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The role of intangibles in firm-level productivity – evidence from Germany

Felix Roth[a], Ali Sen[a] and Christian Rammer[b]

[a]Department of Economics, University of Hamburg (UHH), Hamburg, Germany; [b]Economics of Innovation and Industrial Change, Leibniz Centre for European Economic Research (ZEW), Mannheim, Germany

ABSTRACT

This paper analyses the impact of intangibles on firm-level productivity. Unlike previous studies we capture all dimensions of intangibles for both goods-producing and service industries. Based on data from the German part of the Community Innovation Survey (CIS) for the period 2006 to 2018, our results show that intangible capital investment is equal in size to investment in tangible capital since the early 2000s. We find a highly significant and positive relationship between intangible capital and output, with elasticities in line with previous findings for other large EU economies. This positive impact of intangibles on the firm-level productivity is driven by non-R&D intangibles, notably software & databases, training and advertising & marketing. While this finding holds for both goods and service sectors, we find that non-R&D intangibles impact firm-level productivity more strongly in the services. Investment in R&D affects productivity only in the high-tech manufacturing sector.

KEYWORDS

Intangible capital; R&D; firm-level productivity; Germany; knowledge economy

JEL CLASSIFICATION CODES

D24; O30; L22; C33

1. Introduction

As highly developed countries advance towards knowledge economies, the drivers of productivity at the firm level are changing. In addition to investment in physical assets, investment in knowledge capital has become a key element for building up a capital stock for producing and distributing goods and services in a competitive way (Teece 1998; Lev and Radhakrishnan 2005). For a long time, investment in research and development (R&D) has been regarded as the key component for creating knowledge capital (Griliches 1984, 1998). More recently, other types of investment in knowledge capital have been identified, including skills of employees, organisational capabilities, as well as branding and product design (Webster and Jensen 2006). The process of digitalisation reinforced the importance of knowledge investment as software routines, data bases and new digital technologies such as artificial intelligence have become a major base for productivity advance (see Brynjolfsson, Rock, and Syverson 2019; Corrado, Haskel, and Jona-Lasinio 2021; Rammer, Czarnitzki, and Fernández 2022; Czarnitzki, Fernández, and Rammer 2022; Yang 2022; Damioli, Van Roy, and Vertesy 2021).

CONTACT Felix Roth Felix.Roth@uni-hamburg.de Department of Economics, University of Hamburg (UHH), Von-Melle-Park 5, 20146 Hamburg, Germany.

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In order to measure investment in the various types of knowledge capital, the concept of intangibles (as opposed to tangible capital, such as machinery, equipment and buildings) has been introduced in the literature (see OECD 1998; Nakamura 2001). For example, the seminal work of Corrado, Hulten, and Sichel (2005), hereafter CHS, proposes a unifying framework containing three broad categories of intangibles in firms: i) computerised information (software and databases), ii) innovative property (results of R&D and other innovative or creative activities) and iii) economic competencies (firm-specific human capital and other non-tangible resources, such as brands and organisational routines).

This unifying framework has been applied at the macro and industry levels to analyse the links between intangibles and productivity, including country case studies (e.g. for the US Corrado, Hulten, and Sichel 2009; for the UK Marrano, Haskel, and Wallis 2009; for Sweden Edquist 2011) and cross-country studies (e.g. for the EU Roth and Thum 2013; Roth 2022a) as well as cross-country industry-level studies (e.g. for the EU Niebel, O'Mahony, and Saam 2017; Roth 2022b). At the firm level, economic analyses mostly concentrated on specific intangibles such as software, training, branding or organisation capital (Brynjolfsson and Hitt 2000; Brynjolfsson, Hitt, and Yang 2002; O'Mahony and Vecchi 2009; Bloom, Sadun, and van Reenen 2012).

Applying a unified framework of intangibles at the firm level has been limited by the lack of comprehensive firm-level data, as official business statistics do not capture investments on all types of intangibles. Business statistics rarely include investment data on innovative property (except for R&D), firm-specific training, computer databases, branding, and organisation capital. Some prominent studies have tried to employ balance-sheet data (Marrocu, Paci, and Pontis 2012) drawing e.g. on the Amadeus database of Bureau van Dijk. While balance-sheet data are a very valuable source as they provide comparable panel data for a large fraction of the enterprise population, they miss several intangibles such as firm-specific human capital, most of brand value, and organisation capital. Moreover, because of data limitations such comprehensive cross-country studies on intangibles could not consider the case of Germany, the largest European Union and Euro Area economy.

Although a few firm-level studies of intangibles with respect to the German case exist (Crass and Peters 2014; Rammer and Peters 2016; Kaus, Slavtchev, and Zimmermann 2020), a comprehensive analysis of the German case is still missing. First, the existing studies do not compare intangible investments obtained from the German firm-level data with existing databases on intangible capital at the macro and sectoral level such as e.g. the evidence from the INNODRIVE (Roth and Thum 2013) or the harmonised EU KLEMS 2019 dataset (Roth 2023). Second, they do not calculate and analyse the effect of an aggregate index of intangible capital on firm-level productivity for the complete German market economy to be able to compare their results with those of other large EU cases (Marrocu, Paci, and Pontis 2012). Third, they do not provide an analysis of all dimensions of intangibles from the unifying CHS framework for the individual goods-producing and service industries of the economy. Analysing the individual sectors, however, would be highly relevant to understand the drivers of sectoral productivity growth (Roth 2022b, 2023; Ortega-Argilés, Piva, and Vivarelli 2015; Kumbhakar et al. 2012).

The main aim of this paper is to overcome these gaps in the literature by offering the first comprehensive analysis of intangibles for firm-level productivity for the case of

Germany. Using a unique firm-level data from the German part of the Community Innovation Survey (CIS)[1] for a time period from 2006 to 2018 and estimating a gross output production function with the help of control-approach estimation techniques (Levinsohn and Petrin 2003; Olley and Pakes 1996) based on a sample of 11,321 firms with 26,400 firm-year observations, we find four novel results for the case of Germany vis-à-vis the existing literature.

First, our results reveal that investments in intangible capital by German firms have been of similar size as those in tangible capital throughout the 13-year time period 2006–2018. This micro-evidence contrasts with patterns in intangible capital investments for Germany derived from the existing international datasets at the macro- and sectoral level, such as e.g. the evidence from the INNODRIVE (Roth and Thum 2013) and the harmonised EU-KLEMS 2019 (Roth 2023) datasets.

Second, in line with the empirical evidence for six other EU economies (Marrocu, Paci, and Pontis 2012, 392), we find a highly significant and positive relationship between intangible capital and firm-level productivity in Germany. The estimated magnitude of intangible capital on firm-level productivity for Germany is slightly larger than that found for France and Spain, but smaller than the results for Italy and the UK.

Third, our results show that this greater impact of intangibles at the firm-level is driven by non-R&D intangibles, in particular software & databases, firm-specific training, and advertising & marketing. While this finding holds for both the goods producing sector and the services, non-R&D intangibles affect firm-level productivity more strongly in services, which is in line with the results at the sectoral level (Roth 2022b, 2023). Within services, finance, administrative and support services show the highest productivity impact of non-R&D intangibles.

Fourth, by considering all types of intangibles our results show a very weak effect of R&D on firm-level productivity. In most service subsectors as well as in low-tech and medium- tech manufacturing, R&D has no significant productivity effect. In line with the results by Kumbhakar et al. (2012) and Ortega-Argilés, Piva, and Vivarelli (2015) a strong positive and significant effect of R&D is limited to high-tech manufacturing.

