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Summary

Most studies on knowledge diffusion and productivity focus on either R&D, foreign direct investment or patent citation flows, and rarely consider complementary, intangible investments such as business process redesign, the co-invention of new products and business models, and investments in human capital. Although the effects of complementary investments and their spillovers are often mentioned in the literature (Corrado, Haskel, Jona-Lasinio, & Iommi, 2013; Griliches, 1992), there is a lack of in-depth research.

This study aims to fill this gap. Specifically, we focus on knowledge diffusion, taking into account complementarities between different intangible assets, and analyse the effects on productivity. Following previous work (Ang & Madsen, 2013; Orlic, Hashi, & Hisarciklilar, 2018), we analyse the import knowledge diffusion channel, and assess intangible asset complementarities using a principal component analysis to obtain endogenous, composite intangible indices. This approach is able to take account of complementarities between intangibles, and overcome the issue of multicollinearity between them.

The analysis is conducted on an unbalanced country-industry panel dataset of 15 European countries, constructed from a combination of sources such as INTAN-INVEST, WIOD and EU-KLEMS. We evaluate intangible complementarities using a niche overlap index that divides the sample into two groups, as a function of R&D intensity. We develop a total factor productivity proxy, and estimate the effects of knowledge diffusion on productivity by means of fixed and random effects regressions.

KNOWLEDGE DIFFUSION CONSIDERING COMPLEMENTARITY BETWEEN INTANGIBLES AND PRODUCTIVITY: EMPIRICAL CASE OF EUROPEAN COUNTRIES

1 INTRODUCTION

The rapid evolution of information and communication technology (ICT) means that the global economy is transforming into a knowledge-based system in which knowledge and technology are increasingly central. Knowledge has been regarded as an important driver of economic growth and productivity since the development of endogenous growth theory, which explains growth in terms of endogenous factors such as knowledge, innovation and human capital. Although these factors can be generated internally, they can also be obtained externally, through spillovers. The scientific process referred to as *knowledge diffusion* is an example of this phenomenon, as knowledge that enhances innovation and productivity spreads through the economic system.

A large body of literature has sought to explain the linkages between knowledge creation, its spillovers, and productivity. *Knowledge spillover* is the process of gaining new knowledge from others (Ramadani, Abazi-Alili, Dana, Rexhepi, & Ibraimi, 2017), and it takes place when knowledge created by one person creates an additional opportunity for others (Hur, 2017). Typically, the literature measures it with patent- and research and development- (R&D) based indicators. An important distinction can be made between *explicit knowledge* and *tacit knowledge*. Explicit knowledge refers to knowledge that is codified or stored, while tacit knowledge refers to knowledge that is not. Patent-based measurements refer to explicit knowledge; knowledge diffusion is measured via codified knowledge contained in patents, while R&D-based measures cover a broader range of knowledge.

Some authors, such as Engelbrecht (1997), have pointed out that the above approaches are somewhat limited, as they ignore other types of intangibles (e.g. human capital) that play a key role in explaining the impact of knowledge on productivity. It appears that knowledge requires complementary, intangible investments to exploit its potential to improve productivity, and these intangible investments must be measured to fully understand their contribution. Even the literature that takes into account these complementarities (Corrado et al., 2013; Griliches, 1992) only considers a limited number of intangible assets. However, intangibles are both numerous and interdependent, and should, therefore, be considered together. Put another way, an appropriate proxy for knowledge should consider a wider range of intangibles than simply R&D.

This deliverable examines knowledge spillovers, taking into account the above-mentioned complementarities between intangibles. We develop a new proxy that considers a wide range of intangible assets, together with import-weighted knowledge from foreign countries. Following the classification given in Corrado et al. (2016), we start with eight intangibles: R&D; Brand; Design; Entertainment, Artistic and

Literary Originals and Mineral Explorations; New product development costs in the financial industry; Organizational Capital; Computer software and databases; and Training. Then, we assess complementarities following Delbecque et al. (2015), and use a principal component analysis (PCA) to obtain endogenous, composite intangible indices. This approach enables us to not only consider complementarities, but also to tackle the problem of multicollinearity caused by the high degree of correlation between different types of intangibles. We account for externalities using inter-country trade, as in Coe and Helpman (1995), with a focus on the "imports" channel of knowledge diffusion. Lastly, we distinguish between inter- and intra-industry spillovers, as a function of the type of industry (the same industry in a different country, or a different industry not necessarily in a different country). To the best of our knowledge, our approach is the first attempt to address intangible complementarity and knowledge diffusion.

The econometric analysis is conducted on an unbalanced panel covering 15 European countries observed for the period 2000 to 2014. Data is taken from multiple sources, including INTAN-Invest, WIOD and EU-KLEMS. The dependent variable is computed as a total factor productivity (TFP) measure starting from income factor shares. Intangible complementarities are computed as the niche overlap index, selecting for variables that have higher levels of complementarity.

This deliverable is structured as follow. In section 2 we review the related literature, in section 3 we describe the data, in section 4 we explain the empirical strategy, section 5 presents the results, and section 6 outlines some conclusions.

2 LITERATURE REVIEW

Intellectual capital has consistently been regarded as one of the main drivers of future growth in a knowledge-based economy (Aghion & Howitt, 2006; Pelle & Végh, 2015); consequently, understanding knowledge and its diffusion is becoming increasingly important. Understanding knowledge is complex, and there is no clear definition of what it constitutes. The previous section highlighted two forms of knowledge that are identified by knowledge management theory: explicit and tacit. It is generally believed that the proportion of the latter is much higher than the former.

