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Tangible and intangible assets across Europe

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Complementarities in capital formation and production: Tangible and intangible assets across Europe[*]

Anna Thum-Thysen, Peter Voigt, Christoph Weiss

Abstract

This paper investigates capital formation with a view at various tangible and intangible assets across Europe. Using novel datasets both at macro and firm level, we estimate translog production functions to assess complementarities at different aggregation levels. At macro-level, our evidence suggests complementarities between tangibles and intangibles and between National Accounts and non-National Accounts intangibles. Using firm-level data, we explore more disaggregated asset classes and find that investing simultaneously in software, training of employees, and business process improvements is associated with better firm performance. Our analysis demonstrates that policy support that aims at stimulating investment only in certain assets may fall short in unlocking its own full potential. The emphasis should rather be on addressing investment bottlenecks arising from market imperfections, while remaining non-discriminatory with a view at what sort of capital deepening is envisaged and leaving it to the firm to find the most appropriate mix of assets.

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1. INTRODUCTION

Production processes typically require a combination of different inputs such as e.g. machines and buildings, computer hardware and software, data and workers with digital skills. Complementary inputs can have different forms, such as capital and labour, and can be classified in tangible and intangible assets.[1] Arguably, there are good reasons to believe in complementarities among different assets, i.e. an investment in one type of assets may affect the success (productivity) of an investment in another. And, in turn, a barrier that works detrimental to the use of or the investment in one asset type may affect – and thus *ex ante* hold back – the use of or investment in another. Clearly, tangible assets also have synergies (e.g. a bus and a bus stop, machines and buildings, etc.), but what is different about intangible investment is "*…the scope of different ideas to interact and the fact that ideas are not expended when they are combined, makes the potential synergies bigger…*" (Haskel and Westlake, 2017, p.81).

While there is ample and a comparably congruent literature on drivers of and barriers to investment (see e.g. Thum-Thysen *et al*., 2019), the empirical evidence on complementarities among assets remains mixed and inconclusive – based mainly on the fact that the different studies concentrate either on a particular country or on specific asset types. However, in order to understand what drives and what eventually holds back investments in the EU and thus productivity (growth), a thorough understanding of the inter-relationship between different asset types is key at pan-EU level. Accordingly, in this paper, we tackle three analytical and policy-relevant questions:

- Do we find evidence of complementarities among different assets types in the EU, in particular tangibles and intangibles, and eventually among subcategories thereof? If so, what roles do non-National Account (NA) intangibles play in this regard, which are typically not captured in common statistics as assets but rather as intermediate consumption?

- Does the level of aggregation play a role for such analyses, i.e. are there differences between analysing macro- and micro-level data?

- What lessons can be learned with a view at ensuring a 'balanced mix' of investments (portfolio of investments in various tangible and intangible asset types) in the EU? Do we need to enlarge our scope of analysis when exploring drivers of and barriers to investment, i.e. taking into account all relevant asset types jointly, thus including also asset categories – such as non-National Account (NA) intangibles – we currently often leave aside?

Conceptually, our analysis aims at building new empirical evidence on the relationship between tangible and intangible capital in the business sector at different levels of aggregation. Using novel data on investments in intangible assets, we apply various methodological approaches. We start by putting the emphasis on macroeconomic data and estimate a general translog production function, using a sample of 15 European countries (EU14 + UK) over the period 1995 to 2015. In a second step, we analyse asset complementarities by estimating micro-level production functions, using firm-level data of the EIB

[1] Characteristically, intangible assets do not have physical embodiment. In the literature, they are also often (synonymously) termed as 'intellectual assets', 'knowledge assets', 'knowledge based capital' or 'intellectual capital'. See Section 3 for more details.

Investment Survey (EIBIS), which is representative for 27 EU countries and the UK, over the period 2016-2019.

We show evidence for complementarities using both macroeconomic and microeconomic data, which allows us to gain insights both on the within-country effects over time and within-sector effects. At macro-level, we find evidence for a joint effect on labour productivity of NA and non-NA intangibles as well as a (smaller) joint effect of tangible and non-NA intangibles when controlling for the direct impact of all assets, as shown by the estimated coefficients on the interaction terms. At the micro-level, we find that firms that invest simultaneously in different assets can benefit from spillover effects. For instance, focusing on interactions of intangible investments, investing simultaneously in software and training of employees is associated with better firm performance. Similarly, the combination of investing in training of employees and business process improvements also tends to lead to higher productivity.

The remainder of this paper is organised as follows: Section 2 discusses the relevant literature on complementarities of asset types. Section 3 outlines our database, while Section 4 develops an analytical approach for the empirical analyses of asset complementarities and presents the corresponding results at macro- and micro-level, respectively. Section 5 provides some conclusions.

2. LITERATURE REVIEW

The importance of investment in intangible assets for productivity, competitiveness and economic growth has been widely researched in the recent economic literature, thus highlighting that our economies are becoming increasingly ‘intangible’. In their seminal contribution, Haskel and Westlake (2017) discuss the rise of the intangible economy, where capitalism requires less physical capital, with the emergence of global digital companies that rely on intangible assets to revolutionise entire industries. Among others, Jorgenson and Stiroh (2000), Oliner and Sichel (2000), Corrado, Hulton and Sichel (2009, hereinafter CHS), Roth and Thum (2013), van Ark (2015) or Thum-Thysen *et al*. (2017) also demonstrate the growing importance of intangible investments. See Roth (2019) for a comprehensive literature review.

Haskel and Westlake (2017) argue that synergies (considered to be a synonym of ‘complementarities’) and spill-overs[2] (a concept closely related to complementarities) are two of the four main features characterising intangible capital and making it different from tangible capital – the other two are a ’sunkeness’ and ’scalability’. Clearly, tangible assets also have synergies (e.g. machines and buildings, a bus and a bus stop, etc.), but what is different about intangible investment is ”…*the scope of different ideas to interact and the fact that ideas are not expended when they are combined, makes the potential synergies bigger*…” (Haskel and Westlake, 2017, p.81). Spillover effects need to be considered especially when analysing the joint production effects of spending on different assets, as outlined by Haskel and Westlake (2017) and Thum-Thysen *et al*. (2017). Based on a survery of the R&D literature, Becker (2014) points, furthermore, to the importance of having in place a well-endowed infrastructure of public intangibles and hence opens up yet another area of possible asset complementarities.

Obviously, the main determinant of potential complementarities or substitutabilities lies in the production process of a firm, with common patterns within certain industries being rather likely, while

[2] See Haskel and Westlake (2017), pp.58ff, where they argue that “…*if the spillovers of intangibles encourage companies to keep their investments to themselves, or at best to share in a self-interested way, then the synergies of intangibles have the opposite effect.*” (p.83).

the aggregate picture is also of interest. Accordingly, we argue that the aggregation level plays a role when interpreting results relating to complementarities, which motivates us to perform corresponding empirical analyses both at macro- and micro-level. In this literature review, we discuss the evidence for complementarities between different asset types: the broad categories tangibles and intangibles, ICT (including hardware) and various intangible assets (training or organisational capital), intellectual property (R&D or patents) and other intangible assets and, finally, different R&D asset categories (namely own R&D versus machinery-embedded R&D). We concentrate on empirical studies at country level, industry or firm level that cover either only one country or a range of EU countries.

Beside the empirical studies trying to analyse complementarities, there is also comprehensive literature reflecting on complementarities (in various meanings and from different perspectives), conceptually based on theoretical considerations. They key findings are related to the (management) literature on corporate strategy, industry evolution, and organisational structures. For instance, Stieglitz and Heine (2007) argue that complementary assets play a crucial role in explaining sustainable competitive advantages and innovations. They show how complementary assets raise the need for strategic direction by a firm's top management and magnify internal incentive problems, while having an impact on the innovativeness of a firm through affecting the internal appropriation of innovative rents. Cooper and Johri (2007) look at dynamic complementarities and link the stocks of human and organisational capital, which are influenced by past levels of economic activity, to current levels of productivity. Jackson and Ni (2013) identify a series of methodological challenges related to understanding complementarities as organisational configurations, and examine how such elements combine to produce joint effects on business performance.

2.1 INTANGIBLES AND TANGIBLES (BROAD CATEGORIES)

Using country-level data and an accelerator model, Thum-Thysen *et al*. (2017) find evidence for complementarities between investments in intangible and tangible assets as well as among different types of intangible assets. Goodridge *et al*. (2016) and Corrado *et al*. (2017) show that an industry receives a positive total factor productivity (TFP) effect from the intangible capital accumulated in other industries, implying that intangible investments carried out in one industry may spill over into all the others. Elnasri and Fox (2017) use data for Australia and find that private intangible investments have a general positive TFP effect, interpreted also as a spillover effect. Moreover, using data for the EU28 and the period 2000-2014, Tsakanikas *et al*. (2020) suggest a positive relationship between a country's intangible inputs and its productivity performance once the interaction between intangible inputs and the participation in global value chains is taken into account.

Pastor-Augustin *et al*. (2011) analyse Spanish firms and find evidence of interrelations between intangible and tangible capital in investment decisions. Using firm-level data for Germany, Belitz *et al*. (2017) show that investments in tangible and intangible assets tend to complement each other, but with remarkable differences across industries. Using data on Japanese firms, Hosono *et al*. (2016) document both complementarity and substitutability between tangible and intangible capital, but confirm substantial heterogeneity in this regard across industries.

2.2 ICT (INCLUDING HARDWARE) AND VARIOUS INTANGIBLE ASSETS

Chen *et al*. (2016), based on data for gross value added (GVA) and tangible and intangible investments in EU countries, tend to find that the most ICT-intensive sectors have also higher returns in productivity from intangible investments. This finding supports the hypothesis that intangibles and ICT (including tangible assets) are complementary in production. Using data for 10 EU Member States from 1998-2007 and 26 market industries, Corrado *et al*. (2017) explore complementarities between ICT stocks and intangible investments and the channels through which intangible assets may affect productivity growth. They show that there are complementarities among levels of ICT stocks (hardware) and a full set of intangible capital including significant knowledge spillovers from investments in intangible capital and skills. In their study, intangible capital investments also trigger wider productivity effects.

Brynjolfsson and Hitt (2000) and McAfee and Brynjolfsson (2012) find for the US that the effective implementation of new technologies tends to require complementary investments especially in (other) intangible assets, such as e.g. redesigned business models and organisational structures, tacit knowledge (due to training of staff) and generally high-skilled employees.[3] They highlight how investment in ICT (the focus of their study) needs high commitments to modern forms of firms' organisational structure and to firm-specific human capital to be effective. They estimate that the ratio between ICT (hardware, i.e. tangible assets) and complementary intangible investments is 1:9. Several other studies also suggest that the use of information technology is only complementary to high skills, decentralisation of decisions and team-oriented production (Black and Lynch, 2001; Brynjolfsson *et al*., 2002; Autor *et al*., 2003; Brynjolfsson and Hitt, 2000, 2003).

However, Hall *et al*. (2013) and Mohnen *et al*. (2018), who also use micro data (firms in Italy and the Netherlands), do not find conclusive evidence with a view at the relationship between ICT and intangible investment (R&D). They argue that, while individually both types of investment contribute to productivity growth, their joint investment does not necessarily give an additional boost to productivity.

2.3 INTELLECTUAL PROPERTY AND VARIOUS OTHER INTANGIBLE ASSETS

O'Mahony and Vecchi (2009) analyse spillover effects at the firm level arising from investments in R&D and better-skilled workforces and find that those firms operating in the most R&D- and skill-intensive sectors experience a 2-5 percent higher productivity growth, which is understood as the spillover effect accruing to firms operating in such an intangible-intensive industry. Using micro data for Italy and Germany, Hall *et al*. (2013) and Crass and Peters (2014) show synergies between R&D and skills of employees. Crass and Peters (2014) also find R&D and patents to be complementary and underline general links between innovative property and human capital ('economic competences' in the Corrado, Hulten and Sichel 2009 framework; see Section 3), thus highlighting the importance of skills to be able to exploit and reap the benefits of innovation activities.