The paper is structured as follows. In section 2 we discuss the relevant literature on firm- level estimates of intangible capital and productivity. Section 2 introduces our empirical model along with a description of the data used in the analysis. Section 3 presents our descriptive results, and section 4 contains the econometric results. We summarise our results and discuss policy conclusions in the final section 5.

2. Related literature

The importance of intangibles for economic growth has been long recognised in the economics literature. Endogenous growth theory (Romer 1986; Lucas 1988; Grossman and Helpman 1991) emphasises the critical role of investments in human capital and

[1]The CIS is a series of surveys executed by national statistical offices throughout the European Union and in other European countries, with the aim of producing information on the innovativeness of different sectors and regions. Differently to other national CIS, the German part is designed as an annual panel survey, called the 'Mannheim Innovation Panel' (MIP, see Peters and Rammer 2013). Important for this study, the MIP contains information on various types of intangible investment, in addition to measures on tangible assets, gross output and intermediary inputs, which allow to implement the CHS framework at the firm-level.

innovation, as well as knowledge spillovers, for achieving increases in productivity. For a long time, empirical analyses focused on the role of R&D (see Griliches 1998) and investment in skills (see Black and Lynch 1996) as key drivers of productivity. A more comprehensive approach to conceptualising and measuring 'knowledge-based assets' relevant for productivity was developed during the 1990s (see OECD 1998) and was summarised in a unified framework by Corrado, Hulten, and Sichel (2005). They developed a broader conceptualisation of innovation and identified three main dimensions of knowledge assets: i) software, ii) innovative property, including scientific R&D and design and licences and iii) economic competencies, including branding, training and organisational structure. Drawing on standard intertemporal capital theory, CHS (2005) define investments as 'any use of resources that reduces current consumption in order to increase it in the future' and treat intangibles, in contrast to the national accounting framework, as investments rather than intermediate goods.

A larger number of empirical studies at the macro and industry levels (including country case studies for the US by Corrado, Hulten, and Sichel 2009; for the UK by Marrano, Haskel, and Wallis 2009; for Sweden by Edquist 2011; cross-country studies for the EU by Roth and Thum 2013; Roth 2022a; cross-country industry-level studies for the EU by Niebel, O'Mahony, and Saam 2017; Roth 2022b) apply a comprehensive framework of intangibles. At the firm level, data restrictions prevented research from applying the comprehensive framework. Most studies hence focused on selected dimensions of intangible capital only (Verbic and Polanec 2014; Ilmakunnas and Piekkola 2014; Battisti, Belloc, and Del Gatto 2015; Gomez and Vargas 2012; Arrighetti, Landini, and Lasagni 2014). This is mainly due to the fact that official business statistics do not collect data on all types of intangibles, while dedicated business surveys on intangibles remain one-off exercises (see Awano et al. 2010a, 2010b; for the UK and Perani and Guerrazzi 2012 for Italy) and are not suited for micro-econometric productivity analysis.

Bontempi and Mairesse (2015) and Marrocu, Paci, and Pontis (2012) are among the few studies that attempted to consider most dimensions of intangible capital. The highly influential study of Marrocu, Paci, and Pontis (2012) for example estimate a firm-level production function that includes an aggregated intangible capital index for six EU countries (France, Italy, the Netherlands, Spain, Sweden and the United Kingdom) for the period 2002–2006. However, their measure still misses some relevant intangibles for production as they use the balance sheet category of intangible fixed assets of the Amadeus database.

However, three more recent strands of the literature with its respective evidence need to be mentioned in order to contextualise our German firm level study on intangible capital and labour productivity growth. First, latest cross-country-industrial evidence on intangible capital and labour productivity growth by Roth (2022b) and Roth (2023) finds that while investments in R&D dominate the manufacturing sector, investments in Non-R&D intangibles dominate the individual service sectors. Moreover, whereas R&D investments are the main driver of productivity growth in the manufacturing sector, Non-R&D intangibles are the main drivers of productivity growth in the individual services sectors.

Second, evidence on the impact of R&D investments on productivity in the manufacturing sector highlights the importance of differentiating the manufacturing sector into three technological levels: low-, medium- and high-tech manufacturing (e.g.

Kumbhakar et al. 2012; Ortega-Argilés, Piva, and Vivarelli 2015). These studies show that R&D investments impact productivity in particular in high-tech firms, where such investments lead to technological progress and higher efficiency. In contrast, low-tech firms need more tangible capital to increase their productivity.

Third, latest evidence on the ongoing process of digitalisation and its investment in new digital technologies such as artificial intelligence (AI) reinforced the importance of investment in intangible capital (see Brynjolfsson, Rock, and Syverson 2019). Although the cross-country- sectoral level study by Corrado, Haskel, and Jona-Lasinio (2021) finds no empirical evidence for the J-curve assumption by Brynjolfsson, Rock, and Syverson (2019), the firm-level studies by Yang (2022), Damioli, Van Roy, and Vertesy (2021) and Czarnitzki, Fernández, and Rammer (2022) find an important contribution of AI-related intangible capital to productivity.

For Germany, three recent studies analysed the effects of intangible capital assets on the productivity of German firms: Crass and Peters (2014), Rammer and Peters (2016), and Kaus, Slavtchev, and Zimmermann (2020). While Crass and Peters (2014) and Rammer and Peters (2016) use data from the Mannheim Innovation Panel (MIP) for a shorter time period, Kaus, Slavtchev, and Zimmermann (2020) rely on a variety of surveys (investment, cost structure, monthly and quarterly production) from business statistics of the Federal Statistical Office of Germany.

Crass and Peters (2014) study the impact of R&D, design and licences, patent stock, training, high-skilled labour, and advertising & marketing on total factor productivity based on 11,021 firm-level observations for the time period 2006–2010 by utilising an Olley and Pakes (1996) estimation approach. An updated econometric estimation is performed by Rammer and Peters (2016) for the time period 2006–2014 based on 17,804 observations. In contrast to Crass and Peters (2014), they also include software as an additional intangible capital indicator. Both studies find that intangibles related to economic competencies (advertising & marketing and training) have the greatest impact on the firm-level labour productivity. Intangible capital related to innovative property also positively contributes to firm-level productivity, but on a smaller magnitude. Kaus, Slavtchev, and Zimmermann (2020) consider the role of intangible capital for productivity of app. 22000 manufacturing firms with an overall number of 95,638 firm-year observations. They combine different firm-level data sources and cover intangibles related to software and innovative property but do not include economic competencies. Their analysis of manufacturing firms concludes that R&D has the greatest output elasticity among different intangible capital types, followed by a lesser extent by software.

However, none of the three existing German firm-level studies offers a comprehensive analysis of the German case. First, they do not compare intangible investments obtained from the German firm-level data with existing databases on intangible capital at the macro and sectoral level. Second, they do not calculate and analyse the effect of an aggregate index of intangible capital on firm-level productivity for the complete German market economy. Third, they do not provide an analysis of all dimensions of intangibles from the unifying CHS framework for the individual goods-producing and service industries of the economy. In particular, this lack of emphasis on the individual services sector prevents the existing studies to understand the micro-drivers of productivity for the aggregate economy[2]

We complement the German firm-level studies on intangibles in a threefold manner. First, we derive estimates on the size of intangible investments for Germany and comparing these estimates with existing international databases on intangibles, such as the INNODRIVE and latest harmonised EU KLEMS dataset. Second, following the seminal approach by Marrocu, Paci, and Pontis (2012) we calculate and analyse the effect of an aggregate index of intangible capital on firm-level productivity. Third, following the approach by Roth (2022b) and Roth (2023), as well as Kumbhakar et al. (2012) and Ortega-Argilés, Piva, and Vivarelli (2015), we analyse all dimensions of intangibles from the unifying CHS framework on firm- level productivity for individual industries in the goods producing and services sectors.