Two main issues arise in the knowledge spillover literature. The first is the choice of the variable used to proxy knowledge, since, as it is intangible, it cannot be observed and measured directly. It is embedded in many new technologies, products and services and various measures have been used. Examples are R&D investment, patent citations and other types of investments in intellectual capital.

The second issue concerns measuring knowledge spillovers. Among the papers that address this issue, Chen et al. (2016) and O'Mahony and Vecchi (2009) measure spillover by comparing the effects of knowledge on productivity in different industries. Spillover is tested through a comparison of effects on two groups. The latter authors investigated the impact of intangible assets on productivity in five OECD countries (the United States, the United Kingdom, France, Germany and Japan). They used dummy variables to compare the effects of intangibles in manufacturing and non-manufacturing companies, and found that firms operating in R&D and skill-intensive sectors had higher productivity. This finding suggests that more knowledge-intensive industries tend to reap greater benefits from knowledge externalities.

Another approach relies on flows of intermediate inputs between countries and industries. For example, Ang and Madsen (2013), using both R&D and patent citations as proxies, analysed six channels of international knowledge transmission (imports, exports, inward foreign direct investment (FDI), patents, geographical proximity, and a general channel that includes all the above). They examined six Asian countries from 1955 to 2006, and showed that knowledge was transmitted through all channels.

Among these channels, FDI deserves more attention, as it has been widely used to examine spillovers from foreign affiliates to domestic firms (Ang & Madsen, 2013; Driffield & Love, 2007; Fernandes & Paunov, 2012; Hale & Long, 2011; Havranek & Irsova, 2011; Marcin, 2008; Orlic et al., 2018). The underlying assumption is that the knowledge and experience obtained from foreign producers, through FDI, may increase the productivity of domestic firms. FDI spillover effects can be divided into three types: horizontal (within-sector: FDI of each firm), backward vertical (between-sector: from FDI to downstream) and forward vertical (between-sector: from FDI to upstream). Marcin (2008) examined FDI spillover effects using a firm-level data panel covering the Polish corporate sector, and found horizontal and backward vertical spillover effects. Orlic et al. (2018) explored the relationship between FDI spillover and productivity in manufacturing firms in five European transition countries, and reported backward and forward vertical effects. Noting that results vary across methods and countries, Havranek and Irsova (2011) conducted a meta-analysis based on previously-reported estimations, and found that backward spillover was economically significant, while forward spillover was significant, but limited.

Imports have also been studied by many scholars (Acharya, 2016; Ang & Madsen, 2013; Coe & Helpman, 1995; Engelbrecht, 1997; Goodridge, Haskel, & Wallis, 2017; Keller, 2001). All of these empirical studies find that positive spillovers through imports make a significant contribution to TFP. Keller (2001) argues that bilateral trade accounts for the majority of all differences in bilateral technology diffusion.

In addition to the literature mentioned above, a new strand has emerged that complements earlier measurements with other types of intangible capital. A consensus has emerged among researchers that a wide range of complementary investments in intangibles are needed to fully exploit the benefits of knowledge for productivity (Brynjolfsson & Hitt, 2000; Brynjolfsson, Rock, & Syverson, 2017; Chang, Wang, & Liu, 2016; Corrado, Haskel, & Jona-Lasinio, 2017; Orlic et al., 2018). *Complementary investments* refer to investments in intangibles, including business process redesign, co-invention of new products and business models, and investments in human capital (Brynjolfsson et al., 2017). Engelbrecht (1997), among others, pointed out the limitations of simply using R&D capital. He stressed that although it is difficult to capture the importance of human capital in economic growth, it should be included in empirical studies, along with R&D.

However, not many researchers have followed his recommendation, and only a limited number of intangibles have been considered in the literature. For instance, Goodridge et al. (2017) studied spillovers from a range of intangibles for British industries from 1992 to 2007. The authors used intermediate weights to measure external R&D, and found a statistically-significant correlation between TFP growth and knowledge stock growth in both external R&D and total intangibles (without R&D). A further example is Chang et al. (2016). The latter authors investigated spillover effects on productivity using the proportion of university graduates among all workers in a city as a proxy for human capital. They found evidence in favour of a positive human capital spillover, with a stronger effect in industries that make intensive use of high technology.

The final strand of the literature related to our paper focuses on increased productivity derived from ICT. This literature often considers not only ICT itself, but also the role of complementary assets. Chen et al. (2016) used INTAN-Invest data at the level of 1-digit NACE industries to examine complementarities between investments in intangible and ICT capital. Industries were classified using a measure of ICT intensity, and the authors showed that intangible investments had a bigger impact on productivity in ICT-intensive industries. Corrado et al. (2017) also used INTAN-Invest and EU-KLEMS datasets to examine the direct and indirect (e.g. spillover) channels through which intangible capital affects productivity growth, and showed that intangible assets and ICT complement labour productivity. Similarly, Brynjolfsson and Hitt (2000) found that intangible capital (specifically, organizational and human) are complementary to ICT. Brynjolfsson et al. (2017) investigated the case of artificial intelligence (AI), and noted that complementary intangibles were required to exploit the potential of AI to increase labour productivity.

3 DATA

The analysis was conducted on a panel of 15 countries at industry level. Data from multiple sources (e.g. EU-KLEMS, INTAN-Invest, and WIOD) was combined. EU-KLEMS data includes measures of gross output, value-added and productive factors for 26 EU member states, the United States and Japan from 1995 to 2014 (Mahony & Timmer, 2009). These data were used to compute a proxy for TFP. Intangible capital information was collected from the INTAN-Invest database. INTAN-Invest provides intangible investment data for 19 European countries and the United States between 1995 and 2015 (Corrado, Haskel & Jona-lasinio, 2016). The list of intangibles is classified into three pillars: *computerized information* (software and databases), *innovative property* (R&D, design, product development in financial services, mineral exploration, and spending on the production of original artists), and *economic competencies* (branding, training, and organizational capital). Lastly, WIOD data was used to measure the country-industry level spillover effect. The WIOD was developed by Timmer et al. (2015), and it provides measures of bilateral trade flows of intermediate inputs between countries and industries for a total of 43 countries, including EU member states, between 2000 and 2014.