2.4 COMPLEMENTARITIES AMONG R&D ASSETS

Using data at industry level in 15 countries in the 2007-2013 period, Bruno *et al*. (2019) focus on the factors determining the productivity gap across the EU and explicitly at the interaction between R&D intensity (i.e. own R&D activities; a type of intangible assets) and R&D embedded in purchased equipment and machinery (tangible assets). The authors find no evidence for complementarities at this level of aggregation. They test the hypothesis that complementarities between investments in these two asset types are enhancing absorption and assimilation of foreign technology, which would make them essential in closing a productivity gap. However, while the signs for both asset types are positive, the

[3] Brynjolfsson *et al.* (2017) state for instance that, while artificial intelligence (AI) appears as a very promising general-purpose technology that will bring a positive productivity shock to most economic sectors, similar to ICT capital, AI will need complementary investments in intangible capital, such as complementary investments in firm-specific human capital and organisational structures.

interaction between the two is not (across three of the four analysed sectors).[4] For the case of investing in own R&D vs. investing in ready to use equipment and machinery (including embedded R&D performed by another market participant, operating possibly in a different sector or country), an explanation could lie in the relative investment costs. In fact, the investment decision at firm level might be a matter of doing either one or the other, but not both at the same time, which may indicate potential substitution effects between the two options, at least at firm level.

This discussion of the empirical literature suggests that the existing evidence of complementarities among various asset types (and subcategories thereof) and at different aggreation levels still remains somewhat mixed – even though it tends towards identifying complementarities. Our paper aims at contributing to this literature by providing additional empirical evidence, both at macro- and micro-level, in terms of nature, directionality and observed magnitude of the corresponding relationships for EU countries over time –considering both tangibles and intangibles as well as sub-classes of intangibles. While studying macro-economic data is expected to provide us with the aggregate picture at the within-country level, exploring more disaggregated data at the firm level allows us to take into account various types of heterogeneity and explore effects at the within-sector level. Microeconomic data analysis also tends to reduce standard errors and increases variation and estimation precision, but at the same time increases possible instances of measurement error and sample selection bias.

3. DATA

Table 1 provides an overview of asset types included in our empirical analyses.

Table 1. **Types of capital assets** (exact definition may slightly differ per aggregation level)

Definition by Corrado, Hulton and Sichel (2009)	Macro analysis	Micro analysis	Capitalised in National Accounts: Yes / No?
Tangible assets			
ICT (hardware)	ICT hardware equipment		Y
(Non-ICT) plant and & machinery	Non-ICT machinery, buildings etc.	Machinery and equipment	Y
Buildings		Land, business buildings and infrastructure	Y
Transport equipment			Y
Intangible assets			
R&D	Computerised information (CI)	R&D (including acquisition of IP)	Y*
Software (and data)		Software, data, IT networks, websites	Y*
Firm-specific skills (training)	Economic Competencies (EC)	Training of employees	N
Organisational capital		Organisation and business process improvements	N
Mineral exploration	Innovative Property (IP)		Y
Artistic originals			Y
Design			N
Financial product innovation			N
Branding			N

Notes: For the analysis at aggregated level, we exclude dwellings from tangible capital thus reducing a bias potentially arising from different approaches in associating value to buildings. * signifies that while data(bases) are capitalised in the system of national accounts (SNA), in practice, only a proportion of actual investment activity is captured by current methods.

[4] Bruno *et al.* (2019) highlight that investments in R&D (intangible asset), once materialising as improved equipment and machinery, may be accounted for as (embedded in) a tangible asset. They argue that this can play an important role – at least for analysing productivity gap and convergence (see especially pp. 12ff).

Accordingly, for the macro-analyses, figures for tangible assets were derived from EUROSTAT while data concerning intangibles are taken from INTAN-Invest. Tangible capital = ICT + non-ICT; intangible = CI + EC + IP.

Much of the focus on intangibles has been on investment in R&D, key personnel and software. Nevertheless, the range of intangible assets is considerably broader. In a seminal paper, Corrado *et al.* (2005) group intangible assets into 'innovative property' (mineral exploration, 'R' and 'D', entertainment and artistic originals, new products and designs), 'computerised information' (software and databases) and 'economic competences' (brand equity, employer-provided training and organisational structures). Throughout our analysis, we refer to this set of assets but also categorise them according to which of them are accounted as investment in the system of national accounts ('NA intangibles') and those which are (still) accounted for as intermediate consumption ('non-NA intangibles'). The latter are economic competences as well as new products and designs.

3.1 MACRO-ECONOMIC LEVEL

For the analysis at the macroeconomic level, we use data from Eurostat on National Accounts and the INTAN-Invest database.[5] INTAN-invest is a harmonised macro-economic database on intangibles produced by a scientific consortium, following up on the work done by two EU-funded research projects (INNODRIVE and COINVEST). The data is constructed as close as possible to the National Accounts data and methodology. This dataset extends the asset boundary to include non-NA intangibles as investment rather than intermediate consumption in production statistics. The database covers the NACE-coded business sectors A-N, R and S, excluding the real estate sector L, and provides data for 1995–2015 for EU member states, the UK and the US. Previous applications of this dataset include work by Corrado *et al*. (2011, 2014, and 2016) or e.g. Jona-Lasinio *et al*. (2010).

In this paper, our sample captures data for 15 European countries for 1995 to 2015 (EU14 + UK). More concretely, adjusted GVA[6] and investment in non-NA intangible capital were taken from INTAN-Invest (both chain-linked). Hours worked as well as chain-linked tangible capital stocks were taken from the Eurostat National Accounts database.

To obtain stock estimates of accumulated intangible assets (both NA and non-NA) in million Euros and real terms, the perpetual inventory method (PIM) was applied using the investment estimates provided by INTAN-Invest and the depreciation rates suggested by COINVEST.[7] The initial value for the capital stock was calculated on the basis of a ratio between investment and stocks taken from the first release of the INTAN-Invest database.[8] For deflating nominal series a GVA deflator was computed on the basis of GVA data in current and previous year prices from Eurostat ("National Accounts aggregates by

[5] See http://www.intaninvest.net/ for details concerning statistical sources of INTAN data. For a discussion of data processing, related assumptions and challenges associated with this database see Corrado *et al.* (2013) and Corrado *et al*. 2016.

[6] Adjusted since non-NA intangible assets are accounted for as investment rather than as intermediate consumption.

[7] See Corrado *et al*. (2011), Table 2, p.25. The depreciation rates for tangible assets and for software are taken from EU KLEMS and that for mineral exploration is from US BEA. All other depreciation rates are as assumed in Corrado *et al*. (2005).

[8] This procedure – while conceptually coherent to obtain comparable approximations for capital stocks across countries – may however lead to stock figures that are numerically different compared to those reported in Eurostat. However, for our analytical purposes, the relative volumes and the corresponding dynamics are of highest relevance.

industry (up to NACE A*64)" [nama_10_a64]). Exchange rates were taken from Eurostat. The approach follows the work that was done in previous releases of INTAN-INVEST (see for example Corrado *et al*. 2011, 2012, 2014 and 2016 as well as Jona-Lasinio *et al.* 2010).[9]

3.2 FIRM LEVEL

The firm-level analysis is based on the first four waves (2016-2019) of the EIB Investment Survey (EIBIS). This survey is administered annually since 2016 to a stratified random sample of firms in each of the 27 EU Member States and the UK.[10] Since 2019, EIBIS also includes a sample of US firms. EIBIS covers non-financial firms in various sectors of the economy, from C (Manufacturing) to J (Information and Communication) according to the NACE classification.

The total sample size is about 12,300 interviews each year. The sample size varies across countries depending on the size of the population and ranges from 180 enterprises in Cyprus and Luxembourg to 600 in France, Germany, Italy and the UK, and 800 firms in the US. Each year, EIBIS includes a panel component and a top up sample, where panel firms (close to 40% in each wave) are firms that participated in a previous wave of the survey and consented to be re-contacted in the following wave. The top-up sample consists of firms that did not participate in the preceding wave.

The EIBIS sample is stratified disproportionally by country, industry group and firm size class, and stratified proportionally by region within each country (see Ipsos, 2019, for a detailed review of the survey and sampling methodology). For the purpose of descriptive statistics, firms can be weighted using value added to make them representative of the economy based on country, sector and firm size (employment), where the population distribution is reported by Eurostat Structural Business Statistics (SBS).

EIBIS is a rich source of information on investment in Europe (and the US) with a number of unique characteristics. First, EIBIS collects basic information on firms (e.g. number of employees, value of fixed assets, sales), which is matched to administrative data.[11] This feature makes it possible to cross-check survey responses against data from administrative sources and hence to assess the quality of the survey data. Brutscher *et al*. (2020) provide evidence on representativeness of the data for the business population of interest (enterprises above five employees) by comparing distributions in EIBIS with the corresponding population in Eurostat SBS. Second, EIBIS data is collected in a consistent manner for a large number of firms across many countries and industries, thus permitting us to carry out comparative

[9] Note that for Ireland tangible capital stocks are not available for the business sector aggregate because the manufacturing sector is missing due to confidentiality issues. We extrapolated the 2015 value based on information of the tangible capital stock dynamics since 2010.

[10] The respondents of the interviews are senior persons with responsibility for investment decisions and how investments are financed – e.g. the owner, Chief Financial Officer or Chief Executive Officer. The minimum number of employees of all enterprises is five, with full-time and part-time employees being counted as one employee and employees working less than 12 hours per week being excluded. An enterprise is defined as a company trading as its own legal entity. As such, branches are excluded from the target population. However, the definition is broader than a typical enterprise survey given that some company subsidiaries are their own legal entities.

[11] The data on each firm from EIBIS is matched to ORBIS. The matching is done by Ipsos MORI, which provided anonymised data to the EIB. This means that EIBIS does not have the name, the address, the contact details or any additional individual information that could identify the firms in the final sample. Note that not every firm in EIBIS has complete information in ORBIS (e.g. ORBIS may have missing information on employment, while EIBIS does not).

analysis. Third, EIBIS gathers data on many different aspects of investment and investment finance activities, which are often not available in standard official sources.

In this paper, in addition to information on the country, financial year, sector, and firm size classes, we use data on investment in different asset types, namely: (A) land, business buildings and infrastructure, (B) machinery and equipment, (C) R&D (including the acquisition of intellectual property), (D) software, data, IT networks and website activities, (E) training of employees, and (F) organisation and business process improvements (such as restructuring and streamlining). We consider categories (A) and (B) as tangible investment, and categories (C) to (F) as intangible investment.

EIBIS reports investment (flows) in different tangible and intangible categories. It does not provide a measure of stocks of the various intangible categories – and this measure would not be available in ORBIS data, which are matched to the firms. There is a variable in EIBIS that asks the firm to report the value of total fixed assets, i.e. tangible assets (e.g. buildings, equipment, vehicles) and intangible assets (e.g. patents, trademarks and copyright). While our main empirical specification uses investment flows, a robustness check exercise also uses proxies of the stocks of tangible and intangible fixed assets. To construct a measure of the stock of fixed (tangible) intangible assets, we compute the average share of investment that was allocated to (tangibles) intangibles for firms in the same country, sector, year and size category. We then multiply this share with the value of total fixed assets of the firms.

An alternative could lie in applying PIM, similar to the approach used for processing the investment data at macro-level. However, apart from the problem of identifying appropriate starting values for stocks of different assets for each company in the first year of inclusion in EIBIS, due to the nature of the sample consisting of individual survey waves (an unbalanced panel), we would be losing many observations (notably all firms that have not been surveyed by EIBIS year after year). Accordingly, after selecting all observations with non-missing values on our variables of interest, the final sample in the empirical analysis has 42,669 firm-year observations (see Table A2.2. in the Appendix for descriptive statistics).