3. Model specification, estimation approach, data and model variables

3.1. Model specification

We consider the following production function at the firm-level:

$$Y_{i.t} = A_{i.t} M_{i,t}^{\theta} K_{i,t}^{\alpha} L_{i,t}^{\beta} R_{i,t}^{\gamma} \tag{1}$$

where $Y_{i,t}$ denotes the gross output, $A_{i,t}$ the total factor productivity, $M_{i,t}$ the intermediate inputs, $K_{i,t}$ the physical capital, $L_{i,t}$ labour, and $R_{i,t}$ the intangible capital. We consider a standard production function apart from the inclusion of the intangible capital. We do not put any restrictions on the elasticity parameters θ, α, β, γ. In the case of $\theta + \alpha + \beta + \gamma = 1$ our functional form reduces to the well-known Cobb-Douglas case.

When we log-normalise the Equation (1), we get the following equation (where the lower-case variables indicate the log-normalised values):

$$y_{i,t} = a_{i,t} + \theta m_{i,t} + \alpha k_{i,t} + \beta l_{i,t} + \gamma r_{i,t} \tag{2}$$

We also assume that the productivity term $a_{i,t}$ consists of a common factor ω, an unobservable productivity term $q_{i,t}$ known by the firm, time dummies d_t controlling for shocks that affect all firms, and a vector of control variables $x_{i,t}$ and an error term $\boldsymbol{\varepsilon}_{i,t}$ which satisfies the standard properties:

$$a_{i,t} = \omega + q_{i,t} + d_t + \delta x_{i,t} + \varepsilon_{i,t} \tag{3}$$

Inserting Equation (3) into Equation (2) yields the following Equation (4) :

$$y_{i,t} = \omega + q_{i,t} + d_t + \theta m_{i,t} + \alpha k_{i,t} + \beta l_{i,t} + \gamma r_{i,t} + \delta x_{i,t} + \varepsilon_{i,t} \tag{4}$$

[2]Analysing the link between intangibles and firm-level productivity in the service sectors is particularly relevant due to the size of this sector (it accounts for 75% of employment in Germany in 2020) and its heterogeneous makeup in terms of productivity growth (Duarte and Restuccia 2020; Duernecker, Herrendorf, and Valentinyi 2019)..

3.2. Estimation approach

Endogeneity is a well-known problem of estimating firm-level production functions expressed in Equation (4). Endogeneity arises since a firm decides about the inputs to the production process based on knowledge about likely productivity shocks resulting from input decisions. When input choices are affected by the firm's productivity level, inputs will be correlated with productivity and hence the error term in the productivity equation. In such a case, OLS estimators become biased and inconsistent (Marschak and Andrews 1944). To resolve this endogeneity issue, different econometric approaches have been suggested (see Ackerberg, Caves, and Frazer 2015). In the empirical literature on firm-level productivity analysis, the methods proposed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) have been widely used (see Marrocu, Paci, and Pontis 2012; Crass and Peters 2014). The OP approach solves the endogeneity problem by using a non-parametric investment function. The observable investment decision of the firm is used as a proxy for unobserved productivity shocks. Empirically, we use the accumulated stock of tangible assets as the state variable, tangible investments as the proxy variable, while labour and intangible investments are free variables.[3] The LP approach builds upon the OP approach, but uses intermediate inputs instead of the capital stock as control for productivity shocks observed by the firm. In the model estimations, we use both approaches, but focus on LP as main estimation results since the use of intermediary inputs has been recommended as the more appropriate control variable (Ackerberg 2021). For robustness checks, we also display the OP results.

3.3. Data

Our paper uses data from the Mannheim Innovation Panel (MIP) covering the period 2006–2018. The MIP is Germany's contribution to the Community Innovation Surveys (CIS) of the European Commission. Unlike most national CIS, the MIP is an annual panel survey based on a stratified random sample of firms, which is updated biennially to adjust for panel mortality (see Peters and Rammer (2013) for more details). Another important difference is that the MIP also includes a number of questions on financial variables, including expenditures related to different types of intangibles (firm-specific training, advertising & marketing, software & databases, research & development, and other innovation expenditure) as well as sales, labour costs and cost of intermediary inputs. In addition, it covers a wider set of service industries (i.e. most services of NACE sections M and N) and size classes (i.e. also 5 to 9 employees) than the standard CIS. The MIP has been conducted by the Centre for European Economic Research (ZEW) in Mannheim on behalf of the German Federal Ministry of Education and Research since 1993. As the MIP is Germany's contribution to the CIS, it is subject to rigorous quality controls and represents the most reliable and comprehensive data base on innovation-related activities in German firms.

3.4. Model variables

The MIP data provides information on all model variables, which are defined as follows:

[3]The stata command *prodest* developed by Rovigatti and Mollisi (2018) is used for the LP and OP estimations.

- Gross output variable is measured as total turnover.
- Labour input refers to the total number of employees in full-time equivalents.
- Intermediate inputs are measured as the total costs of purchased materials, energy, and services.
- The physical capital stock is obtained from the questionnaire and defined as net stock of fixed assets. Missing values were imputed based on data on gross investments in physical capital and using the perpetual inventory method (PIM) with sector specific depreciation rates obtained from existing data on physical capital stock and investments.
- Total intangible capital is measured as the sum of i) computerised information, ii) innovative property and iii) economic competencies. Since we neither have information on initial capital stocks for intangibles nor on depreciation rates for each type of intangible, constructing a capital stock for each intangible asset based on the PIM will be strongly depend on the assumptions that have to be made (see here also Ortega-Argilés, Potters, and Vivarelli 2011). This is particularly true for the length of the economic life time of each intangible, which tends to be rather short (see Awano et al. 2010a, 2010b and Perani and Guerrazzi (2012) for firm-level estimates). In addition, firm-level investment data for each intangible in our data base is usually available for a short period of time for each firm and is strongly perforated (i.e. for most firms, there is no time series of investment data per intangible). This data structure would require imputation for missing years, which would add another layer of assumptions on the capital stock estimates. Moreover, Crass and Peters (2014) demonstrated that productivity estimation results based on intangible capital stocks and intangible investment expenditures are almost identical, suggesting that the amount of investment for a specific intangible is a very good proxy for the firm's capital stock of this intangible. We therefore use intangible investment expenditures as a proxy for intangible capital at the firm-level.
- Computerised information is measured by expenditure for software & databases (only available from 2011 onward), covering both in-house costs for computer programming and database work as well as purchases of software and databases.
- Innovative property covers in-house and external expenditure for R&D as well as other current innovation expenditure. The latter mainly includes in-house and external expenses on design, licences and other external knowledge, but excludes expenditure for physical capital. For brevity reasons, we call the latter group 'design & licences'.
- Economic competencies are measured by in-house and external expenditure for firm- specific training of employees (excluding cost of vocational training for apprentices) and for advertising & marketing. As the latter includes all expenditure for advertising and branding (including commercial marketing), reputation building, conceptual design of marketing strategies, market and consumer research, and the installation of new distribution channels, we follow Landes and Rosenfield (1994) and consider only 60% of these expenditures as investment in intangibles[4] A measurement for organisational capital is missing. The MIP survey made an attempt to collect investment data on this intangible for one year only (2012). The attempt failed, however, due to a lack of information on the side of firms, and also

[4]As a robustness check, we also estimate regressions (5) and (7) in Table 4 with an advertising & marketing variable that considers 100% of expenditure as investment in intangibles. Table A5 in the supplementary material clarifies that our results for advertising & marketing does not change significantly. However, the coefficient of R&D in regression (5) in Table 4 becomes insignificant.

due to the fact that most activities to build up organisational capital are not associated with measurable expenditures (see Trunschke, Rammer, and Roth 2020).