Our final datasets covered 15 European countries for the period 2000 to 2014. The European countries we considered were: Austria (AT), the Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Hungary (HU), Italy (IT), Luxembourg (LU), Netherland (NL), Sweden (SE), Slovenia (SI), Slovakia (SK), and the United Kingdom (UK). The United States was excluded. Based on the Industrial Classification of All Economic Activities (ISIC Rev. 4), 16 industries were selected: A, B, C, D–E, F, G, H, I, J, K, L, M–N, O, P, Q, R–S, while some industries (D–E, M–N, and R–S) were aggregated to ensure compatibility with the WIOD database.

Table 1. Data sources

Variables	Database
Gross-output	EU-KLEMS
Labour	EU-KLEMS
Capital	EU-KLEMS
TFP	EU-KLEMS
Intangibles	INTAN-Invest
Intermediate flows	WIOD

4 EMPIRICAL STRATEGY

4.1 Niche overlap index

To address the complementary relationship of intangibles, we calculated a niche overlap index, developed by (Pianka, 1973). The index originates from ecology (Gotelli, 2000; Sá-Oliveira, Angelini, & Isaac-Nahum, 2014), and is employed in many fields of research. For example, in ecology, it is used to check ecological similarities, namely the degree of competition between two ecological units. In media studies it is used to measure complementarity or competition among media channels (Dimmick, Feaster, & Ramirez, 2011), for example to study the degree to which two media are dependent on the same sources.

We adopt a similar approach to measure complementarity among intangibles. In our case, the index measures the similarity between pairs of intangibles with respect to the amount of resources that are invested (Dimmick et al., 2011). We then use information from the index to select intangible types that are more complementary to each other (and especially R&D, since it is the most common measure of knowledge used in the literature). These are used in a later step to compute proxy indices of knowledge. To compute the index, we apply the formula given in Pianka (1973):

$$\text{Niche. Overlap}_{jk} = \frac{\sum_i^n p_{ij} p_{ik}}{\sqrt{\sum_i^n p_{ij}^2 \sum_i^n p_{ik}^2}}$$

where p_{ij} is the proportion of the intangible j in i's intangibles, p_{ik} is the proportion of the intangible k in i's intangibles, and n is the total number of observations. A niche overlap value close to 1 indicates perfect overlap or complementary resource use, while a value close to zero reflects zero overlap or competitive resource use.

As complementarities between intangibles may vary as a function of the industry, we distinguish between R&D-intensive and less R&D-intensive industries, and compare the index for these two subsamples. The need to account for heterogeneity between industries has been pointed out in other studies. For example, Kaoru et al. (2016) tested complementarity and substitutability between tangible and intangible capital with Japanese, firm-level data, and noted that the relationship was heterogeneous among industries. Biagi & Parisi (2012) investigated the effect of ICT and complementary assets on labour productivity in manufacturing firms in Italy, but found no evidence of complementarity between ICT investment and organizational change.

4.2 TFP estimation

In order to develop a proxy for our main dependent variable, TFP, we adopt the estimation method proposed in Ilmakunnas and Piekkola (2014) and Foster et al. (2008). The method makes it possible to tackle several issues connected to the estimation of production functions and TFP, such as the well-known endogeneity of capital and the unrealistic capital coefficient often found in, notably, industry-level analyses (Ilmakunnas & Piekkola, 2014). Specifically, we develop a TFP proxy at industry level based on the income shares of labour and capital. We write the Cobb–Douglas production function in logarithms as:

$$logY_{c,i,t} = \beta_1 logL_{c,i,t} + \beta_2 logK_{c,i,t} + logTFP_{c,i,t}$$

where c, i, and t refer to the country, industry and year. The labour share β_1 is computed as the ratio labour compensation over value added, and the capital share β_2 as $1-\beta_1$. Taking hours worked and capital stock as proxies for labour and capital, and value added as a proxy for Y, it is straightforward to retrieve TFP as the difference:

$$logTFP_{c,i,t} = logY_{c,i,t} - \beta_1 logL_{c,i,t} + \beta_2 logK_{c,i,t}$$

4.3 Measurement of knowledge diffusion with consideration of complementarities of intangibles

We used a PCA to consider complementarities and combinations between intangible assets. Based on the orthogonal transformation, PCA allows us to convert possibly-correlated variables into a new set of linearly uncorrelated variables (Kim, Hwang, Jung, & Kim, 2019). Several previous studies have adopted the practice of using results from a PCA as a new index for intangibles (Chao & Wu, 2017; Delbecque et al., 2015; Filmer & Pritchett, 2001; Vyas & Kumaranayake, 2006). The index obtained from the PCA, also known as the principal component, is measured by summing the product of input variables and the coefficient of the principal component. Regarding complementarities between intangibles, Delbecque et al. (2015) conducted a PCA with intangibles in France, and used the measured principal components as a proxy for intangible complementarities.

The method of creating a new index from the PCA has two advantages. Firstly, complementarities between intangibles can be considered. Principal components are linear combinations of input variables, where the coefficient indicates its importance or weight. Each principal component, therefore, can be interpreted differently by observing how their coefficients combine. Secondly, it helps to address the issue of multicollinearity. All of the intangibles we consider are highly correlated, making coefficient estimates inconsistent when they are all included in a single model. The PCA not only provides new indices that are orthogonal to each other, but also reduces the final number of variables, based on their importance in terms of proportion of variance. Thus, we conducted our PCA on intangibles taken from INTAN-INVEST to obtain new indices, and used the latter as proxies for intangible complementarities.

