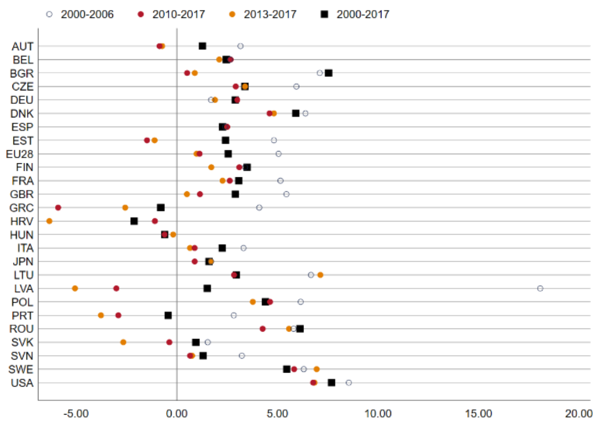
20_POST



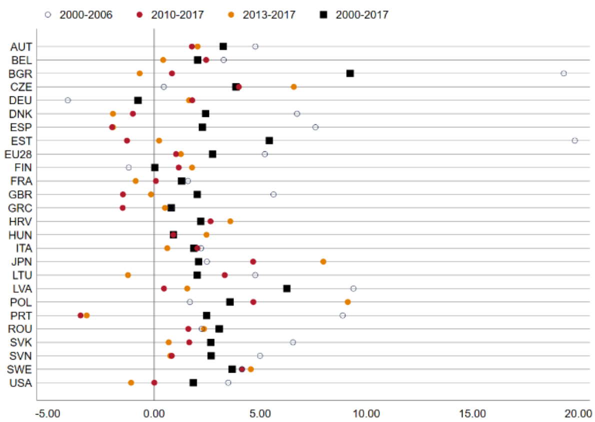
21_ACCO



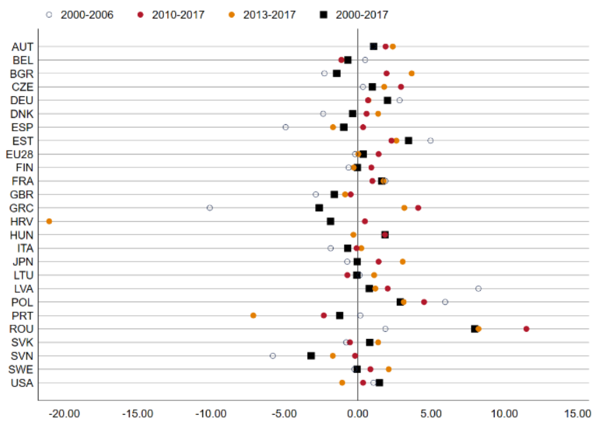
22_INFO



23_FINA

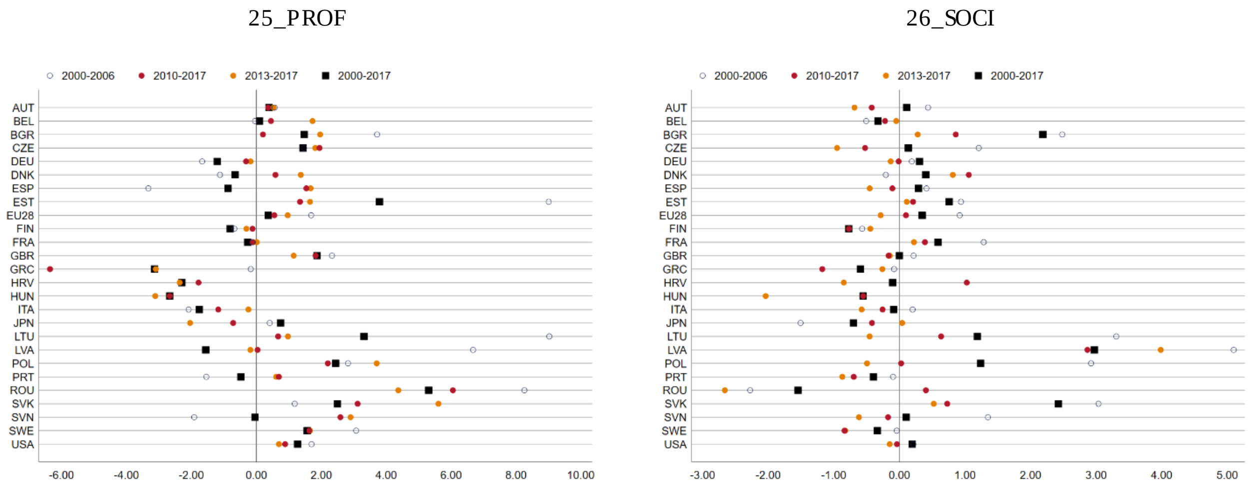


24_REAL



Source: own computations based on the EU KLEMS 2019 data.

Figure A2 (cont.)



Source: own computations based on the EU KLEMS 2019 data.

Table A2. Capital asset composition by sectors (average across countries and years 2000-2017)

SEC	EconComp	ICT	NonICT	OInnProp	RD	Soft_DB
1_AGRI	0.22%	0.48%	98.42%	0.44%	0.29%	0.14%
2_MING	0.79%	0.84%	89.66%	6.70%	1.60%	0.41%
3_FOOD	5.37%	1.25%	87.17%	1.31%	3.58%	1.32%
4_TXTL	3.31%	1.04%	86.83%	1.26%	5.65%	1.91%
5_WOOD	2.11%	2.65%	89.05%	1.31%	3.14%	1.73%
6_COKE	2.23%	1.42%	88.75%	2.09%	4.29%	1.23%
7_CHEM	2.78%	1.24%	61.70%	1.22%	31.42%	1.64%
8_RUBB	2.60%	1.44%	85.72%	1.52%	7.23%	1.50%