4. EMPIRICAL ANALYSES

In this section, we present the analytical approaches at different aggregation levels (macro and micro). Conceptually, our first choice for analysing complementarities is estimating a translog production function, with the capital input split into various capital asset types and special focus on the corresponding translog interaction terms.

4.1 FRAMEWORK AND METHODOLOGY

In order to identify complementarities among different asset types, we estimate a translog production function, which is more flexible than the widely used Cobb-Douglas production function, as it allows for non-linear effects as well as for complementarity of assets.[12] We stress that the setting does not allow us to provide estimates that have a causal interpretation. The translog production function usually takes the form:

[12] The translog production function was originally proposed by Kmenta (1967) as an approximation of the Constant Elasticity of Substitution (CES) production function.

$$ln\left(\frac{Y}{L}\right) = ln(A) + \alpha_{K^T} ln\left(\frac{K^T}{L}\right) + \alpha_{K^I} ln\left(\frac{K^I}{L}\right) + \frac{1}{2}\left[\beta_{K^T K^I} ln\left(\frac{K^T}{L}\right) ln\left(\frac{K^I}{L}\right)\right] \tag{1}$$

$$+\frac{1}{2}\left[\beta_{KK^T} ln^2\left(\frac{K^T}{L}\right) + \beta_{KK^I} ln^2\left(\frac{K^I}{L}\right)\right]$$

where Y represents real gross value added (GVA), L are labour services in terms of hours worked, A is a term capturing unmeasurable technology, K^T are tangible capital stocks, K^I are measurable knowledge capital stocks (intangibles), while α and β denote the respective parameters to be estimated. Subscripts for time and country are dropped for simplicity. In our estimations, K^I is further split into knowledge services that are currently captured as investment in the system of national accounts (NA intangibles) and those that are currently captured as intermediate consumption (non-NA intangibles).[13] As discussed further below, multi-collinearity is an issue in our setting and we hence drop the quadratic terms, assuming only a linear relationship when it comes to the direct effects. At macro-level, we estimate equation (2), including also fixed effects and an error term:

$$ln\left(\frac{Y}{L}\right) = ln(A) + \alpha_{K^T} ln\left(\frac{K^T}{L}\right) + \alpha_{K^I} ln\left(\frac{K^I}{L}\right) + \frac{1}{2}\left[\beta_{K^T K^I} ln\left(\frac{K^T}{L}\right) ln\left(\frac{K^I}{L}\right)\right] \tag{2}$$

At the firm-level empirical, we estimate the following equation (3) including also fixed effects and an error term:

$$ln\left(\frac{Y}{L}\right) = \alpha_{IK^T} ln\left(\frac{IK^T}{L}\right) + \alpha_{IK^I} ln\left(\frac{IK^I}{L}\right) + \left[\beta_{IK^T IK^I} ln\left(\frac{IK^T}{L}\right) ln\left(\frac{IK^I}{L}\right)\right] \tag{3}$$

where Y represents anual turnover (or sales) of the firm i, L is the number of employees, IK^T is investment in tangible capital over the same financial year, IK^I is investment in intangible capital. Investment can be further disaggragated in six different asset types, namely two different types of tangible capital and four different types of intangible capital (see Table 1 and Section 3.2 for details). In contrast to the macro-level analyses, at firm-level, the dependent variable is based on turnover (or sales). This is because EIBIS includes precise information on turnover, but only rather rough proxies for value added (which, in addition, would make us lose observations). However, as a robustness check, we also report estimates using value added data that turned out to be qualitatively similar, which is quite reassuring.

[13] The INTAN-invest database provides for that distinction and would allow disaggregating the intangible capital component even further. However, which each further category of intangibles considered separately in the translog model, the number of corresponding parameters due to be estimated is rising exponentially, while with the total number of observations in our sample is relatively small.

In the analysis at firm-level, unless stated otherwise, we control for country (27 EU Member States and the UK), sector (manufacturing, construction, services, and utilities), year (four years, 2016–2019) and firm size (four categories: micro, small, medium-sized, and large). The empirical analysis at macro-economic level includes 15 European countries[14] for the years 1995-2015, and we distinguish between tangible and two different types of intangibles (NA and non-NA intangibles).[15] This difference in the structure of the samples needs to taken into account when interpreting the results, which is why we also report estimates for EU15 when we use firm-level data.

Moreover, while EIBIS obtains rich information on investment flows in six asset types at firm level, including four different intangible categories, as outlined in Section 3.2, it do not have direct information on the stock of intangibles. The micro-economic analysis is thus based on investment flows instead of capital stocks. This may make it more difficult to interpret the estimates or compare them directly to the results based on country-level data and capital stocks.[16] As a robustness check, we also use measures of the stocks of tangible and intangible fixed assets, where total fixed assets have been multiplied by the the average share of investment that was allocated to (tangibles) intangibles for firms in the same country, sector, year and size category. To further cross-check our results, we also run the macro-economic analysis with investment flows. We find significant evidence for complementarities between tangible and intangible investment when using investment data also at the macro level (see Table A3.3).

Production function estimation may typically suffer from multi-collinearity, endogeneity, non-stationarity, omitted variable bias or additional problems specific to the aggregation level of the data. Sample size and variation in the data can also pose problems in terms of generating comparably large standard errors. For the empirical estimation using macro-economic data, we apply a least-squares dummy variable estimator with robust standard errors, which helps us addressing issues of heterosceasticity and autocorrelation. Country and time dummy variables allow us to eliminate a bias that may stem from unobservable factors that change over time but are constant over countries and/or from unobservable factors that differ across countries but are constant over time. We therefore exploit the within-country variation, controlling for time-effects that apply to all countries (such as the Great Financial Crisis).

As our model is specified in reduced form, omitted variable bias may be an issue and, for example, considering further intangible assets (beyond the CHS definitions)[17], labour market and product market regulations or certain spillovers could additionally affect labour productivity. By including country and sector fixed effects we control for time-invariant factors. Wald tests point to the joint significance of the

[14] AT, BE, DE, DK, EL, ES, FI, FR, IE, IT, LU, NL, PT, SE and the UK.

[15] This is because of the number of observations and the parameters of the translog function due to be estimated.

[16] Conceptually, when basing our analyses on investment flows rather than stocks, we relate investment in a certain moment in time (year t) to our measure of productivity. That would not necessarily an issue if investments firm-level in a certain asset type at were uninterrupted (i.e. the firms invest continuously over years). However, we know that firms can invest their available resources in a specific asset and investment project in year t_0 and then in t_{+1}: while being perfectly aware that the two investments are connected and that the correspondingly created assets (ideally) will complement each other and produce synergies, affecting jointly productivity. The interpretation of the estimated coefficients (the effect on labour productivity) changes as we switch from capital stocks to investment and as we relate this year's output to labour and this year's investment (rather than the full capital stock). Basing the regression on capital stocks, as is done at macro-level would address these issues but capital stocks are hard to calculate and may also include a bias. Hence, investment can be seen as a proxy for capital stocks. Nevertheless, as a sensitivity check for our results, we estimate the macro- and the firm-level models using both stocks and investments.

[17] For a discussion of possible definitions of the (intangible) asset boundaries, see e.g. Thum-Thysen *et al.* 2017.

inclusion of country and year fixed effects – and in the case of the micro-level analysis – additionally also sector-level and firm size class fixed effects. Future work could include testing the inclusion of further structural variables, though we stress throughout the paper that we focus on correlations rather than on causal relationships.

In the analysis at macro-level, the sample size is relatively small and we face the issue of severe multi-collinearity – particularly when adding quadratic and interaction terms in the regression (or when trying to split up the intangible capital into further components thereof). To address multi-collinearity, centring the variables, dropping terms or increasing the number of observations could help. Since it is not possible to increase the number of observations in this sample, we concentrate on the former remedies in our analysis, i.e. we drop the quadratic terms and group together the asset types and include a total capital intensity variable together with the interaction terms. This reduces the multicollinearity problem, but affects the overall interpretation of the production function and the estimated coefficients. While we can interpret the coefficient of the interaction term as evidence for complementarity between asset types (i.e. as a measure of the productivity effect of the combination of two assets), we can no longer determine the direct effect per asset (which is made up of the estimated coefficients on the direct asset effect and the interaction term) since the assets are grouped into a single indicator with one coefficient associated with total assets.

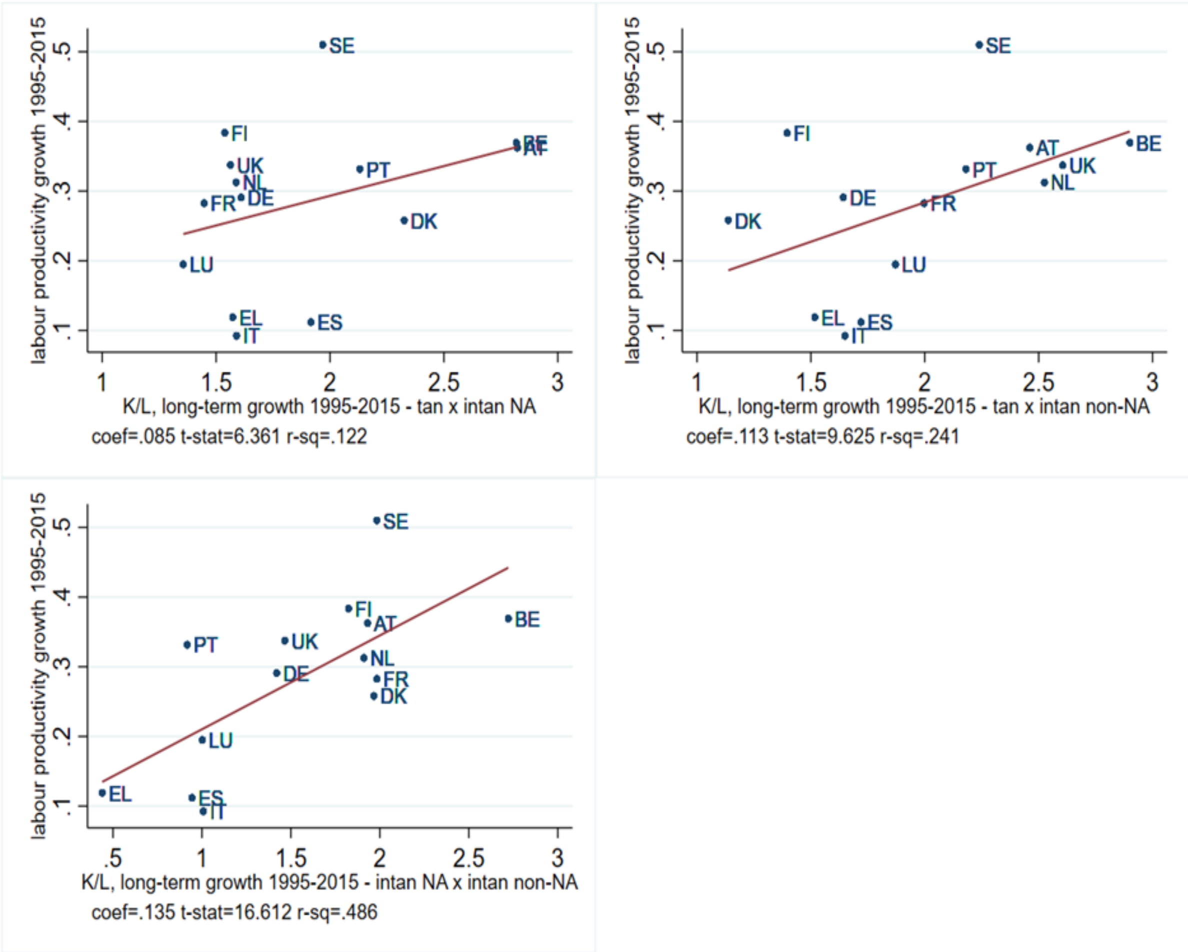
As mentioned above, the setting does not allow us to provide estimates that have a causal interpretation. Endogeneity is an issue that is difficult to address in our setting. Wooldridge (2009) and Ackerberg *et al*. (ACF, 2015) provide control function-based approaches to instrument for endogeneous variables in their estimation of total factor productivity (TFP). This paper uses labour productivity as the dependent variable in the analysis. At macro level, the limited size of the sample is an issue particularly when using algorithms that make use of General Method of Moments (GMM) estimation as in ACF (2015) and Wooldridge (2009) and we hence do not view this method to be appropriate in the macro context. At micro level, we do not have the data to address the endogeneity issue associated with firm-level investment decisions, as EIBIS does not provide information on material costs or spending on intermediate inputs (which are often used as an instrumental variable for investment decisions). Moreover, we would need different instrumental variables for investments in tangible and intangible capital (or for the six different asset types). With the data at hand, finding convincing instrumental variables appears to us to be an unsurmountable challenge.