The next step was to include spillover effects. To this end, we followed the approach proposed by Coe and Helpman (1995), henceforth known as the CH method. The CH method measures the knowledge spillover effect using import-weighted knowledge from foreign countries. This approach has been widely accepted, and used in empirical studies of knowledge spillover and productivity (Acharya, 2016; Coe & Helpman, 1995; Engelbrecht, 1997; Orlic et al., 2018).

However, the CH method only considers R&D capital, and we need to account for a wider set of intangibles based on the PCA indices, computed as described above. Thus, intangible complementarity spillover is described as follows:

$$\mathrm{IC.spillover}_{it} = \sum_{K}^{k=1}\left(\frac{i's\ import\ from\ k_t}{i's\ import_t} * INT_{kt}\right) \ (1)$$

where *INT* refers to intangible complementarity, i and k indicate the country-industry, and t represents the year. In the above equation, $\mathrm{IC.spillover}_{ik}$ measures spillover from intangible complementarities received from other countries by multiplying the proportion of country-industry *i*'s imports from an exporting country-industry k in year t, and exporter k's intangible complementarity.

4.4 Empirical model

We developed the following model to estimate the effect of intangible complementarities and their spillover on productivity:

$$\mathrm{TFP}_{it} \sim \mathrm{PCI}_{it} + \mathrm{PCI.spillover}_{it} + Final.Consumption_{it} \ (2)$$

Here, i and t refer to the country-industry and year, respectively. The dependent variable, TFP, is computed as explained in the previous section. PCI represents a vector of principal component indices obtained with the PCA method. In addition, we account for unobserved economic conditions by adding final consumption (taken from WIOD data) as a control variable. Final consumption is computed as the sum of all consumption expenditure (including household, non-profit organizations serving households, the government), gross fixed capital formation, and change in inventories and capital. The final equation represents not only each country-industry's production of final products, but also the economic situation, which may vary among country-industries. The panel model is estimated both with fixed and random effects.

5 RESULTS

5.1 Niche overlap index results

Prior to the econometric analysis, we examined complementarity relationships between intangibles using the niche overlap index. Here, the aim was to select intangible components that were most complementary to each other, and especially R&D. In order to account for possible heterogeneity between industries, we divided the sample into two groups based on the average value of R&D intensity, by industry (Figure 2). R&D intensity for each country-industry was computed as the proportion of R&D investment to value added. Country-industries with higher (lower) R&D intensity than average were categorized into R&D-intensive (less R&D-intensive) groups. This analysis found that mining and quarrying (B), manufacturing (C), information and communication (J), and professional, scientific and technical activities, and administrative and support service activities (M–N) were R&D-intensive industries, while the remainder were less intensive.

We show the results of the niche overlap index for these two categories in Tables 2 and 3. Values of the index closer to 1 indicate perfect complementarity, while values closer to zero imply an independent relationship or zero complementarity.

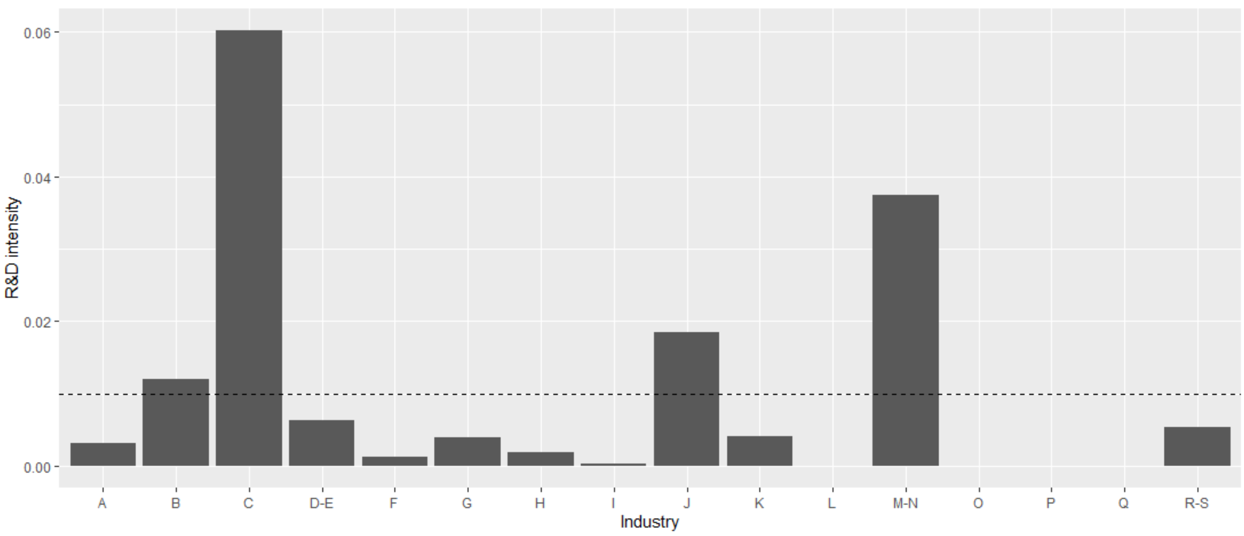

Figure 2: R&D intensity

In the case of R&D-intensive industries, R&D is complementary to all intangibles except Entertainment, Artistic and Literary Originals + Mineral Explorations Design (Minart), and new product development costs in the financial industry (Nfp). On average, the niche overlap index in R&D-intensive industries is 0.5. Training, Brand, and Design strongly complement R&D, with values exceeding 0.86. The same is true for Organizational capital, and there is high niche overlap with Training, Design, and Software and databases. Here again, Minart and Nfp have the lowest niche overlap values. In sum, overlap values are high for all intangibles, except Minart.