- The control variables include various characteristics of the firm and its environment that may affect productivity. Following the seminal study by Marrocu, Paci, and Pontis (2012), as well previous studies on firm-level productivity using MIP data (Crass and Peters 2014; Rammer and Peters 2016) we use the following control variables: a dummy for whether a firm is part of an enterprise group, a dummy for whether a firm is an exporter, an indicator for business cycle variation (change in real GDP) in order to capture likely effects of the recession in the year 2009, the age of the firm, the size class of the firm, the region a firm is located[5], and 28 industry dummies.

Table 1 provides the summary statistics of the main variables used in our firm-level estimations. Additional Tables of summary statistics including the summary statistics of all control variables (Table A1), a break-down of the summary statistic of the main model variables for the individual goods-producing (Table A2), services sectors (Table A3) and the four German regions (Table A4) can be found in the supplementary material.

4. Descriptive results

This section summarises the descriptive results on the development of intangible investment in the market economy in Germany. The data are derived from extrapolations of the MIP firm- level data to industries and economy totals, complemented by data from German national accounts statistics at the industry level on certain variables missing in the MIP (such as software & databases expenditures before 2011). The extrapolations of MIP data on intangibles apply the same methods used for producing aggregate innovation indicators for European innovation statistics. As the weighting scheme is based on

Table 1. Summary statistics of main variables used in the firm-level estimations.

	N	Mean	SD	Min	Max
Gross output (million Euro)	26,400	173.0	1,845	0.015	76,729
Intermediary input (million Euro)	26,400	109.8	1,339	0.001	61,167
Labour (head count)	26,400	503.1	4,232	1	183,991
Tangible capital stock (million Euro)	26,400	101.6	1,206	0	55,630
Investment in intangible capital (excl. software) (million Euro)	26,400	10.59	168.6	0	8,126
Investment in intangible capital (incl. software) (million Euro)	16,614	11.90	196.1	0	8,531
Investment in research & development (million Euro)	26,400	6.96	114.9	0	5,800
Investment in design & licences (million Euro)	26,400	1.37	20.4	0	1,015
Investment in training (million Euro)	26,400	0.39	4.6	0	350
Investment in advertising & marketing (million Euro)	26,400	1.87	33.5	0	1,495
Investment in software & databases* (million Euro)	16,614	0.91	12.7	0	665

All values are expressed in millions of euro, except labour (no. of employees). * Data on Software & Databases is available for the period 2011 to 2018 only, resulting in a lower number of observations. Min: minimum value; Max: maximum value; SD: standard deviation; N: number of firm-year observations. Source: Mannheim Innovation Panel (MIP).

[5]As can be seen from Table A6 in the supplementary material the impact of intangible capital in firm level productivity is higher in Northern and Southern Germany.

data from the official German business register, the data are fully comparable with data from other business statistics.

Figure 1. shows the volume of tangible and different types of intangible investments for 2006 to 2018. The total amount of intangible capital investment is about the same as the volume of tangible capital investment in the period considered (denoted in the remainder of this paper as the ratio of intangible over tangible capital investment, or RITC). The ratio increased from 0.90 in 2008 to 1.07 in 2015 and fell below 1.00 in 2017 and 2018. A close to equal RITC is consistent with the evidence from other advanced economies such as the US (see Nakamura 2010). Among the different types of intangible investment, R&D accounts for the largest share followed by advertising & marketing, while software & databases, other IPRs, design & licences and training have lower shares.

Our results based on extrapolations of firm-level data challenge previous findings on the relationship between intangible and tangible investment in the German economy derived from macro-economic data. Estimates based on macro-level databases that have been established in different EU-level research projects suggest that the ratio of intangible over tangible capital (RITC) is below 0.7 (see Table 2). Our firm-level evidence suggests an aggregate intangible investment rate of close to 1.0. Although we are not able to account for organisation capital, our investment rate for intangibles is substantially

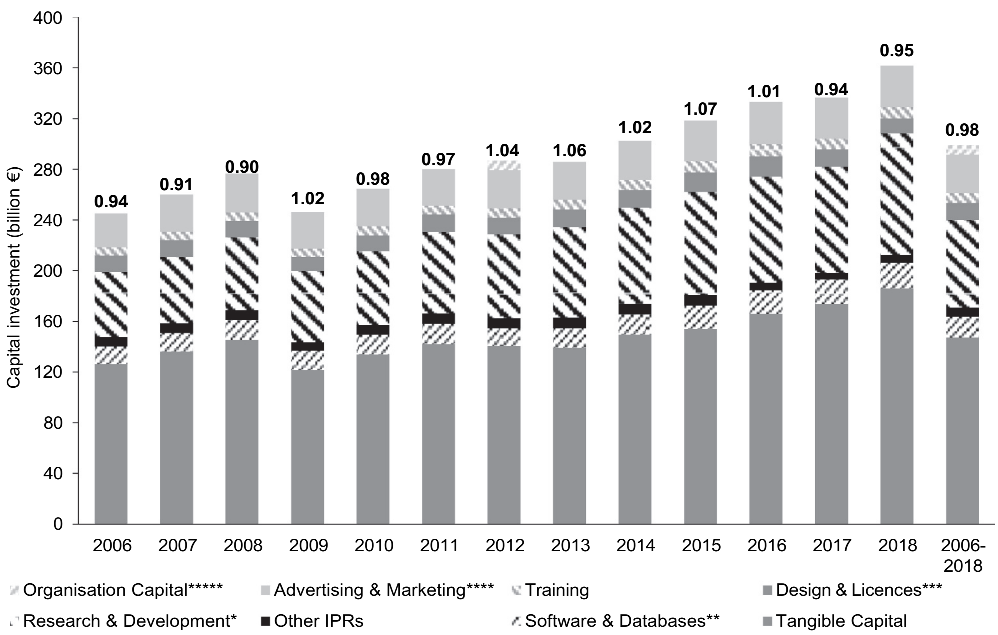

Figure 1. Volume of tangible and intangible investment in Germany, 2006 to 2018. * R&D includes extramural R&D and expenditure for software development as part of R&D activities. ** Software excludes software development as part of R&D activities. Data on aggregate software & databases before 2011 are obtained from the Destatis. *** Estimates for 2015 to 2017. **** Following Landes and Rosenfield, (1994), only 60 percent of the actual expenditure on advertising & marketing was considered investment. ***** Data collected for 2012 only. The figure above each bar gives the ratio of intangible over tangible capital investment (RITC). Source: Mannheim Innovation Panel (MIP); Destatis: detailed National Accounts statistics.

higher (10.9% of gross value added) than the ones obtained from macro-economic estimates. Our findings for Germany are much more in line with the results on RITC for the US as shown in Nakamura (2010).

Table 3 provides more details on likely sources for the discrepancy between MIP results and macro-economic estimates in the KLEMS results. The higher intangible investment rate based on MIP data is largely due to higher investment rates for advertising & marketing. This result is plausible as MIP data also include the firms' in-house expenditure on developing marketing strategies and brand value whereas KLEMS data mainly reflect purchased services. Higher values are also reported for R&D (which partly reflect the fact that software expenditures in the context of R&D are reported under R&D and not software), training and other IPRs.