4.2 RESULTS AT MACRO-ECONOMIC LEVEL

Graph 1 shows positive cross-country correlations between long-term labour productivity growth and pairwise interaction terms for long-term growth in capital intensity (or capital deepening[18], used synonymously throughout the paper) of specific asset types, notably (1) tangible and NA intangible capital, (2) tangible and non-NA intangible capital, and (3) NA and non-NA intangible capital. The positive correlation is particularly strong between NA intangibles and non-NA intangibles. However, these graphs do not control for the direct effects of the asset types and do not include all interaction effects simultaneously, which is why we turn to regression analysis.

[18] Capital deepening refers to an increase in the proportion of the capital stock to the number of labor hours worked. Movements in this ratio are closely tied to movements in labor productivity, all other things held equal. An increase in capital per hour (or capital deepening) leads to an increase in labor productivity.

Figure 1. **Labour productivity and interaction terms**



Notes: Cross-country correlation between long-term labour productivity growth and pairwise interaction terms for long-term growth in capital intensity ($\Delta K/L$) of specific asset types, notably (1) tangible and NA intangible capital, (2) tangible and non-NA intangible capital, and (3) NA and non-NA intangible capital. Please note that Ireland is excluded as an outlier since there was an atypical surge in intellectual property products over the sample period.

The results from estimating Equation (1) including country and time fixed effects are reported in Table 2. Column (1) provides the parameter estimates for a baseline production function excluding intangibles. Within countries, tangible capital deepening is overall positively related with labour productivity in our sample. Columns (2)-(4) show estimates for a production function including intangibles. The change in the coefficient of tangible capital intensity when adding intangibles (columns (2)-(3)) – and in the coefficient of NA intangibles when adding non-NA intangibles (column (4)) – already provides some evidence for complementarities. In fact, when adding intangible capital intensity, the coefficient of tangible capital intensity becomes insignificant at any conventional measure of statistical significance.

Column (5)-(9) show translog production functions with interaction terms, while quadratic terms have been dropped to address multicollinearity issues. When adding an interaction term between tangible and intangible capital, tangible capital turns negative and statistically significant. This is likely to be linked to the (from a graphical point of view) weakly positive relationship between tangible capital intensity and labour productivity within countries (see Figure A2.1, which shows divergence in labour productivity and tangible capital intensity for some countries, such as Finland – driven also be the development of the knowledged economy). This effect is somewhat attenuated when adding the right-hand side terms in lags (see Table A3.1). When we use data on investment (instead of stock), this does not hold and the relationship between tangible investment intensity remains positive throughout all specifications. A reason for this could be that if investment in tangible assets is stable in volume over time (but diminishing in relative terms of total investments), the corresponding capital stock intensities would indeed be decreasing over time.[19]

To partially address the severe multi-collinearity issues apparent in columns (6) (see the Variance Inflation Factor which is in fact always higher than 10), we sum up the assets and include a total capital intensity variable together with the interaction terms in regressions (6), (8) and (9). The total capital intensity term adds up capital intensity across the different asset types. As mentioned above, this remedy comes at the cost of interpretability of the direct effects. In columns (5) and (6), we see that the direction and significance of the interaction term does not change when introducing a grouped direct effect, which we interpret as a robustness check for the "total capital intensity" specification. Column (9) shows the corresponding results when excluding Ireland, which is considered somewhat an outlier as it displays an atypical surge in NA intangible capital over the sample period.

Two alternative specifications are added in Annex 3: Table A3.1 shows results when lagging all the right-hand side terms to control for the fact that capital intensity may have a lagged effect on labour productivity. This specification is added as a robustness check only because at the firm-level it would imply a loss in the sample size. As mentioned above, in this setting the main difference is that the negative correlation between tangible capital deepening and labour productivity is attenuated – possibly since in a lagged specifictation the decline in capital intensity is postponed. Table A3.2 shows results when excluding Ireland from the regressions. When dropping Ireland, the within effects of tangible capital deepening are even stronger (and more significantly negative) than in the baseline specification (see Table A3.2). Figure A2.1 shows that the relationship between tangible capital deepening and labour productivity is weak, as in a few countries tangible capital deepening is declining while labour productivity is increasing (driven by the development of the knowledge economy). Dropping one country in which this relationship is positive can have a strong impact on the overall relationship between tangible capital deepening and labour productivity.

The regressions at macro level provide evidence for a joint effect of NA- and non-NA intangibles as well as a (smaller) joint effect of tangible and non-NA intangibles on labour productivity when controlling for the direct impact of all assets, as shown by the coefficient estimates for the interaction terms. In addition, they provide evidence for complementarities between tangible and intangible capital. These results are in line with the literature discussed in Section 2. However, the various caveats discussed above, in particular issues due to multi-collinearity and high aggregation of asset types, suggest some caution with interpretations of the empirical results and we therefore turn to analyse asset complementarities empirically more refined at firm level. The analysis at firm-level also allows us deeper insights into complementarities across different sub-asset classes.

[19] This change in the sign of the estimated coefficient on tangible assets when we move from capital stocks to investment flows is also observed for the results at the firm-level (discussed in the next Section).

Table 2. **Translog production function estimates, expressed in labour productivity terms**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total capital deepening							-0.111***	0.184***	0.108**
							(0.0424)	(0.0397)	(0.0424)
Tangible	0.174***	0.0307	-0.0210	-0.0226	-0.134***	0.216***			
	(0.0611)	(0.0456)	(0.0363)	(0.0373)	(0.0344)	(0.0580)			
Intangible		0.502***			-0.0821				
		(0.0618)			(0.0943)				
Intangible NA			0.251***	0.249***		-0.184			
			(0.0335)	(0.0352)		(0.144)			
Intangible nonNA				0.111*		0.127			
				(0.0576)		(0.165)			
Tangible x Intangible					0.262***		0.228***		
					(0.0433)		(0.0246)		
Tangible x Intangible NA						0.0872		0.00399	-0.0226
						(0.0807)		(0.0211)	(0.0161)
Tangible x Intangible nonNA						-0.0740		0.00145	0.0313*
						(0.0795)		(0.0204)	(0.0189)
Intangible NA x Intangible nonNA						0.194***		0.186***	0.165***
						(0.0352)		(0.0303)	(0.0334)
Observations	315	315	315	315	315	315	315	315	294
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.976	0.984	0.983	0.984	0.986	0.989	0.985	0.989	0.992
Adj. R-squared	0.973	0.982	0.981	0.982	0.984	0.987	0.982	0.987	0.991
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wooldridge test AR(1) (p-value)	3.75e-07	3.57e-06	5.11e-07	3.20e-06	3.82e-06	3.78e-06	2.18e-06	3.43e-06	2.43e-07
highest VIF	14.39	98.73	52.91	67.80	355.1	1774	111.1	177.7	187.8
Wald country dummies (p-value)	0	0	0	0	0	0	0	0	0
Wald year dummies (p-value)	0	6.94e-06	0.000434	0.000503	6.38e-07	1.39e-06	1.39e-06	1.39e-06	1.39e-06

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Columns (6),(8),(9) show estimates for a translog production function including a total capital intensity term that adds up capital intensity across the different asset types. This specification was chosen to address issues of multi-collinearity. Column (9) excludes Ireland from the sample.

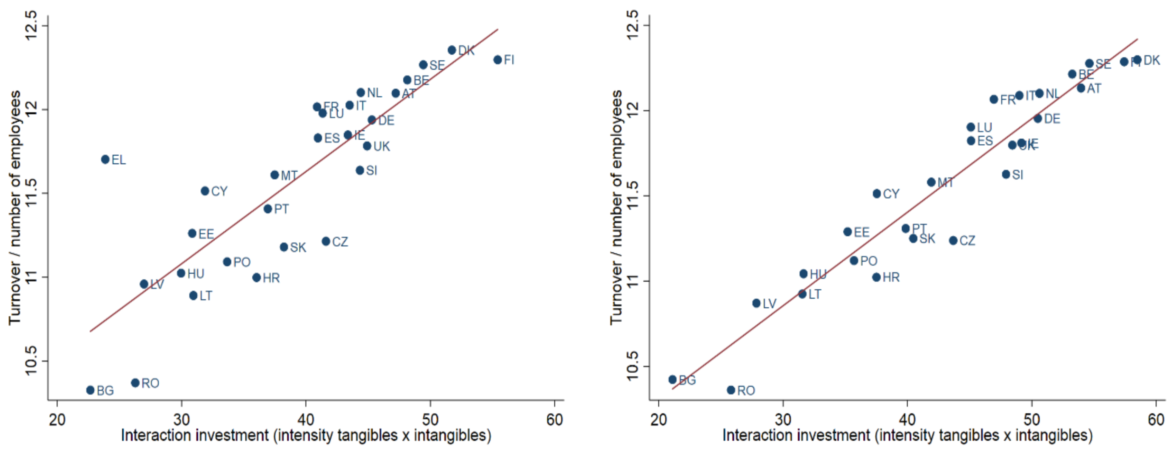
4.3 RESULTS AT FIRM-LEVEL

We start our analysis using firm-level data by distinguishing between investments in tangible and intangible assets, thus following an approach very similar to the analysis at macro-level. Our dependent variable is labour productivity (turnover per employee, in logarithm). The explanatory variables are the investment intensities, i.e. investment in tangibles or intangibles divided by the number of employees (also in logarithm) and the interactions of the investment intensities between tangibles and intangibles. The interaction terms are illustrated in Figure 2, along the corresponding values in labour productivity on the y-axis.[20] It suggests that, across countries, higher degrees of interaction between investment in tangible and intangible capital tend to be directly associated with labour productivity, thus pointing to some complementarities in the corresponding capital formation. Note that the vast majority of firms (more than 75%) in the sample invest both in tangible and intangible assets at the same time. This is

[20] Figures 1 and 2 differ to the extent that Figure 2 shows the level of labour productivity (in logarithm) and the level of the interactions of tangibles and intangibles, while in Figure 1 we use growth rates from 1995 to 2015. Moreover, we do not make a distinction into the two different categories of intangibles discussed in section 4.2 (depending on whether they are included in the system of national accounts or not) and group instead all intangibles together.

notably driven by firm size, as smaller firms are less likely to invest in tangible and intangibles in the same financial year.[21]

Figure 2. **Scatter plots for average (left panel) and median (right panel) labour productivity, by country; data pooled for all four waves (2016-2019)**



Notes: Investment intensities: investment in tangibles and intangibles divided by the number of employees (in logarithms). Firms are weighted with value added (by country, sector, firm, year and firm size classes) to make the sample representative of the business population using Eurostat SBS statistics. Left panel: Scatter for average log(turnover / number of employees), by country. Correlation coefficient: 0.8391. Right panel: Scatter for country-specific median observation log(turnover / number of employees), by country (Greece excluded). Correlation coefficient: 0.9562.