In less R&D-intensive industries, the pattern of relationships is slightly different. Firstly, the average niche overlap index is lower (0.4) compared to R&D-intensive industries. Overall, overlap values are lower, indicating that the complementarity relationship is weaker. R&D and Software and databases have the highest index (0.512), but all other values are below 0.5. Organizational capital (Orgcap) has the highest overlap with Software and database (Softdb). This suggests that the complementarity between organizational capital and training is stronger in R&D-intensive industries. Like R&D-intensive industries, Minart and Nfp have lowest complementarity. Regardless of the level of R&D intensity, complementarity is weak between Design and other intangibles.

In sum, we found that the level of complementarity differs by level of R&D intensity, while Minart and Nfp weakly complement other intangibles.

Table 2 Niche overlap values (R&D-intensive industries)

	R&D	Orgcap	Softdb	Minart	Design	Nfp	Brand
Orgcap	0.713						
Softdb	0.639	0.766					
Minart	0.073	0.188	0.470				
Design	0.866	0.835	0.677	0.115			
Nfp	0.000	0.000	0.000	0.000	0.000		
Brand	0.882	0.663	0.664	0.233	0.882	0.000	
Training	0.917	0.849	0.776	0.245	0.911	0.000	0.888

Table 3 Niche overlap values (Less R&D-intensive industries)

	R&D	Orgcap	Softdb	Minart	Design	Nfp	Brand
Orgcap	0.438						
Softdb	0.512	0.850					
Minart	0.180	0.090	0.154				
Design	0.302	0.514	0.441	0.070			
Nfp	0.183	0.627	0.625	0.009	0.217		
Brand	0.464	0.715	0.734	0.104	0.424	0.368	
Training	0.482	0.796	0.793	0.165	0.594	0.366	0.714

5.2 PCA results

Based on the results presented in the previous subsection, we selected intangible components with higher complementarity, and ran a PCA to obtain several indices of knowledge. Given the low complementarity identified by the niche index, we excluded Minart and Nfp from the analysis, keeping the remaining six categories. The results of the PCA are shown in Table 2. The first two principal components (highlighted in bold) account for more than 92% of variability, thus, they were used as indices of intangible complementarity in the rest of the analysis. We then interpreted the two indices according to their relationship with R&D. A positive coefficient was found for all variables in principal component 1 (PC1), while only the R&D coefficient was negative in principal component 2 (PC2). Figure 1 is the biplot of the two components; loading factors of component 1 are plotted on the horizontal axis, and component 2 on the vertical axis. These plots clearly highlight the main difference between the two components: although both have positive loadings for almost all intangible types, R&D for PC1 has a positive loading while PC2 has a negative loading. Given this difference, we can distinguish the two components as a function of their correlation with R&D. For this reason, hereafter, we refer to these two components as high knowledge intangible complementarities (HKIC) and low knowledge intangible complementarities (LKIC).

Table 2 PCA result (PC1 & PC2)

Intangibles	**PC1**	**PC2**	PC3	PC4	PC5	PC6
Brand	**0.204**	**0.041**	0.000	−0.737	0.556	0.322
Design	**0.233**	**0.043**	−0.196	−0.497	−0.805	0.099
Orgcap	**0.414**	**0.739**	−0.418	0.287	0.100	0.127
Rnd	**0.785**	**−0.565**	−0.035	0.241	0.060	0.025
Softdb	**0.286**	**0.341**	0.886	0.023	−0.124	0.041
Training	**0.186**	**0.119**	−0.040	−0.261	0.116	−0.932
Proportion of variance	**0.764**	**0.156**	0.041	0.020	0.014	0.005
Cumulative Proportion	0.764	0.920	0.961	0.981	0.995	1.000

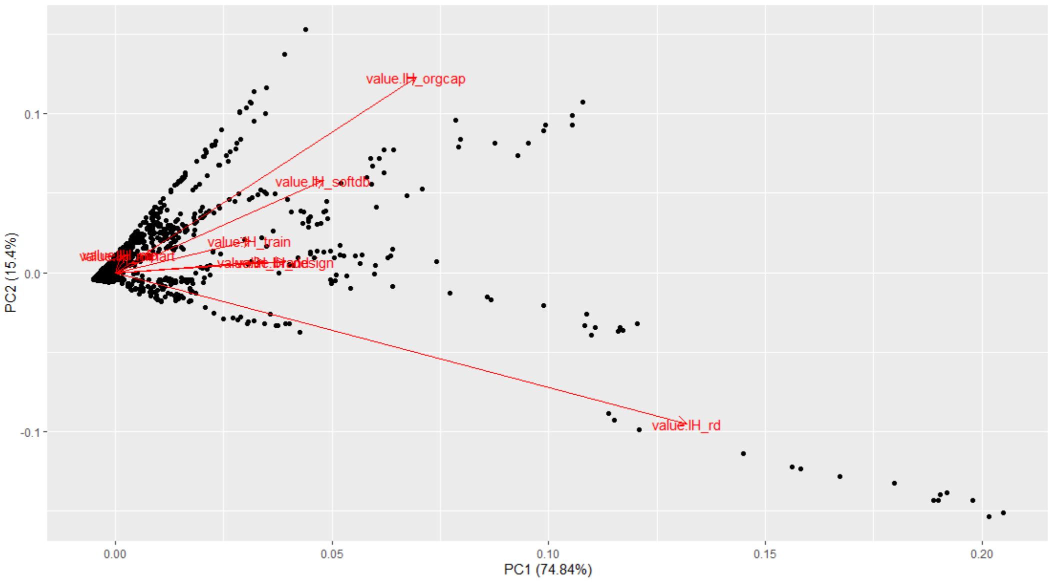

Figure 1: PCA results (PC1 & PC2)

In Figures 2 and 3, we plot average values of the two components for each country over time. Germany (DEU), France (FRA), and the United Kingdom (GBR) are the leading countries in HKIC. France and the UK also lead in LKIC, while DEU has low LKIC, with high levels of R&D in general. France and the UK both have high levels of HKIC and LKIC, meaning that they invest significantly in intangibles, regardless of R&D intensity.