9_METL	2.41%	1.71%	86.15%	1.66%	6.43%	1.63%
10_ELEC	2.92%	2.58%	41.68%	1.67%	46.04%	5.11%
11_MACH	3.58%	1.59%	65.69%	3.03%	22.65%	3.46%
12_TRAN	2.64%	1.70%	62.00%	2.34%	28.69%	2.62%
13_OMAN	3.99%	1.70%	73.58%	2.49%	14.79%	3.46%
14_GASW	0.62%	1.30%	95.88%	0.86%	0.75%	0.59%
15_CONS	2.03%	0.76%	84.35%	11.75%	0.49%	0.61%
16_TRMO	7.45%	1.77%	86.34%	1.72%	0.70%	2.01%
17_WHTR	9.88%	3.39%	74.63%	3.52%	3.55%	5.02%
18_RETR	6.18%	3.02%	86.10%	1.23%	0.41%	3.05%
19_TRSR	0.99%	1.45%	95.89%	0.77%	0.23%	0.67%
20_POST	3.37%	6.82%	77.76%	2.40%	2.08%	7.56%
21_ACCO	2.78%	1.71%	94.13%	0.78%	0.06%	0.54%
22_INFO	4.26%	14.90%	60.20%	7.18%	5.03%	8.43%
23_FINA	6.31%	3.66%	77.11%	1.65%	1.81%	9.46%
24_REAL	0.07%	0.05%	99.61%	0.25%	0.00%	0.02%
25_PROF	9.15%	4.48%	61.09%	8.36%	13.35%	3.56%
26_SOCI	0.75%	1.21%	91.64%	0.96%	4.56%	0.88%

Source: own computations based on the EU KLEMS 2019 data.