The results from estimating Equation (3) are reported in Table 3, again following a similar logic as in Table 2 of Section 4.2. Accordingly, Column (1) in Table 3 reports the estimates of a translog production function (without quadratic terms), with controls for country, sector, firm size and time fixed effects for the EU27 and the UK, while Column (2) focuses on the EU15 (analogue to Column (5) in Table 2).[22] Columns (3) and (4) report the estimates obtained for a simplified production function including a total capital intensity term (total annual investment divided by employment) which adds up capital intensity across the different asset types, while keeping in the interaction term of the two considered capital assets (analogue to Column (6) in Table 2 above). The estimated coefficient on the interaction term of investing both in tangible and intangible investment is only statistically significant in Columns (3) and (4), when tangible and intangible investment intensities are grouped in this single variable.[23]

Below we further disaggregate tangibles and intangibles into six different asset categories and find evidence for complementary, but also substitution effects across the six categories. We do not observe strong complementarities in columns (1) and (2), possibly because of the combination of these complementary and substitution effects when aggregating tangible and intangible assets into just two

[21] To make the graph easier to read, Greece was excluded from the right panel in Figure 2 because of the relatively low share of firms that invest both in tangible and intangible assets. But Greek firms are included in the rest of the analysis of this section.

[22] In Table 3, we dropped squared terms. Accordingly, in analogy to Section 3.1, our results rely on estimating a reduced form of the translog function.

[23] The results are virtually identical when Ireland is excluded from the regression analysis – following what is has been done in Table A3.2, where Ireland is excluded from the analysis at macro-level. The estimates are also similar to Table 3 where observations are weighted using Eurostat SBS statistics to make them representative of the business population, even though the statistical significance is weaker for some of the estimates. See Solon *et al.* (2015) for a discussion of the use of sample weights in regression analysis.

categories. Note also that the interaction term is positive and statistically significant when the direct effect of investment (both tangible and intangible) is aggregated into a single category in Columns (3) and (4). These results also highlight that the level of aggregation is critical for the analysis.

Table 3. **Firm-level regressions using investment in tangible and intangible assets**

	(1)	(2)	(3)	(4)
VARIABLES	EU27 + UK	EU15	EU27 + UK	EU15
Investment intensity			6.666***	6.247***
			[0.304]	[0.402]
Tangible investment	2.597***	1.273***		
	[0.318]	[0.428]		
Intangible investment	6.226***	5.146***		
	[0.384]	[0.477]		
Tangible x intangible	-0.020	0.085	0.250***	0.174***
	[0.054]	[0.067]	[0.027]	[0.033]
Observations	42,669	24,665	42,669	24,665
R-squared	0.275	0.108	0.280	0.114

Notes: Dependent variable: ln(turnover/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Investment intensity: ln(total investment per employee). Tangible investment: ln(tangible investment per employee). Intangible investment: ln(intangible per employee). All regressions control for country, sector, year and firm size fixed effects. Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

Table 4. **Firm-level regressions using the stocks of tangible and intangible assets**

	(1)	(2)	(3)	(4)
VARIABLES	EU27 + UK	EU15	EU27 + UK	EU15
Total capital intensity			1.110	-12.396***
			[2.454]	[3.527]
Tangible capital	-3.662**	-12.180***		
	[1.856]	[2.618]		
Intangible capital	5.395***	-0.626		
	[1.950]	[2.707]		
Tangible x intangible	0.984***	1.627***	1.017***	1.604***
	[0.154]	[0.191]	[0.132]	[0.184]
Observations	41,868	24,093	41,868	24,093
R-squared	0.318	0.164	0.317	0.163

Notes: Dependent variable: ln(turnover/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Total capital intensity: ln(total fixed assets per employee). Tangible capital: ln(tangible fixed assets per employee). Intangible capital: ln(intangible fixed assets per employee). All regressions control for country, sector, year and firm size fixed effects. Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

To check the validity of the results reported in Table 3, we also use data on the value of total fixed assets of the firms reported in EIBIS, which refers to the stock of both tangible and intangible fixed assets. While we do not have measures of the stocks of tangible and intangible assets reported sperately by each firm, we compute the average share of investment in (tangible) intangible invested by firms in the same country, sector, year and size category. We then multiply this share with the value of total fixed assets. We report the estimates in Table 4. The most striking message arising from the parameter estimates in Table 3 and 4 is that the interaction term of investments in tangible and intangible assets is positive (and statistically significant at 1% level) for most of the tested specifications (except in Columns (1) and (2) of Table 3). Overall, this suggests evidence for complementarities among the tangible and intangible assets.

As additional robustness check exercises, we repeat the analysis of Table 4 but use value added as a dependent variable. In EIBIS, value added is only a proxy because profits are only reported in intervals (less than 2% of sales, 2% to 4%, 5% to 9%, 10% to 14%, 15% or more). The results are reported in Table A.3.4 in the Appendix and are very similar to those reported in Table 3. We also did the estimation of Table 3 with firms grouped in four different aggreage sectors separately. We find that the estimates for firms in manufacturing, construction and utilities are very similar to the main specification. However, for the services sector, the estimated coefficient on the interaction term for investing in tangible and intangible assets is somewhat weaker and only statistically significant at 10%. This could be driven by the fact that firms in services allocate investment across tangible and intangibles differently from firms in the other sectors (EIB, 2020): in relative terms (i.e. as a share of total investment), firms in services invest less in machinery and equipment as well as R&D, but more in land and business buildings as well as business process improvements.

We also consider a specification that focuses on firms observed in (at least) two consecutive years and use the lagged values of investment intensities from the previous year as explanatory variables in the regression analysis and labour productivity in the current year as the dependent variable. While this approach certainly does not solve all endogeneity issues, it helps us address the simultaneity problem. The results reported in Table A.3.5 in the Appendix are similar to those reported in Table 3, which could be also driven by the relatively short lagged time horizon: investments are made in the previous year, while labour productivity is captured in the consecutive year.

In a second step of our analysis, we gradually disaggregate the individual asset types further into six different categories and re-estimate the translog production function. The estimates in the first row of Table 5 suggest that firms with higher investment intensity generally tend to perform better. In fact, firms that have a higher level of 'total capital intensity' (where intensity is defined as investment per employee), tend to have higher labour productivity (Columns 3 and 4). And similarly when we consider investments in different asset types, even though investment in R&D and business process improvements is not associated with higher labour productivity (Columns 1 and 2). Note that the decision to invest in organisation and business process improvements also includes restructuring and streamlining, which may not necessarily be immediately associated with higher labour productivity as the investment may need some time to have positive effects.

Table 5 shows some positive relations across investments in different asset types, which suggests complementarities, e.g. for investment in machinery and R&D. But for other assets we also find evidence of substitutional relations (e.g. investment in machinery and training) or no significant interaction of the corresponding capital formation at all. In other words, complementarities between different types of investment can often make a difference in terms of labour productivity.

Table 5. **Firm-level regressions using investment in six different tangible and intangible assets**

VARIABLES	(1) EU27 + UK	(2) EU15	(3) EU27 + UK	(4) EU15
Investment intensity			6.651***	5.907***
			[0.288]	[0.376]
Land and buildings	0.888**	0.808		
	[0.427]	[0.560]		
Machinery and equipment	2.140***	0.947**		
	[0.292]	[0.388]		
R&D	-0.156	-1.123		
	[0.648]	[0.740]		
Software and data	3.446***	2.911***		
	[0.475]	[0.579]		
Training of employees	4.986***	2.983***		
	[0.528]	[0.636]		
Business process improvements	-0.774	-0.858		
	[0.628]	[0.804]		
Land x Machines	0.234***	0.271***	0.148***	0.196***
	[0.050]	[0.060]	[0.035]	[0.043]
Land x R&D	0.067	0.072	0.113**	0.108*
	[0.052]	[0.058]	[0.051]	[0.057]
Land x Software	-0.092	-0.081	-0.059	-0.037
	[0.057]	[0.069]	[0.053]	[0.064]
Land x Training	-0.063	-0.026	0.009	0.027
	[0.066]	[0.080]	[0.061]	[0.071]
Land x Business processes	-0.046	-0.060	-0.044	-0.055
	[0.058]	[0.069]	[0.056]	[0.067]
Machines x R&D	0.243***	0.222***	0.196***	0.133**
	[0.065]	[0.071]	[0.051]	[0.058]
Machines x Software	-0.145**	-0.158**	-0.053	-0.104**
	[0.060]	[0.071]	[0.038]	[0.046]
Machines x Training	-0.284***	-0.148*	-0.066*	-0.122***
	[0.067]	[0.079]	[0.038]	[0.046]
Machines x Business processes	-0.033	-0.064	-0.142***	-0.145**
	[0.068]	[0.080]	[0.055]	[0.065]
R&D x Software	-0.038	0.033	-0.094	-0.053
	[0.073]	[0.080]	[0.063]	[0.069]
R&D x Training	-0.191**	-0.098	-0.205***	-0.174**
	[0.084]	[0.096]	[0.075]	[0.083]
R&D x Business processes	-0.073	-0.093	-0.086	-0.113*
	[0.061]	[0.068]	[0.060]	[0.066]
Software x Training	0.243***	0.274***	0.745***	0.672***
	[0.077]	[0.092]	[0.057]	[0.066]
Software x Business processes	0.096	0.156*	0.040	0.112
	[0.077]	[0.090]	[0.070]	[0.080]
Training x Business processes	0.220**	0.268**	0.233***	0.232**
	[0.088]	[0.105]	[0.079]	[0.091]
Observations	42,669	24,665	42,669	24,665
R-squared	0.278	0.114	0.286	0.125

Notes: Dependent variable: ln(turnover/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Total capital intensity: ln (total investment per employee). All regressions control for country, sector, year and firm size fixed effects.Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

Focusing on the *interaction of tangible investments*, firms that simultaneously invest in land, business buildings and infrastructure as well as in machinery and equipment (Table 5 – "Land x Machines") tend to have higher labour productivity, which points to complementarities between these two asset types as well. Looking at *tangibles and intangibles* altogether reveals that firms that invest (per employee) simultaneously in machinery and equipment as well as in R&D also tend to perform better. Arguably, in-house R&D spending, especially in medium/high-tech branches, increases the technological readiness of a firm (i.e. and its absorptive capacity), which suggests that capital formation in these the two types of assets can complement each other. However, the interaction of investment in machinery and equipment (per employee) with investment in software and data is negative, suggesting that they could be substitution effects between the two asset types. Similarly, the interaction term on investment in machines and training, or machines and business process improvements is also negative.

Overall, firms that invest simultaneously in *different areas of intangible assets* can benefit from spillover effects. Focusing on interactions of intangible investments, investing simultaneously in software and training of employees is associated with better firm performance. Similarly, the combination of investing in training of employees and business process improvements tends to lead to higher productivity. In turn, the negative interaction terms of R&D with training could be suprising: presumably this could also be associated with the time horizon (increase in labour productivity observed in the same year as a corresponding investment). As investment decisions at firm level within a certain year is conditional to the available budget and often prevail some minimum investment in a certain asset type/project to be effective, it could well be that a company's manager decides to invest, for instance, in either R&D or training, but not necessarily all at the same time. Accordingly, individual asset types may indeed appear to be substitutes (at a certain moment in time), while in the long-run investments in all of them need to happen in an appropriate way and accordingly the corresponding asset types – as in the given case – could complement each other.[24]

As robustness check, Table A3.6 in the Appendix focuses on firms observed in (at least) two consecutive years and use the lagged values of investment intensities from the previous year as explanatory variables. The estimates are qualitatively similar to Table 5 and usually have the same sign, even though some of the estimates are not statistically significant: for example, the positive interaction term on investment in training of employees and business process improvements is no longer statistically significant (when the dependent variable is labour productivity in the consecutive year).