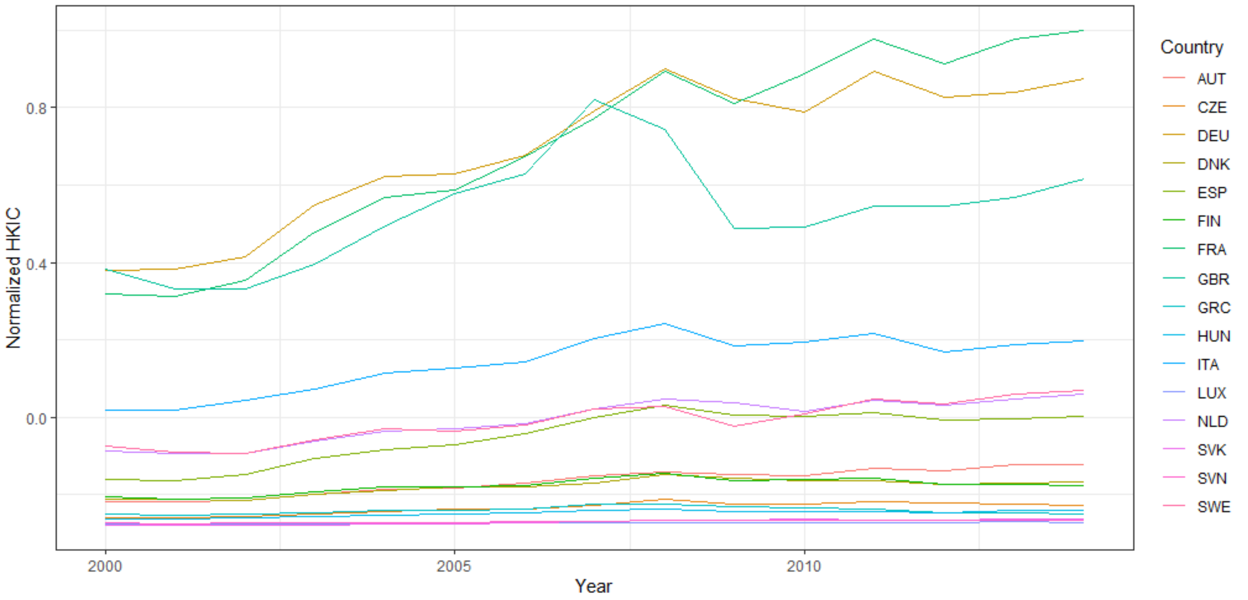

Figure 2: Annual normalized HKIC

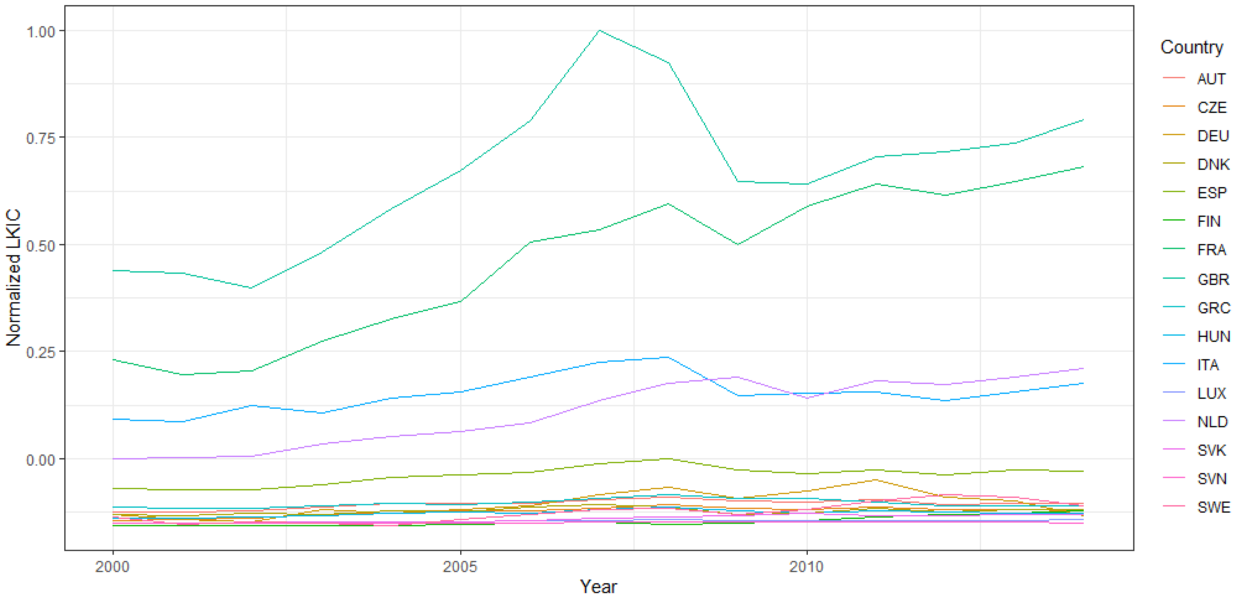

Figure 3: Annual normalized LKIC

5.3 Estimation results

In this subsection, we use the indices of complementarity computed in the above section and show their effect, and the effect of spillovers, on productivity. In particular, plugging the two components into equation (2), the model can be rewritten as:

$$\mathrm{TFP}_{it} = \beta 1\ \mathrm{HKIC}_{it} + \beta 2\ \mathrm{LKIC}_{it} + \beta 3\ \mathrm{HKIC.spillover}_{it} + \beta 4\ \mathrm{LKIC.spillover}_{it} + \beta 5\ Final.Consumption_{it} + e_{it} \quad (3)$$

where HKIC and LKIC denote the above-mentioned high knowledge and low knowledge intangible complementarities. Next, we estimated panel regressions with both random and fixed effects. The result of the fixed effect estimation is shown in Table 3. In all models, final consumption coefficients are positive at a statistically significant level. The positive relationship explains the significant contribution of final products to productivity. In addition, the final consumption coefficient tells us that the economic condition is positively related to productivity, and that the effect of economic condition is fully controlled for.

Column 1 of Table 4 sets out the baseline model, with HKIC and LKIC as independent variables. These two variables were included as they are free from collinearity. To recap, HKIC represents intangibles with greater R&D complementarities and LKIC refers to those with less. Estimates for HKIC point to a positive effect of HKIC, while the LKIC coefficient is negative and statistically insignificant. This result highlights the fact that intangible with high R&D complementarities contribute to productivity, but those with low complementarities do not.

Columns 2 and 4 show the result of the spillover effect of HKIC and LKIC. Since both types of spillover are measured as the product of intangible complementarities and the weight of imports, effects were estimated in separate models. This found a positive and significant coefficient of HKIC spillover, indicating a positive spillover effect of HKIC on productivity. In the case of LKIC, however, the coefficient is negative. This result tells us that the spillover effect is only valid for high intangible R&D complementarities, and not for low.

In columns 3 and 5, we divide intangible spillovers into intra- and inter-industry. Intra-industry spillovers are externalities that relate to the same sector, but in different countries, while inter-industry spillovers refer to different industries either in the same country, or in different countries. For HKIC, both coefficients are positive, showing that the effect of the knowledge externality is positive, regardless of the industry type. In the case of LKIC, however, the intra-industry coefficient is positive but insignificant, while the inter-industry coefficient is negative and significant. We therefore conclude that there is no evidence to support an externality of the second type, to differentiate between either similar or different industries.

Table 4 Regression result (fixed effect)

	Dependent variable:				
	tfp				
	(1)	(2)	(3)	(4)	(5)
HKIC	1.133***	0.435***	0.416***		
	(0.092)	(0.085)	(0.085)		
LKIC	−0.147			−0.153	−0.158*
	(0.094)			(0.096)	(0.096)
HKIC.Spillover		3.621***			
		(0.121)			
HKIC.Spillover.intra			0.317**		
			(0.138)		
HKIC.Spillover.inter			3.648***		
			(0.134)		
LKIC.Spillover				−0.448***	
				(0.087)	
LKIC.Spillover.intra					0.022
					(0.092)
LKIC.Spillover.inter					−0.437***
					(0.088)
Final.Consumption	1.680***	0.817***	0.817***	1.906***	1.907***
	(0.076)	(0.073)	(0.072)	(0.074)	(0.074)
Observations	3,375	3,375	3,375	3,375	3,375
R^2	0.217	0.391	0.398	0.186	0.186
Adjusted R^2	0.157	0.344	0.351	0.124	0.123
F Statistic	289.902*** (df = 3; 3133)	670.787*** (df = 3; 3133)	517.688*** (df = 4; 3132)	239.257*** (df = 3; 3133)	178.754*** (df = 4; 3132)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5 reports random effect estimations. The random effects model assumes that there is an independent relationship between individual-specific effects and independent variables. The results are very similar to before, and the presence of strong knowledge diffusion is confirmed. The only difference relates to intra- and inter-industry spillovers. In the fixed effects model both types of externalities were significantly positive, while in the random effects model only inter-industry spillovers are (column 3).

Table 5 Regression result (random effect)

	Dependent variable:				
	tfp				
	(1)	(2)	(3)	(4)	(5)
HKIC	0.952***	0.468***	0.459***		
	(0.085)	(0.080)	(0.082)		
LKIC	−0.143			−0.147	−0.152
	(0.094)			(0.096)	(0.096)
HKIC.Spillover		3.111***			
		(0.114)			
HKIC.Spillover.intra			0.037		
			(0.052)		
HKIC.Spillover.inter			3.565***		
			(0.120)		
LKIC.Spillover				−0.426***	
				(0.087)	
LKIC.Spillover.intra					0.029
					(0.092)
LKIC.Spillover.inter					−0.431***
					(0.088)
Final.Consumption	1.679***	0.961***	0.913***	1.889***	1.890***
	(0.074)	(0.072)	(0.070)	(0.072)	(0.072)
Constant	−12.034***	−33.065***	−37.145***	−5.101***	−5.269***
	(1.245)	(1.046)	(1.090)	(1.494)	(1.746)
Observations	3,375	3,375	3,375	3,375	3,375
R^2	0.202	0.350	0.373	0.178	0.179
Adjusted R^2	0.202	0.349	0.372	0.178	0.178
F Statistic	855.792***	1,811.476***	2,001.757***	732.141***	732.461***
Note:					*p<0.1; **p<0.05; ***p<0.01

5.4 Robustness check

We tested the robustness of our results by conducting similar regressions, but with value added instead of TFP as the dependent variable. After controlling for production factors, we estimated a production function that included the above-mentioned knowledge diffusion variables (Table 6). Value added, labour and capital were used to estimate TFP in the first stage (value added as a dependent variable, and labour and capital as independent variables). Quantitative results remained unchanged, although coefficients were smaller and some became insignificant. The HKIC coefficient was only significant for inter-industry spillover, and the coefficients of intra- and inter-industry LKIC spillover were not significant. Therefore, our quantitative findings can be seen as robust, as the key variables are significant and the signs of all coefficients are consistent.