Appendix B. Additional country-level regression results

Table B3. Regression results with alternative outlier thresholds

Note: The table shows the estimation results using fixed effects (FE) with standard errors clustered by country (in parentheses). The dependent variable is ΔLn (Labour productivity). *, **, *** indicate statistical significance at the 10, 5 and 1% levels. The estimates reported in columns correspond to the baseline specification with different levels of outlier threshold imposed on the key variables (labour productivity, FDI and capital asset growth rates): '$\mu \pm 2\sigma$', '$\mu \pm 3\sigma$', '$\mu \pm 4\sigma$' denote threshold levels at 2, 3 and 4 standard deviations from the sample mean. The former corresponds to the baseline model. Column 'no outlier cutoff' lists results with all observations (no outlier control).

	$\mu \pm 2\sigma$	$\mu \pm 3\sigma$	$\mu \pm 4\sigma$	no outlier cutoff
Ln (Labour productivity), lag	-0.122***	-0.132***	-0.143***	-0.151***
	(0.021)	(0.019)	(0.027)	(0.023)
ΔLn (Labour services)	-0.333***	-0.293***	-0.246**	-0.155
	(0.073)	(0.091)	(0.093)	(0.101)
ΔLn (Inward FDI stock)	-0.012	-0.015*	-0.011	-0.009
	(0.007)	(0.007)	(0.009)	(0.009)
ΔLn (EconComp, real capital stock)	-0.039*	0.004	0.009	0.029
	(0.020)	(0.025)	(0.030)	(0.022)
ΔLn (ICT, real capital stock)	0.055**	0.036**	0.029*	0.015
	(0.021)	(0.014)	(0.016)	(0.010)
ΔLn (NonICT, real capital stock)	-0.037	0.013	0.058	-0.295
	(0.122)	(0.115)	(0.132)	(0.263)
ΔLn (OInnProp, real capital stock)	-0.002	-0.035	-0.002	0.005
	(0.050)	(0.034)	(0.029)	(0.028)
ΔLn (RD, real capital stock)	0.046	0.045	-0.022	0.016
	(0.039)	(0.040)	(0.053)	(0.051)
ΔLn (SoftDB, real capital stock)	0.085**	0.033**	0.015	0.004**
	(0.031)	(0.014)	(0.017)	(0.002)
Constant	-0.370***	-0.404***	-0.441***	-0.468***
	(0.066)	(0.063)	(0.087)	(0.076)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	216	233	238	248
Adj. R-squared	0.581	0.554	0.508	0.494