To sum up, the obtained results from the micro-level analyses are summarised in Table 6 (illustrating the results presented in column (3) of Table 5), indicating whether evidence of a significant interaction between the investment in various sub-categories of asset types can be found at micro-level and, if so, in what direction this may point. For example, investing in land and business buildings appears to be complemented by investments in machinery and equipment – indicating complementarities among tangible assets. For investments in machinery and equipment, instead, we find evidence of complementarities with spending on R&D – indicating that firms seem to invest in both embedded and own R&D and as a cross-check of the findings in Bruno *et al.* (2019) at firm-level, the EIBIS data would not support the latter findings. Similarly, we find that investing in software and databases, training and organisational structures complement each other – together presumably this stands for investment in modern software solutions.

[24] The results using the stocks of different asset types (i.e. similar to Table 4, but with the six disaggraged categories for tangible and intangible assets) are available from the authors upon request.

Table 6. **Directionality of the interactions between investment intensity in different areas** (tangible and intangible assets; weighted)

Dependent variable:	Interaction with investment in other asset types					
Labour productivity	Direct effect	B. Machinery	C. R&D	D. Software	E. Training	F. Processes
Total investment intensity	+					
A. Land and business buildings		+	0	0	0	0
B. Machinery and equipment			+	0	0	-
C. R&D				0	-	0
D. Software and databases					+	0
E. Training of employees						+
F. Business process improvements						

Notes: Table 6 is based on an OLS regression, where labour productivity (turnover per number of employees, in logarithm) is the dependent variable and the explanatory variables are the total investment intensity (total investment divided by the number of employees, in logarithm) and the interactions of the investment intensities in different assets. The regressions analysis also controls for country, sector, year and firm size fixed effects.The first column lists the six different investment areas. The second column refers to the estimated coefficient on total investment intensity. Columns 3 to 7 illustrates the magnitude of the estimated coefficients on the interaction terms between different asset categories. "+" and "–" mean that the estimated coefficient is positive respective negative and statistically significant minimum at the 5% confidence level while "0" refers to estimated coefficients not statistically significant at the 5% confidence level.

4.4 COMPARISON MACRO AND FIRM-LEVEL RESULTS

As mentioned, a direct comparison especially in terms of magnitude of the effects is to be conducted with caution due to the differences in country samples (EU15 versus EU27), regression specifications (capital stocks versus investments) and time spans (longer in the macro analysis). Complementarities should be interpreted differently at macro and at micro level. Respective analyses at different aggregation levels capture different dynamics: at macro-level we can analyse the dynamics within countries over time while at micro-level we analyse dynamics across firms within country and sector. This can lead to different results. Nevertheless, below we provide a tentative comparison.

We find evidence for complementarities between tangibles and intangibles at both macro (within countries over time) and micro level (across firms, within country and sectors); at micro level, especially in a pooled setting. Regarding the sub-levels of assets, within-countries over time we find complementarities between NA intangibles (mainly intellectual property products) and non-NA intangibles (mainly training, organisational capital, branding, new products) overall. Within firm-level data, we can go into a more granular asset breakdown. Results look a bit different than at macro-level: we find complementarities between (1) land and buildings with machinery (i.e. among tangible assets); (2) software, training and business process improvements (indicating modern ICT solutions) and (3) machines and own R&D (indicating that firms may tend to invest both in embedded and own R&D). However, at firm-level, we do not find that own R&D and other intangibles jointly increase productivity at firm-level. This could indicate that while NA intangibles and non-NA intangibles are complementary overall, this is not necessary the case for all sub-assets.

5. CONCLUSION

In this paper, we assess to what extent there are complementarities between various factor inputs, incorporating both tangible and intangible capital. Based on novel data on investments in intangible assets (including intangibles not covered by the system of national accounts) both at macro and at micro level, we estimate translog production functions.

At the macro-economic level, we document complementarities between tangible and intangible capital intensity and the existence of pairwise complementarities between different components of the deployed capital, in particular between NA (intellectual property products) and non-NA intangible capital (i.e. intellectual property products and economic competencies). Our microeconomic evidence suggests that higher degrees of interaction between investment in tangible and intangible capital tend to be directly associated with labour productivity, thus pointing to some complementarities. In fact, there are significant complementarities when looking at the interactions between tangible and intangible assets , which is reassuring with a view at our initial hypothesis and, moreover, also confirms the findings at macro-level. When zooming in deeper, evidence suggests that certain types of tangible and/or intangible assets can be either complements or substitutes, or may have no obvious relations whatsoever. In fact, we find evidence of tangible and intangible assets being complements (e.g. machinery and equipment with R&D as well as software and databases with training of employees). However, we also show that some capital formation might be a substitute for investing in other asset types as, for instance, investing on tangible assets such as machinery and equipment related to knowledge assets such as organisational structures.

Apparently it is often the case that the investment in one asset can only be fully efficient (i.e. unfold its full impact on production and productivity) if there is a parallel investment in other complementary assets. In turn, depending on the type of business and its characteristics (such as e.g. tech-readiness, absorptive capacity, subsidiary, region, or the business environment), the investment decision is often about doing either this or that (e.g. own R&D vs. purchasing a ready to use solution), but not necessarily both at the same time – as illustrated in our our empirical analyses. There is in fact no uniform answer to the question whether one type of asset complements another or not. The answer depends on many aspects, including most notably the level of details in the data, the time horizon and the aggregation level of the corresponding analyses, which altogether suggests conducting multi-level panel analyses, such as presented in this paper. This rather general conclusion also explains the somewhat inconclusive evidence concerning complementarities in the empirical literature (see our discussion in Section 2).

We would also like to highlight one relevant policy conclusion arising from our analyses. The existence of complementarities suggests that policy support aiming at stimulating investment in certain assets – while excluding others – may fall short in unlocking its own full potential. When looking at the portfolio of investments in tangible and intangible asset types, at different aggregation levels, there is no golden rule that could be applied to define what is a 'balanced mix'. This mix depends on many external and firm-specific aspects. Subdued investment trends in Europe may be effectively tackled by means of policy initiatives stimulating investments e.g. in high-tech equipment or in-house R&D, especially if the latter are indeed the types of assets companies are lacking the most, i.e. underinvestment in such assets benchmarked against a hypothetically optimal capital formation (for a balanced investment portfolio).

Accordingly, policy initiatives in terms of R&D, FDI, tech-transfer / technological diffusion and Global Value Chains (i.e. competition and industrial policies), would need to be well aligned and remain flexible in their scope to ensure that relevant investment barriers can indeed be addressed through the corresponding initiatives. However, too often such initiatives focus on (co-)financing certain types of assets only (often biased towards investments in tangible assets that can be used as collateral), thus falling short to encompass in particular non-NA intangible assets, such as training of employees, which we have found to be complementary to other crucial assets, such as software and databases. Accordingly, we would advocate for a flexible approach to support investment, covering conceptually a wide array of asset types, i.e. tangibles and intangibles, including particularly those not captured in the system of national accounts.

Policy intervention is arguably vital in ensuring market conditions that are enabling and allow companies achieving their individually optimal investment (asset) portfolio and thus unfolding their full productive potential. This can be achieved by addressing investment bottlenecks and market failures (i.e. removing financial constraints for certain types of investment), including by deploying public resources to support the financing of certain types of business sector investments.

To give some examples: Investments in digital and green transition are anchored prominently in the EU Recovery and Resilience Plans (RRPs) as a minimum of 20% and 37%, respectively, of the total funds will be allocated to these priorities. Largely, this will concern tech investments, e.g. deployment of less CO2-emitting technologies, increasing energy efficiency in production and buildings, roll-out of 5G and fiber-infrastructure. These investments are critical for the twin transition together with capital deepening in terms of the (complementary) intangible assets. The RRF also emphasises interlinkages of stimulating investment with coherent sets of reforms in various areas, such as the development of digital skills, life-long learning, digitalising of businesses and the public administration. In fact, these reforms are key elements of the RRPs and their impact particularly with a view at investing in intangible assets may become even more vital in future once the fundamentals and especially the essential (tangible) infrastructures will be settled. In general, infrastructure investment projects, supported in various ways at regional, national, European level, tend to concern mainly fixed assets. Indeed, even though there is a growing emphasis on development of skills and/or setting the ground for the digital economy in less populated areas, the focus of such projects has remained until the recent past on rolling out (tangible) digital infrastructure.

Further analyses are needed to better understand intangibles and their interlinkages among asset types. At macro- and industry-level, these could consist of analyses based on longer time series that would ideally also include a broader sample of countries, while allowing for sectoral disaggregation. The Statisical Module of the EU KLEMS database *inter alia* aims at providing such data for both NA and non-NA intangibles as defined by CHS 2005 (thus following the spirit of INTAN-Invest and COINVEST). After a first release of data in 2019, two further vintages, which will be particularly refined in terms of coverage of non-NA intangible assets, are going to be available by the end of 2021 and 2022. Similarly, including more EIBIS waves that ideally would allow basing the firm-level analyses on stock estimates could also allow refining the analyses. Another dimension that could be added is considering public vs. private investment, possibly at various aggregation levels. In particular, interesting evidence may emerge from the data and the experiences from the investments under the Recovery and Resilience Facility (RRF) in Europe.

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ANNEX

ANNEX 1 – LIST OF VARIABLES USED IN THE MACRO ANALYSIS

Name	Variable Description	Source	Remarks
GVA	Gross value added		
Y_L	Labour productivity		Natural logarithm over GVA over hours worked in thousand Euros per hour worked.
Tangible investment	Total tangible investment over lagged total capital stock (total capital stock = tangible + non-NA-intangible + NA-intangible)	INTAN-INVEST and national accounts	Tangible investment series were taken from Eurostat's national accounts database. Tangible stocks were taken from Eurostat's national accounts database. Non-NA-intangible stocks were computed with PIM in million Euros and real terms. For deflating nominal series a GVA deflator was computed on the basis of GVA data in current and previous year prices from Eurostat ("National Accounts aggregates by industry (up to NACE A*64)" [nama_10_a64]). Exchange rates were taken from Eurostat.
Intangible investment	Total intangible investment over lagged total capital stock (total capital stock = tangible + non-NA intangible + NA-intangible)	INTAN-INVEST and national accounts	Intangible investment was taken from INTAN-INVEST. For the computation of the stocks see above.
NA-intangible investment	National accounts intangible investment over lagged total capital stock (total capital stock = tangible + non-NA-intangible + NA-intangible)	INTAN-INVEST and national accounts	Intangible investment was taken from INTAN-INVEST. For the computation of the stocks see above.
Non-NA-intangible investment	Non-national accounts ("new") intangible investment over lagged total capital stock (total capital stock = tangible + non-NA-intangible + NA-intangible)	INTAN-INVEST and national accounts	Intangible investment was taken from INTAN-INVEST. For the computation of the stocks see above.