Table 6 Robustness check (Productivity function)

	Dependent variable:				
	log(VA)				
	(1)	(2)	(3)	(4)	(5)
Labor	0.402***	0.402***	0.419***	0.385***	0.381***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Capital	0.790***	0.790***	0.789***	0.932***	0.934***
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)
HKIC	0.027***	0.027***	0.027***		
	(0.008)	(0.008)	(0.008)		
LKIC	−0.012			−0.011	−0.012
	(0.008)			(0.008)	(0.008)
HKIC.Spillover	0.205***	0.204***			
	(0.014)	(0.014)			
HKIC.Spillover.intra			0.012		
			(0.013)		
HKIC.Spillover.inter			0.207***		
			(0.015)		
LKIC.Spillover				−0.018**	
				(0.007)	
LKIC.Spillover.intra					0.006
					(0.008)
LKIC.Spillover.inter					−0.010
					(0.008)
Final.Consumption	0.072***	0.072***	0.072***	0.081***	0.082***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	3,681	3,681	3,681	3,681	3,681
R^2	0.836	0.836	0.836	0.825	0.825
Adjusted R^2	0.824	0.824	0.823	0.812	0.812
F Statistic	2,908.216*** (df = 6; 3415)	3,487.904*** (df = 5; 3416)	2,899.857*** (df = 6; 3415)	3,231.705*** (df = 5; 3416)	2,688.851*** (df = 6; 3415)
Note:					*p<0.1; **p<0.05; ***p<0.01

We also examined two alternative variables to ensure that our results were robust to our choice of measure (Table 7). Since our key variables (HKIC and LKIC) were the combination of intangibles, and they were differentiated by R&D, we estimated the same regression model with R&D and a composite intangible indicator obtained from INTAN-Invest. The latter variable is, in essence, the sum of all of the listed intangibles in INTAN-Invest. In general, estimates of both R&D and intangibles show trends that are similar to the result for HKIC. Since R&D plays the most significant role in HKIC, and in overall intangibles, this finding again shows that our results are robust.

Table 7 Robustness check (R&D and intangibles)

	Dependent variable: tfp					
	(1)	(2)	(3)	(4)	(5)	(6)
RND	0.486***	0.153*	0.154*			
	(0.092)	(0.082)	(0.083)			
RND.Spillover		3.703***				
		(0.124)				
RND.Spillover.intra			0.088			
			(0.079)			
RND.Spillover.inter			3.733***			
			(0.134)			
Intangible				1.150***	0.568***	0.574***
				(0.065)	(0.062)	(0.062)
Intangible.Spillover					4.341***	
					(0.153)	
Intangible.Spillover.intra						0.180
						(0.142)
Intangible.Spillover.inter						4.430***
						(0.165)
Final.Consumption	1.879***	0.948***	0.964***	1.586***	0.777***	0.755***
	(0.075)	(0.073)	(0.073)	(0.074)	(0.072)	(0.071)
Observations	3,375	3,375	3,375	3,375	3,375	3,375
R^2	0.186	0.367	0.363	0.253	0.406	0.416
Adjusted R^2	0.124	0.318	0.313	0.196	0.361	0.371
F Statistic	358.130*** (df = 2; 3134)	605.029*** (df = 3; 3133)	445.354*** (df = 4; 3132)	530.531*** (df = 2; 3134)	714.456*** (df = 3; 3133)	557.844*** (df = 4; 3132)
Note:						*p<0.1; **p<0.05; ***p<0.01

6 CONCLUSION

This deliverable contributes to the literature on knowledge diffusion and intangible capital. It adopts a new approach to the measurement of complementarities between intangibles. To the best of our knowledge, this is the first attempt to estimate the productivity spillover effects of knowledge, taking into account intangible complementarities. We first used the niche overlap index to evaluate intangible complementarities; in a second step, we ran a PCA to develop intangible-based knowledge indices and evaluate their effect on productivity, via panel regressions. The inclusion of the above-mentioned knowledge proxies made it possible to include intra- and inter-industry spillover effects. Following Coe and Helpman (1995), we also considered a weighted spillover measurement focused on the import channel of transmission.

Our empirical analysis resulted in the following findings. Firstly, we obtained two new variables (HKIC and LKIC) to capture knowledge creation, while accounting for a wide range of intangible components that are complementary, both to each other and to R&D. These two variables explain more than 90% of intangible data dispersion. By definition, HKIC and LKIC contain a broader definition of knowledge than the one typically used in the literature, which only refers to R&D. The two measures can be differentiated by the proportion of R&D they include.

Second, we found that spillover effects are only present in the case of HKIC. Specifically, spillovers from intangible complementarities with high R&D make a significant contribution to productivity. The positive effect of HKIC not only supports previous findings that have only considered R&D, but also highlights the significant role of R&D in the spillover effect of intangible complementarity. R&D is important – not only in itself – but also as a key element that complements other intangibles. Since knowledge spillover is only valid for intangibles with high R&D, R&D investment should be consistently supported. In addition, we found a greater spillover effect in inter-industry relations. This result supports previous observations that inter-industry spillovers are more likely than intra-industry spillovers (Marcin, 2008), and underlines the relevance of importing knowledge from firms operating in different industries.

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