Figure 2 shows the evolution of tangible and intangible investment over the 13-year period 2006 to 2018. The figure reveals that some investments in intangible capital, notably R&D, grew faster than tangible capital. However, tangible capital still ranks in second place with a similar trend to software, but faster than other investments in intangible capital, such as training and advertising & marketing. Investments in tangible capital are accelerating from 2013 onward.

Figure 3 provides a breakdown of capital investment by types across disaggregated industries and displays the RITC value. Strikingly, we detect that intangible capital investments, driven largely by R&D, well exceed tangible capital investments in the manufacturing sector. This is particularly the case for the high-tech manufacturing sector (RITC = 2.37). On the other hand, the figure suggests a considerable heterogeneity for the service industries. On the one hand, we observe highly tangible capital-intensive industries such as wholesale trade (RITC = 0.61) and transportation and storage (RITC = 0.09). These service industries co-exist with other industries such as professional, technical, and scientific services (RITC = 1.07) and information and communication services (RITC = 1.86). We

Table 2. Investment rates for intangible and tangible capital in Germany.

	Investment Rate for Intangible Capital (% of GVA)	Investment Rate for Tangible Capital (% of GVA)	Ratio of Intangible over Tangible Capital	Time Period
INNODRIVE (Roth and Thum 2013)	9.2	14.5	0.64*	1995–2005
INDICSER (Niebel, O'Mahony, and Saam 2017)	7.2	14.4	0.50*	1995–2007
INTAN-Invest (Roth 2020)	9.1	13.8	0.66*	1995–2017
EU-KLEMS 2019 (Roth 2023)	7.2	13.8	0.53	1995–2017
For comparison: firm-level results from MIP	10.9	11.2	0.98	2006–2018

*Since these databases do not contain any information on tangible capital, the ratio of intangible capital over tangible capital is obtained by using the tangible investment rate from the 2019 EU-KLEMS release (Stehrer et al. 2019).

Table 3. Intangible capital investments by type in Germany: KLEMS vs. MIP.

	Total	R&D*	D&L	A&M**	S&D*	OIPR	Training
KLEMS	8.06	4.08	1.27	0.89	1.29	0.31	0.22
MIP	10.90	5.11	1.04	2.33	1.24	0.59	0.59

R&D: Research and Development; D&L: Design and Licences for Innovation; A&M: Advertising & Marketing; S&D: Software and Databases; OIPR: Other Intellectual Property Rights. The table covers the period 2006–2017. * Only intramural R&D expenditure for both KLEMS and MIP. ** Following Landes and Rosenfield (1994), only 60 percent of the actual expenditure on Advertising & Marketing in the MIP was considered investment.
Source: EUKLEMS 2019 release (Stehrer et al. 2019) and Mannheim Innovation Panel (MIP).

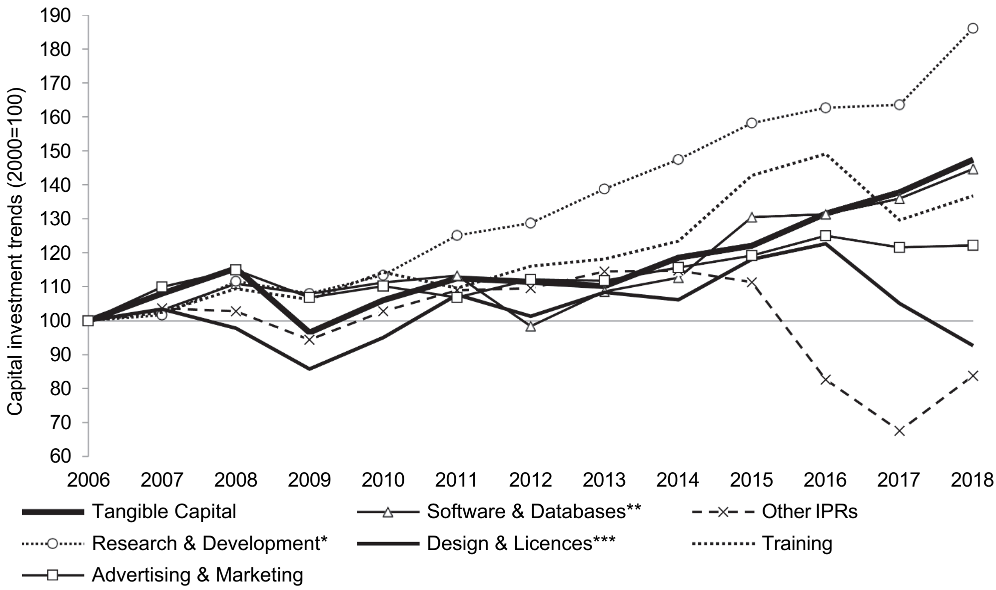

Figure 2. Evolution of tangible and intangible investment in Germany, 2006–2018. * R&D includes extramural R&D and expenditure for software development as part of R&D activities. ** Software excludes software development as part of R&D activities. *** Estimates only for Design & Licences for 2015-2017. Source: Mannheim Innovation Panel (MIP); Destatis: detailed National Accounts statistics.

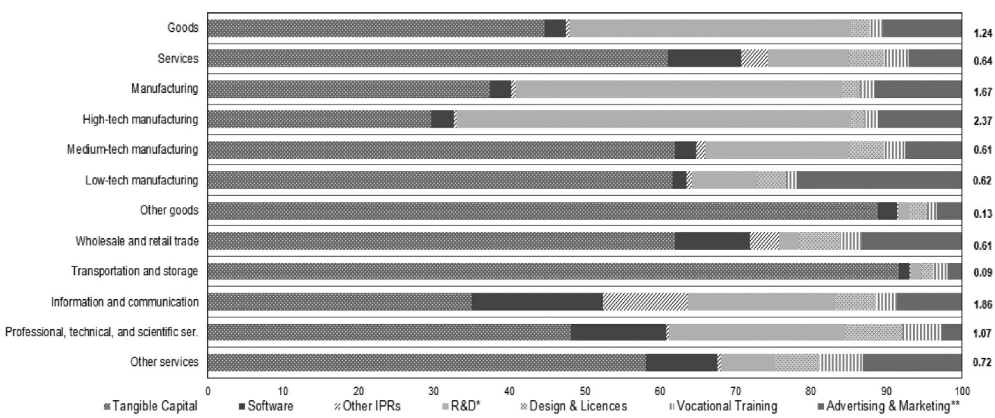

Figure 3. Share of intangible and tangible capital investments and RITCs across industries. The figure refers to values in year 2018. * R&D includes extramural R&D and expenditure for software development as part of R&D activities. ** Software excludes software development as part of R&D activities. Values on the right-hand side of the figure display the ratio of intangible over tangible capital (RITC). Following Landes and Rosenfield (1994), only 60 percent of the actual expenditure on advertising & marketing was considered investment. Source: Mannheim Innovation Panel (MIP); Federal Statistical Office of Germany, National Accounts.

also observe that although the dominance of R&D is clear in the case of manufacturing industries, service industries show somewhat heterogeneous patterns with no single intangible capital type dominating investments over different service industries.

5. Econometric results

The estimation results of Equation (4) are shown in Table 4. They are based on 11,321 different firms with a total number of firm-year observations of 26,400 for the period 2006–2018. In terms of the results for the traditional production factors tangible capital, labour and material, we find elasticities of the usual magnitude. The Wald test reveal constant returns of scale for all model variants.[6] With respect to the key variable of interest, the intangible capital measure, the results of LP and OP estimations suggest an elasticity of 0.021 and 0.020 (Regressions 1 and 2 in Table 4), respectively. In value-added terms, these values correspond to an elasticity parameter that is equal to 0.034 (LP) and 0.031 (OP).[7]

When comparing our results with those found by Marrocu, Paci, and Pontis (2012), our value for the LP estimation is strongly in line with their reported value of 0.038 (see Table 5). Our LP estimation for Germany is larger than that for France and Spain, but significantly smaller than that for Italy or the UK.