ANNEX 2 – DESCRIPTIVE ANALYSIS

Table A2.1 **Descriptive statistics** (macro analysis)

Variables	Nr observations	mean	sd	min	max
Gross value added	315	488003.9	504203.7	16172.25	1883425
Total hours worked	315	14363.76	14259.51	285.797	44796
Tangible capital stock	315	708947.6	730168.5	17349.6	2460382
NA intangible capital stock	315	91020.08	107837.6	571.5167	431311.9
Non-NA intangible capital stock	315	116037.6	127525.9	2755.98	508808.6
Total intangible capital stock	315	207057.7	231237.1	3327.496	914960.1
Total capital stock	315	916005.3	931529.1	20677.1	3240904
Tangible investment	315	62460.75	63306.17	1810.887	250913.4
Intangible investment	306	82262.87	94794.31	1215.937	458551.4
Labour productivity (hours) - log	315	3.549197	.4038965	2.504927	4.268593
Total capital intensity - log	315	4.179007	.4747705	2.442825	4.934626
Tangible capital intensity - log	315	3.918472	.4646809	2.196887	4.675299
Intangible capital intensity - log	315	2.629678	.6498718	.8213086	3.706817
NA intangible capital intensity - log	315	1.641176	.8859786	-.7673793	3.092399
Non-NA intangible capital intensity - log	315	2.110963	.5719674	.5929095	2.961664
Tangible x NA intangible cap int - log	315	3.359298	1.861683	-1.064067	6.973284
Tangible x non-NA intangible cap int - log	315	4.22741	1.442539	.7312155	6.821023
NA intangible x non-NA intangible cap int - log	315	1.935139	1.222783	-.3225987	4.527595
Tangible investment intensity - log	315	1.514671	.4026506	.1173436	2.381369
Intangible investment intensity - log	306	1.569844	1.154724	-.1934511	4.480653
Tangible x intangible investment intensity - log	306	1.32885	1.134535	-.0447226	4.531121

Table A2.2 **Descriptive statistics** (micro analysis)

Variable	Nr observations	Mean	Std. Dev.	Min	Max
Sales - log	42,669	15.23	2.11	5.92	27.29
Value added - log	36,937	13.95	1.96	0.00	24.63
Fixed assets - log	42,669	13.91	2.55	2.38	25.36
Number of employees - log	42,669	3.79	1.51	0.69	11.51
Tangible investment - log	42,669	9.37	5.25	0.00	22.87
Intangible investment - log	42,669	8.47	4.48	0.00	23.40
Labour productivity (employees) - log	42,669	11.49	1.28	0.03	23.80
Share of total investment (%)					
Land and buildings	42,669	0.15			
Machinery and equipment	42,669	0.50			
R&D	42,669	0.06			
Software and data	42,669	0.13			
Training of employees	42,669	0.10			
Business process improvements	42,669	0.06			
Sector (% of sample)					
Manufacturing	42,669	0.30			
Construction	42,669	0.22			
Services	42,669	0.25			
Infrastructure	42,669	0.24			

Figure A2.1 **Labour productivity, capital deepening and intangible capital deepening, logarithms** (macro analysis)

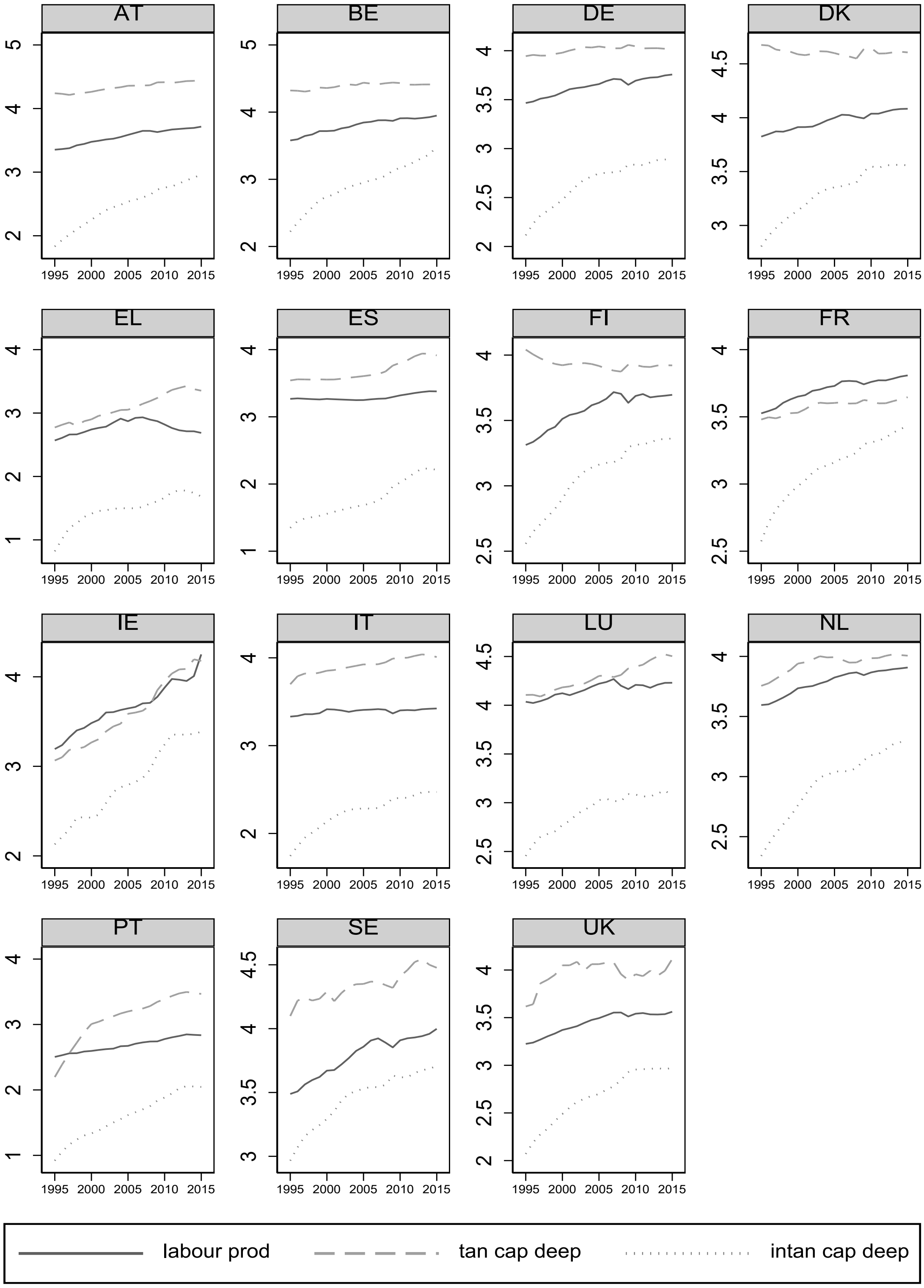


Figure A2.2 **Labour productivity, lagged capital deepening and lagged intangible capital deepening, logarithms** (macro analysis)

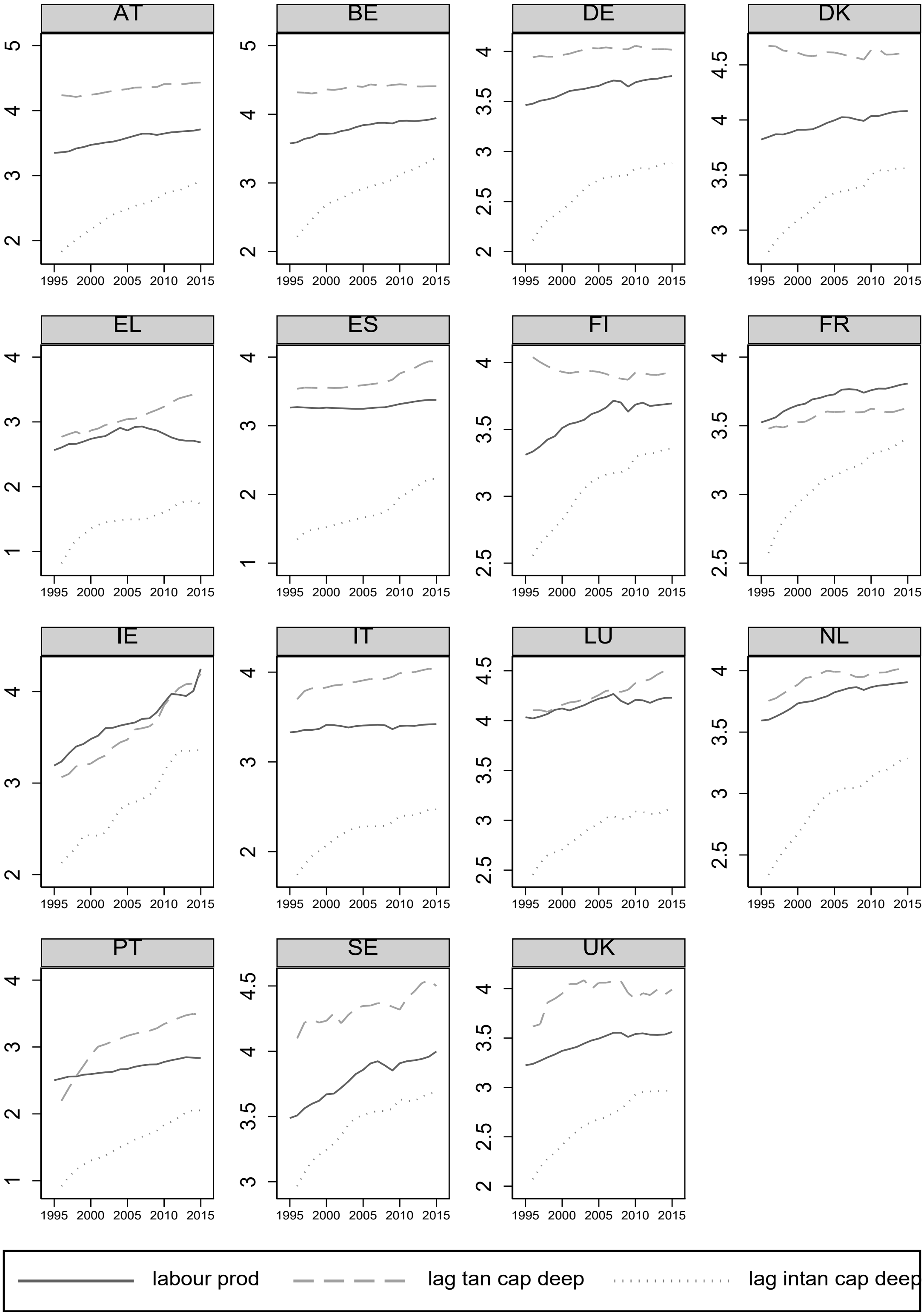
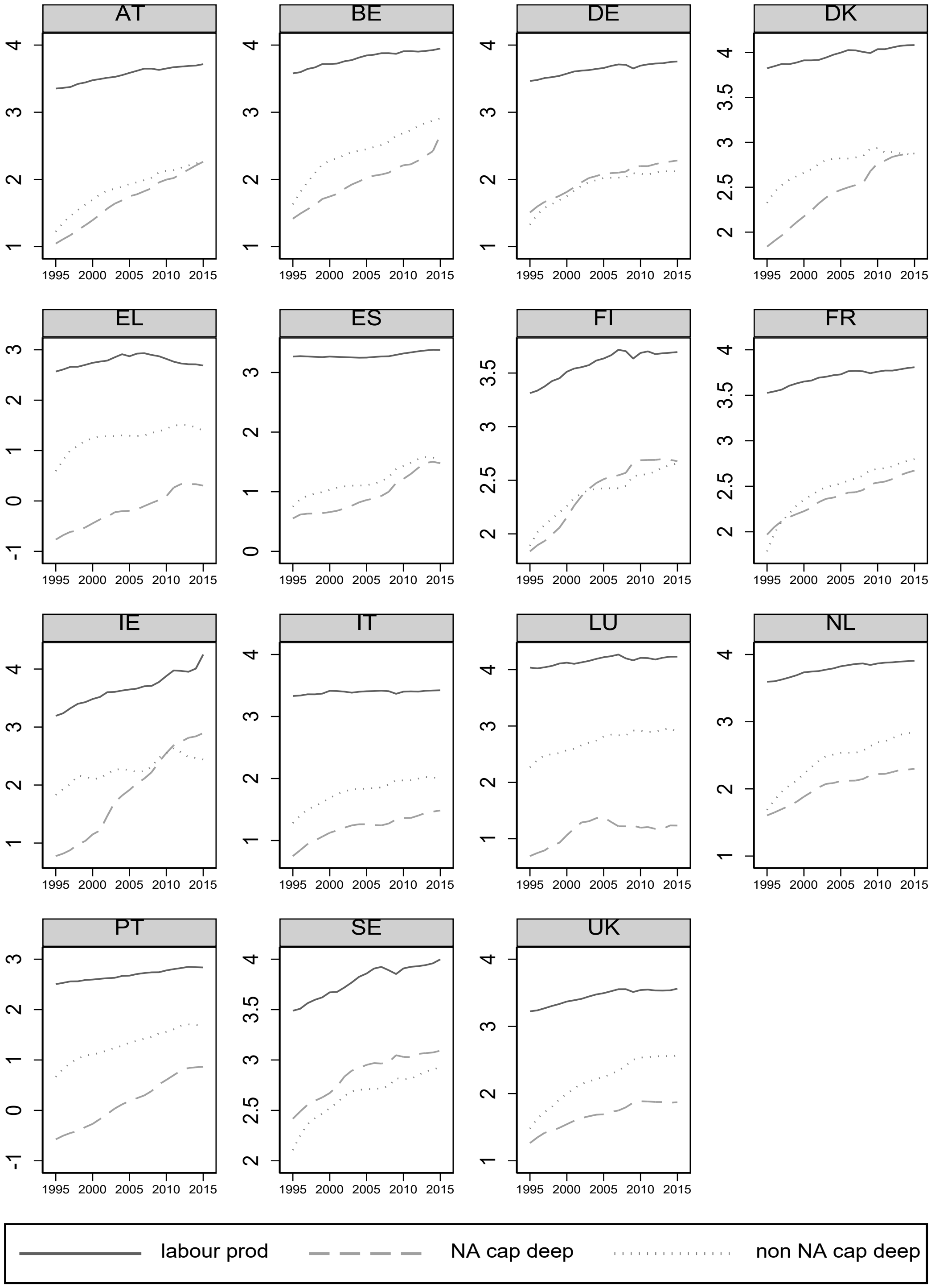