Table B4. Summary statistics with alternative outlier thresholds

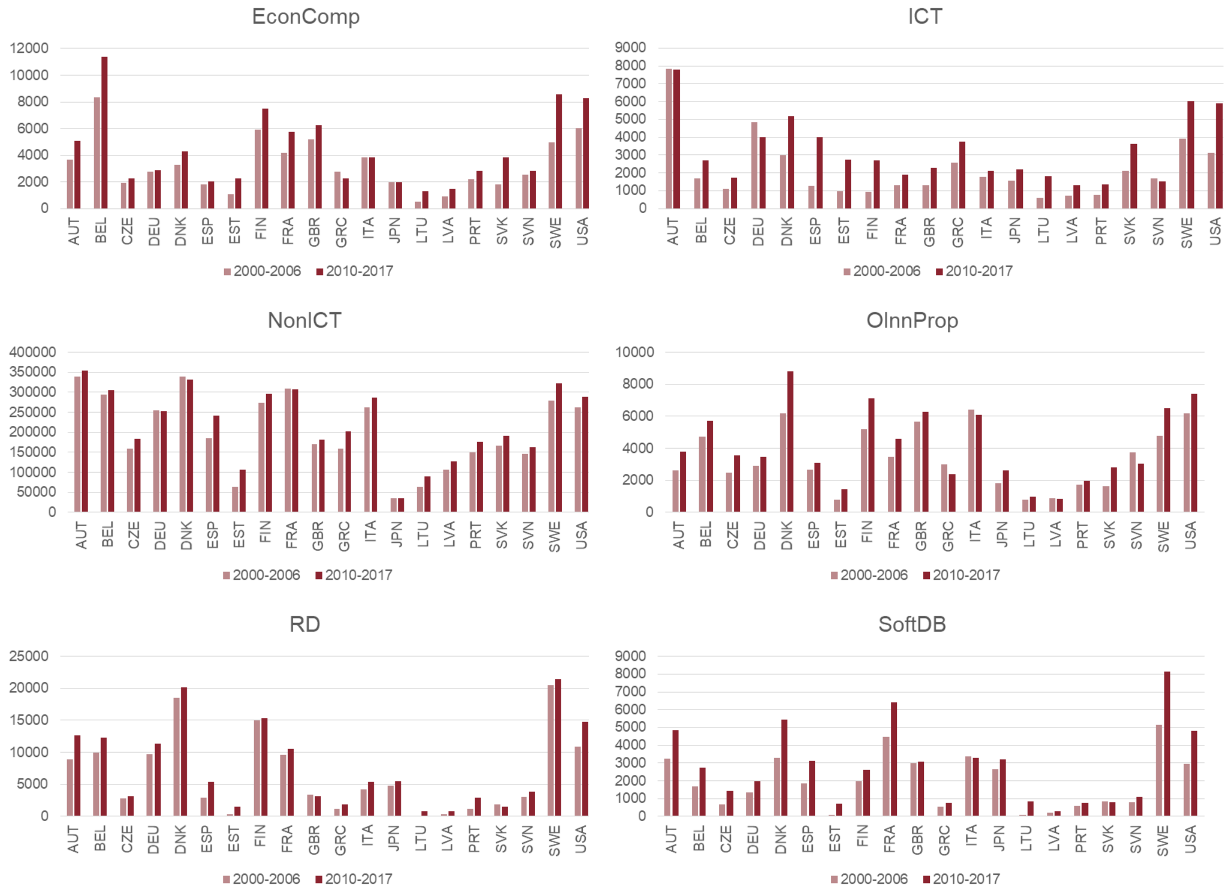
Note: The table shows summary statistics for the regression variables with different levels of outlier threshold imposed on the key variables (labour productivity, FDI and capital asset growth rates): '$\mu \pm 2\sigma$', '$\mu \pm 3\sigma$', '$\mu \pm 4\sigma$' denote threshold levels at 2, 3 and 4 standard deviations from the sample mean; 'no outlier cutoff' lists results with all observations (no outlier control).

	ΔLn (Labour productivity)	Ln (Labour productivity)	ΔLn (Labour services)	ΔLn (Inward FDI stock)	ΔLn (EconComp, real capital stock)	ΔLn (ICT, real capital stock)	ΔLn (NonICT, real capital stock)	ΔLn (OInnProp, real capital stock)	ΔLn (RD, real capital stock)	ΔLn (SoftDB, real capital stock)
					$\mu \pm 2\sigma$					
N	216	216	216	216	216	216	216	216	216	216
mean	0.012	-3.215	0.008	0.043	0.030	0.041	0.011	0.020	0.025	0.037
sd	0.017	0.461	0.022	0.147	0.047	0.056	0.013	0.035	0.032	0.045
min	-0.032	-4.438	-0.182	-0.597	-0.111	-0.107	-0.018	-0.106	-0.069	-0.141
max	0.068	-2.625	0.062	0.483	0.206	0.186	0.048	0.133	0.148	0.199
					$\mu \pm 3\sigma$					
N	233	233	233	233	233	233	233	233	233	233
mean	0.013	-3.248	0.007	0.043	0.030	0.037	0.011	0.019	0.025	0.036
sd	0.019	0.483	0.022	0.148	0.055	0.060	0.013	0.044	0.034	0.066
min	-0.054	-4.438	-0.182	-0.597	-0.144	-0.238	-0.018	-0.158	-0.069	-0.363
max	0.079	-2.625	0.062	0.483	0.289	0.186	0.048	0.223	0.186	0.493
					$\mu \pm 4\sigma$					
N	238	238	238	238	238	238	238	238	238	238
mean	0.012	-3.251	0.006	0.041	0.030	0.039	0.011	0.019	0.025	0.039
sd	0.020	0.484	0.023	0.150	0.060	0.066	0.012	0.045	0.040	0.074
min	-0.061	-4.438	-0.182	-0.597	-0.144	-0.238	-0.018	-0.158	-0.164	-0.363
max	0.079	-2.625	0.062	0.483	0.372	0.445	0.048	0.223	0.272	0.507
					no outlier cutoff					
N	248	248	248	248	248	248	248	248	248	248
mean	0.012	-3.271	0.006	0.038	0.034	0.037	0.011	0.020	0.025	0.040
sd	0.021	0.495	0.023	0.153	0.075	0.116	0.013	0.052	0.040	0.158
min	-0.092	-4.438	-0.182	-0.597	-0.144	-0.818	-0.018	-0.181	-0.164	-0.790
max	0.079	-2.625	0.062	0.483	0.598	1.005	0.090	0.303	0.272	1.942