When we include software & databases, which is only available in the MIP from the year 2011 on, the number of firms that can be used for estimations reduces to 7,928, with a total number of firm-year observations of 16,614. We find that the elasticity of intangible capital increases by 0.006 for the LP and by 0.007 for the OP to 0.027 (Regressions 3 and 4 in Table 4). These elasticities in gross output correspond to an elasticity of 0.034 in value added terms for the LP, and 0.042 for the OP.

In regressions 5–8 in Table 4, we perform production function estimations with disaggregated intangibles: i) the two innovative property intangibles, R&D and design & licences, ii) the two economic competencies intangibles, training and advertising & marketing, and iii) software & databases (covering the time period 2011–2018 in regressions 3–4). For both LP and OP we find that training, advertising & marketing, and software & databases are highly significant, with training displaying the largest effect on productivity, followed by software & databases and advertising & marketing. Interestingly, design & licences remain insignificant in all four regressions and R&D in three out of four regressions we estimate. We interpret our results to be supportive of Brynjolfsson, Hitt, and Yang (2002), who argue that investment in intangible assets such as staff training are complementary to investment in ICT equipment and that firms will reap productivity benefits from ICT investments only if these necessary investments in economic competencies also take an intangible form such as training.

In order to understand the factors that shape sectoral productivity dynamics, we also estimate firm-level production functions for different sectors. Table 6 shows the results

[6]Note that LP and OP estimations are based on maximum-likelihood estimators which do not allow to report standard R^2 as goodness-of-fit measures. As for production functions in general, the inputs considered in the estimations explain the vast majority of output variance, as can be seen from OLS regressions using the same set of variables, which show a R^2 of 0.96 for all model specifications.

[7]These numbers are obtained by dividing the elasticity we find for the intangible capital by the elasticity of value added which equals to 1-the elasticity of materials. That is, the number for LP is obtained by the following equation: 0.034 = [0.021/(1−0.386)] and that for OP by the following equation: 0.031= [0.020/(1−0.357)].

Table 4. Firm-level production function estimates, results of LP and OP estimations for the German business enterprise sector, 2006–2018.

Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time-Period:	2006-18	2006-18	2011-18	2011-18	2006-18	2006-18	2011-18	2011-18
Estimation Method	LP	OP	LP	OP	LP	OP	LP	OP
Labour	0.508***	0.484***	0.519***	0.490***	0.504***	0.481***	0.516***	0.488***
	(0.003)	(0.015)	(0.009)	(0.008)	(0.011)	(0.008)	(0.014)	(0.014)
Material	0.386***	0.357***	0.207***	0.350***	0.346***	0.357***	0.221***	0.350***
	(0.001)	(0.009)	(0.009)	(0.008)	(0.005)	(0.002)	(0.048)	(0.004)
Tangible Capital	0.078***	0.068***	0.041***	0.058***	0.047***	0.093***	0.050***	0.053***
	(0.001)	(0.023)	(0.011)	(0.021)	(0.005)	(0.007)	(0.010)	(0.018)
Intangible Capital	0.021***	0.020***	-	-	-	-	-	-
(excl. software & databases)	(0.001)	(0.002)	-	-	-	-	-	-
Intangible Capital	-	-	0.027***	0.027***	-	-	-	-
(incl. software & databases)	-	-	(0.002)	(0.001)	-	-	-	-
Research &	-	-	-	-	0.001***	0.001	0.000	−0.000
Development	-	-	-	-	(0.000)	(0.001)	(0.000)	(0.000)
Design & Licences	-	-	-	-	0.000	0.000	−0.000	0.000
	-	-	-	-	(0.001)	(0.000)	(0.000)	(0.001)
Training	-	-	-	-	0.015***	0.012***	0.013***	0.010***
	-	-	-	-	(0.001)	(0.001)	(0.002)	(0.001)
Advertising &	-	-	-	-	0.008***	0.008***	0.006***	0.006***
Marketing	-	-	-	-	(0.000)	(0.000)	(0.001)	(0.000)
Software & Databases	-	-	-	-	-	-	0.009***	0.009***
	-	-	-	-	-	-	(0.000)	(0.001)
West Germany	0.054***	0.031***	0.032***	0.021***	0.017***	0.054***	0.023	0.024***
	(0.002)	(0.004)	(0.012)	(0.007)	(0.002)	(0.002)	(0.015)	(0.003)
North Germany	0.043***	0.023**	0.023	0.017*	0.005	0.050***	0.026***	0.023
	(0.002)	(0.010)	(0.018)	(0.009)	(0.004)	(0.003)	(0.005)	(0.016)
East Germany	−0.118***	−0.133***	−0.128***	−0.130***	−0.151***	−0.109***	−0.134***	−0.123***
	(0.001)	(0.004)	(0.005)	(0.014)	(0.002)	(0.009)	(0.033)	(0.018)
No. Firms	11,321	10,136	7,928	6,911	11,321	10,136	7,928	6,911
No. Firms x Years	26,400	22,788	16,614	13,978	26,400	22,788	16,614	13,978
Wald test (χ^2) on CRS	16,530***	86,226***	28,763***	$3.2{\cdot}10^5$***	27,653***	68,838***	59,661***	$1.3{\cdot}10^5$***

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimation results control for industry- and time-specific effects as well as for firm size, firm age, export, group, region and business cycle. LP refers to Levinsohn and Petrin (2003) estimation method and OP refers to Olley and Pakes (1996) estimation method. CRS=Constant returns to scale.
Source: Mannheim Innovation Panel (MIP).

Table 5. Impact of intangible capital on real value added: comparison of marrocu, paci and pontis (2012) results and results for Germany.

		Marrocu, Paci and Pontis (2012)				This paper
	Aggregate	France	Italy	Spain	UK	Germany
Intangible Capital	0.038***	0.030***	0.051***	0.023***	0.081***	0.034***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.000)
Observations	195,701	51,248	78,324	57,631	9,989	26,400

Coefficients are based on Levinsohn and Petrin (2003) estimator. Standard errors in parentheses. ***$p < 0.01$.
Source: Marrocu, Paci, and Pontis (2012) for all columns except for Germany. The results for Germany are our own.

for goods producing sectors (mining, manufacturing, energy and water supply, waste management, construction) for the time period 2011–2018 (regression 1). The intangible capital index shows an elasticity of 0.022 which is noticeably smaller than the value of 0.027 which we found for the aggregate economy in regression 3 in Table 4. When

Table 6. Firm-level production function estimates: results of LP estimations for the goods producing sector in Germany, 2011–2018.