Figure A2.3 **Labour productivity, lagged NA intangible capital deepening and lagged non-NA intangible capital deepening, logarithms** (macro analysis)



ANNEX 3 – ALTERNATIVE SPECIFICATIONS

Table A3.1 **Translog production function estimates, expressed in labour productivity terms, lagged right-hand side terms** (macro analysis)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total capital deepening							0.146***	0.0866**
							(0.0369)	(0.0422)
Tangible	0.165**	0.0178	-0.0309	-0.0358	-0.146***	0.204***		
	(0.0639)	(0.0476)	(0.0384)	(0.0396)	(0.0351)	(0.0605)		
Intangible			0.258***	0.258***		-0.229		
			(0.0338)	(0.0351)		(0.153)		
Intangible NA				0.120**		0.184		
				(0.0552)		(0.163)		
Intangible nonNA		0.523***			-0.0791			
		(0.0620)			(0.0983)			
Tangible x Intangible					0.270***			
					(0.0466)			
Tangible x Intangible NA						0.126	0.0182	-0.00539
						(0.0837)	(0.0206)	(0.0153)
Tangible x Intangible nonNA						-0.0944	0.0124	0.0356*
						(0.0806)	(0.0188)	(0.0185)
Intangible NA x Intangible nonNA						0.176***	0.171***	0.156***
						(0.0324)	(0.0281)	(0.0305)
Constant	2.115***	1.899***	2.866***	2.778***	2.668***	2.078***	2.253***	2.600***
	(0.189)	(0.171)	(0.114)	(0.116)	(0.114)	(0.231)	(0.111)	(0.216)
Observations	300	300	300	300	300	300	300	280
Constant	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.979	0.985	0.984	0.985	0.989	0.991	0.990	0.993
Adj. R-squared	0.976	0.983	0.982	0.983	0.987	0.989	0.989	0.991
Country FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Wooldridge test AR(1) (p-value)	2.34e-06	2.14e-06	1.73e-07	1.67e-06	7.50e-07	8.46e-07	9.25e-07	2.43e-07
highest VIF	15.08	110.6	56.91	73.58	378.5	1820	187.3	200.4
Wald country dummies (p-value)	0	0	0	0	0	0	0	0
Wald year dummies (p-value)	0	0.000572	0.0246	0.0227	4.52e-05	6.15e-06	6.15e-06	6.15e-06

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total capital deepening							0.108**
							(0.0424)
Tangible	-0.0487*	-0.0931***	-0.0881***	-0.0989***	-0.147***	0.120**	
	(0.0294)	(0.0262)	(0.0283)	(0.0276)	(0.0367)	(0.0532)	
Intangible		0.335***			0.0913		
		(0.0498)			(0.0995)		
Intangible NA			0.108***	0.0738***		-0.0805	
			(0.0276)	(0.0256)		(0.132)	
Intangible nonNA				0.245***		0.177	
				(0.0426)		(0.174)	
Tangible x Intangible					0.131***		
					(0.0448)		
Tangible x Intangible NA						0.0174	-0.0226
						(0.0661)	(0.0161)
Tangible x Intangible nonNA						-0.0456	0.0313*
						(0.0751)	(0.0189)
Intangible NA x Intangible nonNA						0.165***	0.165***
						(0.0404)	(0.0334)
Observations	294	294	294	294	294	294	294
Constant	yes	yes	yes	yes	yes	yes	yes
R-squared	0.988	0.990	0.988	0.990	0.991	0.992	0.992
Country FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Adj. R-squared	0.986	0.989	0.987	0.989	0.990	0.991	0.991
Wooldridge test AR(1) (p-value)	1.23e-07	2.32e-07	3.48e-07	2.20e-07	2.07e-07	1.97e-07	2.43e-07
highest VIF	19.71	120.0	82.23	85.70	497.4	1940	187.8
Wald country dummies (p-value)	0	0	0	0	0	0	0
Wald year dummies (p-value)	0	3.43e-06	2.55e-10	5.49e-06	9.39e-07	3.38e-07	3.38e-07

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A3.3 **Translog production function estimates, expressed in labour productivity terms, investment flows instead of capital stocks** (macro analysis)

	(1)	(2)	(3)	(4)
Total investment intensity				0.355***
				(0.0397)
Tangible investment intensity	0.353***	0.261***	0.204***	
	(0.0568)	(0.0320)	(0.0324)	
Intangible investment intensity		0.277***	0.203***	
		(0.0350)	(0.0349)	
Tangible x Intangible investment intensity			0.0892***	0.126***
			(0.0234)	(0.0199)
Observations	315	306	306	306
Constant	yes	yes	yes	yes
R-squared	0.983	0.989	0.989	0.989
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Adj. R-squared	0.981	0.987	0.987	0.988
Wooldridge test AR(1) (p-value)	7.04e-06	9.57e-10	2.53e-10	3.25e-09
highest VIF	14.84	105.7	203.4	182.2
Wald country dummies (p-value)	0	0	0	0
Wald year dummies (p-value)	0	0	0	0

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A3.4 **Firm-level regressions using the stocks of tangible and intangible assets, value added as dependent variable** (micro analysis)

VARIABLES	(1) EU27 + UK	(2) EU15	(3) EU27 + UK	(4) EU15
Total capital intensity			5.388***	5.337***
			[0.247]	[0.332]
Tangible capital	2.269***	1.709***		
	[0.262]	[0.357]		
Intangible capital	5.494***	4.529***		
	[0.309]	[0.394]		
Tangible x intangible	-0.030	0.018	0.238***	0.160***
	[0.044]	[0.055]	[0.022]	[0.026]
Observations	36,937	21,620	36,937	21,620
R-squared	0.412	0.176	0.415	0.183

Notes: Dependent variable: ln(turnover/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Investment intensity: ln(total investment per employee). Tangible investment: ln(tangible investment per employee). Intangible investment: ln(intangible per employee). All regressions control for country, sector, year and firm size fixed effects. Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

Table A3.5 **Firm-level regressions using the stocks of tangible and intangible assets, lagged explanatory variables on the right-hand side** (micro analysis)

VARIABLES	(1) EU27 + UK	(2) EU15	(3) EU27 + UK	(4) EU15
Total capital intensity			5.643***	5.598***
			[0.489]	[0.620]
Tangible capital	1.972***	1.244*		
	[0.508]	[0.651]		
Intangible capital	5.363***	4.475***		
	[0.621]	[0.744]		
Tangible x intangible	-0.012	0.019	0.205***	0.102*
	[0.086]	[0.105]	[0.043]	[0.052]
Observations	13,799	8,520	13,799	8,520
R-squared	0.305	0.133	0.308	0.139

Notes: Dependent variable: ln(value added/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Investment intensity: ln(total investment per employee). Tangible investment: ln(tangible investment per employee). Intangible investment: ln(intangible per employee). All regressions control for country, sector, year and firm size fixed effects. Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

Table A3.6 **Firm-level regressions using investment in six different tangible and intangible assets, lagged explanatory variables on the right-hand side** (micro analysis)

VARIABLES	(1) EU27 + UK	(2) EU15	(3) EU27 + UK	(4) EU15
Investment intensity			5.858***	5.325***
			[0.459]	[0.559]
Land and buildings	-0.070	-0.013		
	[0.695]	[0.907]		
Machinery and equipment	1.942***	1.308**		
	[0.470]	[0.592]		
R&D	0.521	0.482		
	[1.010]	[1.038]		
Software and data	3.971***	2.477***		
	[0.772]	[0.929]		
Training of employees	3.494***	1.955**		
	[0.801]	[0.961]		
Business process improvements	-0.896	-1.538		
	[1.005]	[1.178]		
Land x Machines	0.291***	0.289***	0.146**	0.190***
	[0.081]	[0.098]	[0.057]	[0.073]
Land x R&D	0.058	0.053	0.104	0.092
	[0.082]	[0.087]	[0.081]	[0.085]
Land x Software	-0.064	-0.061	-0.050	-0.063
	[0.094]	[0.111]	[0.088]	[0.102]
Land x Training	-0.077	0.040	-0.087	0.020
	[0.108]	[0.129]	[0.100]	[0.119]
Land x Business processes	-0.075	-0.145	-0.055	-0.119
	[0.091]	[0.098]	[0.090]	[0.097]
Machines x R&D	0.247**	0.159	0.226***	0.152*
	[0.102]	[0.105]	[0.075]	[0.082]
Machines x Software	-0.267***	-0.160	-0.077	-0.060
	[0.100]	[0.117]	[0.063]	[0.073]
Machines x Training	-0.290***	-0.322**	-0.166**	-0.289***
	[0.108]	[0.126]	[0.065]	[0.076]
Machines x Business processes	0.124	0.017	0.003	-0.103
	[0.112]	[0.128]	[0.097]	[0.109]
R&D x Software	-0.111	-0.091	-0.096	-0.089
	[0.114]	[0.124]	[0.100]	[0.110]
R&D x Training	-0.316**	-0.247*	-0.314***	-0.243*
	[0.128]	[0.141]	[0.114]	[0.126]
R&D x Business processes	0.069	0.063	0.074	0.075
	[0.095]	[0.106]	[0.094]	[0.104]
Software x Training	0.408***	0.532***	0.852***	0.790***
	[0.133]	[0.158]	[0.105]	[0.122]
Software x Business processes	-0.245*	-0.063	-0.278**	-0.145
	[0.131]	[0.149]	[0.117]	[0.132]
Training x Business processes	0.223	0.318*	0.194	0.225
	[0.150]	[0.171]	[0.134]	[0.154]
Observations	13,799	8,520	13,799	8,520
R-squared	0.307	0.141	0.315	0.151

Notes: Dependent variable: ln(turnover/number of employees). Note that the dependent variable has been multiplied by 100 to improve the readability of the estimates. Total capital intensity: ln(total investment per employee). All regressions control for country, sector, year and firm size fixed effects. Robust standard errors in squared brackets: *** p<0.01, ** p<0.05, * p<0.1.

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