Appendix C: Additional capital dynamics

Figure C.1 Real capital stocks per person employed by asset groups, 2010 USD

Note: the figure shows real capital stock per person employed (in 2010 USD) by asset group; averages over the period 2000-2006 and 2010-2017. Countries are listed by ISO3 in alphabetic order.



Source: own computations based on EU KLEMS 2019 data

Appendix D. Marginal effects of sectoral productivity analysis

Figure D.1. Marginal impact of FDI, ICT and non-ICT capital on labour productivity by sector

Note: The figure shows the average estimated marginal impact of capital (by aggregate capital asset groups) and inward FDI stock on real labour productivity growth, along with the 90% and 99% confidence intervals (indicated light and dark blue bars, respectively). Capital and FDI variables are real stocks (2010 USD) in log-differences. The regression results associated with the estimates are reported in Appendix Table B1 (Panel B1-A for the six capital asset and FDI 3-year lag estimates and Panel B1-B for the FDI 1-year lag estimates). Sector 20_POST lacks sufficient observations for robust estimations (omitted).

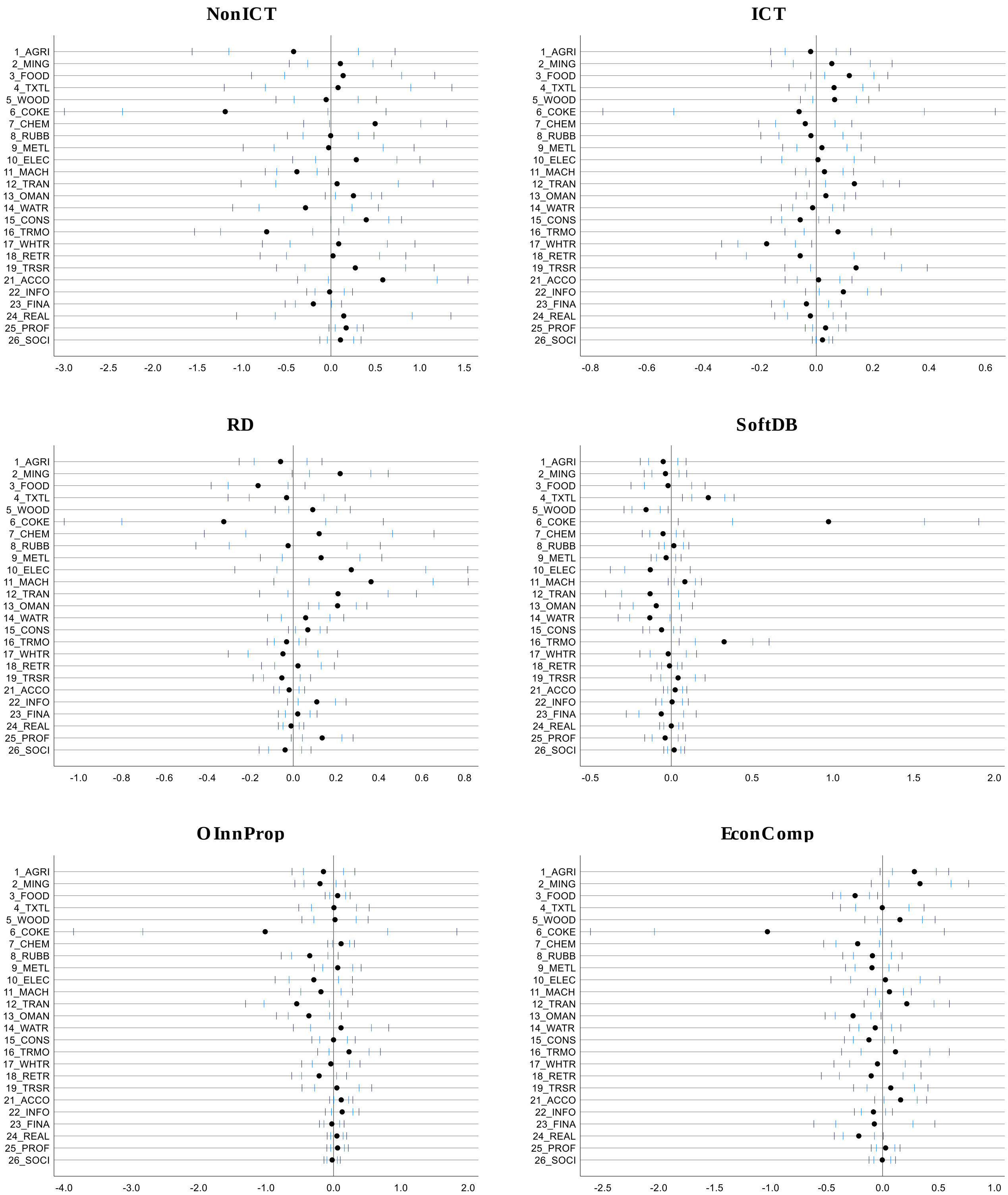
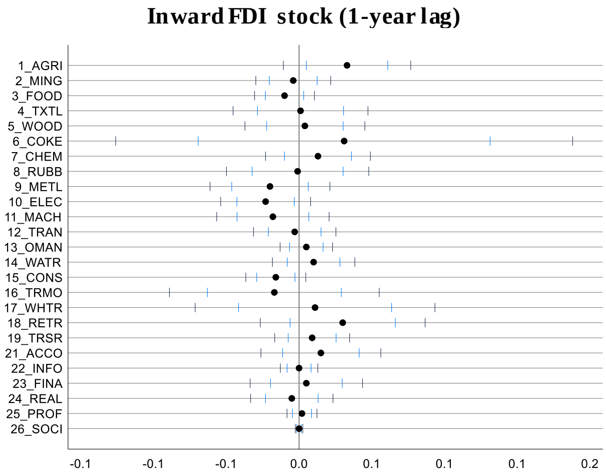
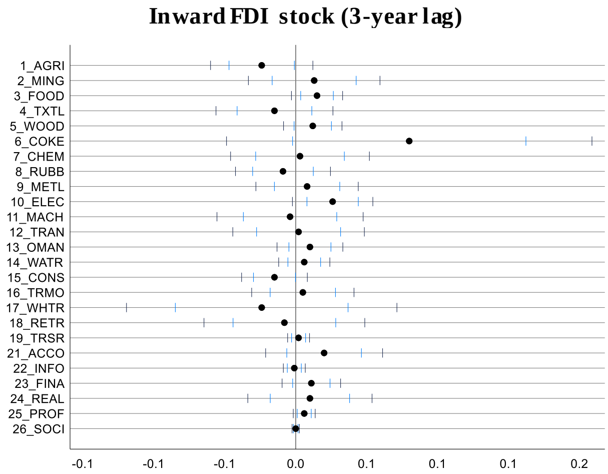


Figure D.1 (cont.)





Source: own calculations

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