	Goods production, total (NACE B to F)		Manufacturing, total (NACE C)		High-tech manufacturing		Medium-tech manufacturing		Low-tech manufacturing		Other goods production (NACE B, D, E, F)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Labour	0.429***	0.426***	0.429***	0.426***	0.364***	0.373***	0.529***	0.525***	0.387***	0.384***	0.432***	0.428***
	(0.015)	(0.007)	(0.014)	(0.015)	(0.013)	(0.016)	(0.016)	(0.021)	(0.020)	(0.019)	(0.026)	(0.031)
Material	0.435***	0.313***	0.461***	0.460***	0.456***	0.488***	0.408***	0.366***	0.296**	0.497***	0.449***	0.417***
	(0.029)	(0.046)	(0.031)	(0.027)	(0.007)	(0.023)	(0.019)	(0.007)	(0.146)	(0.000)	(0.000)	(0.080)
Tangible Capital	0.039***	0.049***	0.058***	0.055***	0.019***	0.057***	0.044***	0.022***	0.071***	0.084***	0.050***	0.041***
	(0.011)	(0.014)	(0.008)	(0.013)	(0.001)	(0.002)	(0.014)	(0.008)	(0.026)	(0.000)	(0.000)	(0.005)
Intangible Capital[a)]	0.022***	-	0.021***	-	0.036***	-	0.016***	-	0.016***	-	0.021**	-
	(0.003)	-	(0.002)	-	(0.003)	-	(0.003)	-	(0.002)	-	(0.008)	-
Research & Development	-	0.001	-	0.002*	-	0.005***	-	−0.000	-	−0.000	-	−0.002
	-	(0.001)	-	(0.001)	-	(0.002)	-	(0.001)	-	(0.002)	-	(0.004)
Design & Licences	-	0.001	-	0.001***	-	0.000	-	0.002**	-	0.004	-	0.001
	-	(0.001)	-	(0.000)	-	(0.001)	-	(0.001)	-	(0.002)	-	(0.004)
Training	-	0.009***	-	0.011***	-	0.016***	-	0.010***	-	0.003	-	0.004
	-	(0.001)	-	(0.002)	-	(0.002)	-	(0.001)	-	(0.002)	-	(0.006)
Advertising & Marketing	-	0.006***	-	0.003**	-	0.002*	-	0.003***	-	0.003	-	0.011***
	-	(0.000)	-	(0.001)	-	(0.001)	-	(0.001)	-	(0.003)	-	(0.003)
Software & Databases	-	0.006***	-	0.006***	-	0.004***	-	0.004**	-	0.010***	-	0.008**
	-	(0.001)	-	(0.001)		(0.001)	-	(0.002)	-	(0.003)	-	(0.003)
No. Firms	4,662	4,662	3,723	3,723	1,282	1,282	1,433	1,433	1,008	1,008	939	939
No. Firms x Years	10,063	10,063	7,831	7,831	2,878	2,878	2,897	2,897	2,056	2,056	2,232	2,232
Wald test (χ^2) on CRS	$1.3{\cdot}10^5$***	29,293***	7.2**	96.2***	955***	20.5***	3,344***	45,065***	0.31	25,182***	0.52	153***

a) incl. software & databases. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimation results control for industry- and time-specific effects as well as for firm size, firm age, export, group, region and business cycle. CRS=Constant returns to scale.

Source: Mannheim Innovation Panel (MIP).

analysing the five disaggregated intangibles in regression 2 in Table 6, we find a similar pattern in regression 7 in Table 4 with training, advertising & marketing and software being highly significantly, while R&D and design & licences being insignificantly related to productivity. Regressions 3 and 4 in Table 6 show the results for the manufacturing sector, which represents 80% of the firm-level observations in the goods producing sector. Similar to the goods producing sectors in total, although we find a significant relationship between R&D and productivity, it is rather weak.

In order to better understand this weak result for R&D, we run separate models for three sub-sectors of manufacturing. Sub-sectors where defined based on their R&D intensity and cover high-tech, medium-tech and low-tech manufacturing (Ortega-Argilés, Piva, and Vivarelli 2015; Galindo-Rueda and Verger 2016). The results are reported in Table 6 (regressions 5 to 10). In high-tech manufacturing, the intangible capital index shows a value of 0.036 (regression 5), which is higher than for medium-tech (0.016, regression 7) and low-tech (0.016, regression 9). More importantly, we find that high-tech manufacturing is the only sector where the coefficient of R&D is statistically significant. Despite its highly significant coefficient, however, the magnitude of R&D is only one third of training in this sub-sector. We view these results as supportive of the hypothesis advanced by Ortega-Argilés, Piva, and Vivarelli (2015), who suggest that the productivity impact of R&D investment is much more pronounced in the high-tech manufacturing sectors. In addition, we tested whether the estimated coefficients for the five types of intangibles in each sub-sector (regressions 2, 4, 6, 8, 10 and 12) were statistically different from each other. The results, reported in Table A7 in the supplementary material, reveal that the significant coefficient for R&D found in high-tech manufacturing is significantly smaller than the one for training and advertising & marketing ($p < 0.01$) while there is no difference to the coefficient for software & databases.

Considering the large size of the services and its heterogeneous makeup in terms of productivity growth, in Table 7 we report the results of production functions for total services and selected service industries separately. Strikingly, regression 1 suggests that the elasticity of intangible capital in services with a value of 0.033 is one and a half times the elasticity found for the goods producing sector. Similar, as in the case of the goods producing sector, this impact of intangibles in the services is driven by training and software & databases. However, their total impact is noticeably greater in services than in the goods producing sector.

Given the importance of the service sector in the economy and the well-known fact that it consists of highly heterogeneous sub-sectors in terms of productivity, it is pertinent to provide estimations for different service industries. Regressions 3, 5, 7, 9 and 11 in Table 7 confirm the heterogeneous character of services in terms of intangible capital impacts. With an elasticity value of 0.051, other services – which include finance, administrative and support services, and real estate (regression 11) – show a much higher productivity impact of intangible capital compared to transportation and storage with a value of 0.022 (regression 5). We also observe a high intangible capital elasticity for professional, technical and scientific services with a value of 0.030 (regression 9). It is important to note that these highly intangible capital-intensive sub-sectors have increasing shares within services (Miles, Belousova, and Chichkanov 2018).

Table 7. Firm-level production function estimates: results of LP estimations for the services sectors in Germany, 2011–2018.

	Services (excl. NACE 72), total		Wholesale and retail trade (NACE G)		Transportation and storage (NACE H)		Information and communication (NACE J)		Professional, technical, scientific services (NACE M, excl. 72)		Other services (NACE I, K, L, N)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Labour	0.583***	0.578***	0.650***	0.669***	0.483***	0.474***	0.674***	0.669***	0.673***	0.666***	0.473***	0.468***
	(0.019)	(0.010)	(0.037)	(0.043)	(0.106)	(0.080)	(0.048)	(0.024)	(0.020)	(0.030)	(0.053)	(0.027)
Materials	0.163***	0.302***	0.151***	0.150**	0.308***	0.263***	0.114***	0.098***	0.225***	0.247***	0.121*	0.254***
	(0.011)	−0.047	(0.008)	(0.060)	(0.103)	(0.023)	(0.032)	(0.010)	(0.038)	(0.020)	(0.071)	(0.063)
Tangible Capital	0.060***	0.071***	0.076***	0.077***	0.054***	0.038***	0.075***	0.079***	0.028***	0.039***	0.071***	0.087***
	(0.013)	(0.012)	(0.012)	(0.006)	(0.008)	(0.011)	(0.029)	(0.014)	(0.010)	(0.007)	(0.013)	(0.021)
Intangible Capital[a)]	0.033***	-	0.029***	-	0.022***	-	0.024***	-	0.030***	-	0.051***	-
	(0.003)	-	(0.005)	-	(0.006)	-	(0.006)	-	(0.007)	-	(0.005)	-
Research & Development	-	−0.001	-	−0.004	-	0.004	-	0.001	-	−0.005***	-	0.008
	-	(0.001)	-	(0.005)	-	(0.004)	-	(0.002)	-	(0.002)	-	(0.007)
Design & Licences	-	0.001	-	0.003	-	0.002	-	0.005***	-	−0.004***	-	0.001
	-	(0.002)	-	(0.003)	-	(0.004)	-	(0.002)	-	(0.001)	-	(0.003)
Training	-	0.015***	-	−0.007	-	0.024***	-	0.010**	-	0.010*	-	0.024***
	-	(0.001)	-	(0.007)	-	(0.006)	-	(0.004)	-	(0.006)	-	(0.003)
Advertising & Marketing	-	0.006*	-	0.018***	-	−0.004	-	0.012***	-	0.004	-	0.006
	-	(0.004)	-	(0.006)	-	(0.004)	-	(0.004)	-	(0.003)	-	(0.004)
Software & Databases	-	0.013***	-	0.004	-	0.013***	-	0.004	-	0.014***	-	0.019***
	-	(0.003)	-	(0.004)	-	(0.003)	-	(0.005)	-	(0.003)	-	(0.005)
No. Firms	3,266	3,266	396	396	496	496	560	560	1,062	1,062	752	752
No. Firms x Years	6,551	6,551	806	806	997	997	1,047	1,047	2,281	2,281	1,420	1,420
Wald test (χ^2) on CRS	152***	548***	133***	64.6***	8.1***	1,652***	4.9*	31.6***	253***	1,136***	1,149***	547***

a) incl. software & databases. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimation results control for industry- and time-specific effects as well as for firm size, firm age, export, group, region and business cycle. CRS=Constant returns to scale.
Source: Mannheim Innovation Panel (MIP).

In regressions 2, 4, 6, 8, 10 and 12 in Table 7 we analyse the disaggregated results for five types of intangibles. For total services in regression 2, we find highly significant effects for our two economic competencies intangibles (training and advertising & marketing) and software & databases. Similar to the goods-producing sectors, training (0.015), followed by software & databases (0.013) and advertising & marketing (0.006) exhibit the largest impact on productivity. The elasticities for training and software & databases in particular are dominant in the other services (regression 12) and in the transportation and storage sector (regression 6) and play an important role in the professional, technical and scientific services (regression 10).

Our results suggest that both knowledge-intensive services (such as other services) as well as service industries with a lower knowledge intensity (such as transportation and storage) benefit from investments in training and software & databases. We view these results as supportive of the hypothesis advanced by both Van Ark, O'Mahony, and Timmer (2008) and Timmer et al. (2010), who suggest that the productivity gap of the EU's service industry with respect to the US could be related to a lower intangible investment rate in the EU. Tests on significant differences of the coefficients estimated for training and software & databases for the individual services sectors (Table A8 in the supplementary material) show that the effect of both intangibles is of a similar magnitude in all sub-sectors.

6. Conclusions and policy implications

This paper analyses the impact of intangibles on firm-level productivity, using panel data from Germany's contribution to the Community Innovation Survey, covering the period 2006 to 2018. Unlike previous German firm-level research on intangibles, we i) derive estimates on the size of intangible investments for Germany and comparing these estimates with existing international databases, ii) calculate and analyse the effect of an aggregate index of intangible capital on firm-level productivity and iii) analyse all dimensions of intangibles from the unifying CHS framework on firm-level productivity for the individual goods producing and services sectors. We therefore provide a comprehensive picture on the role of intangibles for the firm-level productivity in Germany. Our paper presents four novel results vis-à-vis the existing literature.

First, our results show that intangible capital investment by German firms has been of very similar size as compared to investment in tangible capital since the early 2000s. Our firm- level evidence points to a greater aggregate intangible and total investment rate for Germany than suggested by international macro databases.

Second, we find a highly significant and positive relationship between intangible capital and firm-level productivity for Germany. The overall magnitude of our elasticity estimates is in line with previous estimates of an EU aggregate, but our estimates suggest a higher value than those for other large EU economies, such as France and Spain, but a lower value than for Italy and the UK.

Third, we find that non-R&D intangibles such as software & databases, training, and advertising & marketing predominantly contribute to the positive effect of intangibles on the firm-level productivity. Although non-R&D intangibles are important for both goods and services sector, they impact firm-level productivity more strongly in the services.

This positive effect is in particular stronger for other services, including finance, administrative and support services, and real estate.

Fourth, we show that compared to economic competencies and software & databases, R&D does not have an equally strong effect on firm-level productivity. High-tech manufacturing stands out as an industry for which we find a strong productivity effect of R&D. As this sector is responsible for more than half of all R&D expenditures in most countries, this result shows that R&D is indeed a relevant driver of productivity, but only for a specific sector of the economy.

Our results have a number of implications for government policy to strengthen firms' investment in achieving productivity gains, i.e. into more efficient ways to produce and deliver goods and services, and to increase the value of products and services, particularly through innovations.

First, our results suggest a broad and comprehensive policy approach for intangibles that should go beyond manufacturing as a sector and R&D and software as intangibles. Currently, government policies in knowledge-intensive economies focus on supporting R&D, both through grants and tax incentives. We found that other intangibles are also major drivers of productivity, even often exceeding the role of R&D in many sectors, particularly in services. A more consistent policy approach could contribute to fully realising the productivity potential of firms by simultaneously stimulating investment in hardware, software, and various other intangibles (see Brynjolfsson, Hitt, and Yang 2002; Brynjolfsson, Rock, and Syverson 2019). Second, to better inform policy discussion about intangible investments it is essential to update national accounts statistics by incorporating all types of intangibles as assets. For this purpose, a comprehensive set of statistics on investment in intangibles is required. Currently, only data on two types of intangibles are systematically collected as part of official business statistics: R&D and software & databases. There is no internationally harmonised set of statistics for measuring investment in economic competencies such as firm-specific skills or branding and reputation of firms. In the area of firm-specific skills, the European Commission's Continuing Vocational Training Survey (which is currently conducted only every five years) could be a starting point for a more systematic data collection effort. For other types of economic competencies, conceptual work at the international level would be needed to implement survey instruments at the national level in order to produce comparable data.

Third, our results suggest a striking difference between international databases on intangibles and data based on firm-level evidence, which is suggestive of a mismeasurement of intangible capital in the former. We argue that incorporating micro-evidence into the existing macro-level databases could improve the validity of data related to intangibles as envisaged by the GLOBALINTO (2019) project.

This paper took a first step towards exploring the role of intangibles for productivity at the firm level. One dimension not captured in our analysis is the complementarity between different intangibles. Analysing these complementarities could be particularly relevant for a better understanding of the low contribution we found for R&D. For example, it may turn out that R&D exerts a stronger productivity impact if it is combined with investment in computerised information or economic competencies. Such a finding could be linked to the increasing role of digitalisation and servitisation for innovation which require combining new technological knowledge with new business models and new digital capabilities, which in turn would require higher investment in computerised information and economic competencies. Analysing such complementarities was beyond the scope of this paper, however, but should be addressed by future research.

Another area for future research relates to the specific role of intangible investment in software and databases. While we found a strong positive impact of this type of intangible, more detailed information on the type of digital assets used by firms would be required to better understand how investment in digitalisation translates into higher productivity. First analysis based on the same data base that we used for this paper suggest that Artificial Intelligence technologies are a key driver for the positive productivity impacts of software and databases (Czarnitzki, Fernández, and Rammer 2022; Yang 2022; Damioli, Van Roy, and Vertesy 2021; Corrado, Haskel, and Jona-Lasinio 2021). For integrating different types of digital investment into a productivity estimation framework, long time series data of these investments would be needed. Collecting such data is hampered, however, by the rapid change in the relevance of specific digital technologies for productivity advance.

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Data availability statement

The data can be accessed through the Research Data Centre of ZEW (https://kooperationen.zew.de/en/zew-fdz/home).

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