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Intangibles in Light of Industry-level CompNet Dataset

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Abstract

This paper studies the productivity effects of intangible assets using 9th vintage of the CompNet dataset. Descriptive work shows that there is dispersion in usage of intangibles; some firms invest heavily into intangible assets and many firms do not invest at all. In addition, preliminary evidence, using the joint distributions provided by CompNet, implies that intangible assets increase the productivity of the firms that already belong to the 90th productivity percentile. Furthermore, I estimate the output elasticity of intangible assets by a Cobb Douglas production function using data at the 2-digit industry (NACE rev 2) level of aggregation and find output elasticity of intangibles to be approximately between 0.08–0.10.

A special emphasis is placed on development of intangibles in Finland. I find that concentration in intangibles, measured by the Herfindahl-Hirschman index, has increased in the past few years and that intangible assets are concentrated in ICT and manufacturing macro-sectors. In addition, I estimate a Cobb Douglas production function using only data from Finland and find that while output elasticity on intangible assets is approximately 0.05, the coefficient is not statistically significant, and hence, the evidence is inconclusive.

Tiivistelmä

Aineettomat tuotannontekijät toimialatasolla CompNet-aineiston valossa

Tässä tutkimuksessa tarkastellaan aineettoman pääoman vaikutuksia yritysten arvonlisään käyttäen yritystason aineistosta mikroaggregoitua CompNet-tietokantaa NACE rev. 2 toimialatasolla. Kuvailevan analyysin avulla havaitaan, että aineettoman pääoman käytössä on merkittävää hajontaa yritysten ja toimialojen välillä. Tuottavuusvaikutukset aineettoman pääoman käytössä näyttäisivät olevan suurimpia yrityksille, jotka kuuluvat jo valmiiksi tuottavimpaan 10-prosenttiin, eikä aineettoman pääoman käyttö näyttäisi lisäävän tuottavuutta huonoimpaan 10-prosenttiin kuuluvien yritysten joukossa.

Regressioanalyysin avulla estimoin Cobb-Douglas -tuotantofunktion kiinteiden vaikutusten mallilla, joka tuottaa estimaatiksi aineettoman pääoman joustolle (output elasticity) noin 0,09. Analysoin CompNet-aineiston avulla myös, miten aineeton pääoma näkyy Suomessa. Suomessa konsentraatio aineettoman pääoman käytössä on viime vuosina hieman kasvanut, ja lisäksi Cobb-Douglas -tuotantofunktion estimaatti aineettomalle pääomalle on matalampi, joskaan ei tilastollisesti merkitsevä 5-prosentin tasolla. Regressioanalyysin tulosten tulkinnassa tulee kuitenkin olla varovainen, sillä toimialatasolla tehdyn analyysin tulokset ovat herkkiä endogeenisuudelle, eikä mallin avulla voi erottaa, parantavatko investoinnit aineettomaan pääomaan tuottavuutta vai lisääkö parantunut tuottavuus investointeja aineettomaan pääomaan.

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Keywords: Intangible capital, Productivity

Asiasanat: Aineeton pääoma, Tuottavuus

JEL: E22, J24, O52

1 Introduction

Intangible assets are today recognized as important contributors to productivity growth (Roth, 2019). During the last 20 years the link between intangible assets and productivity growth has been extensively studied using various econometric methods and several studies have documented that intangibles contribute to productivity growth. In this paper I use the micro-aggregated CompNet database of 21 European countries and 56 industries (2-digit NACE rev. 2) to replicate these findings. Using this long panel data[1] of a large number of countries and industries I find similar results to those previously estimated in literature (for example Niebel et al. (2017); Roth and Thum (2013)) that output elasticity on intangible assets is positive and statistically significant.

In addition, a special emphasis is placed on the development of intangible assets in Finland, and I replicate all regressions using only data from Finland. While regressions done using only Finnish data would suggest that intangibles contribute relatively less to productivity in Finland, coefficient on intangibles is only weakly statistically significant (10-percent level) and hence evidence is inconclusive.

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2 Theoretical framework

Several stylized facts make the effect of intangibles on productivity seem almost self-evident. Corrado et al. (2022) note that the value in the world's largest firms (measured by market capitalization) seems to be elsewhere than in the tangible capital held by those firms. Similarly, investment into intangible assets, for example in the United States, exceed investments made in tangible assets (Sichel, 2024). In light of these anecdotal examples it would seem unlikely that intangibles and productivity growth were not correlated.

Empirical studies validate this reasoning. Roth (2019) provides an exhaustive review of this literature. Sichel (2024) provides a review of measurement of intangible assets. In addition, there is literature on indirect productivity effects of intangibles. For example, Corrado et al. (2017) find effects of complementarity between ICT-capital and intangible assets and spillovers related to intangibles. Corrado et al. (2021) finds evidence of correlation between productivity dispersion and intangible assets.

The most similar empirical model to this paper is by Niebel et al. (2017). They study

[1] CompNet panel data is from 1999 to 2021, however, the coverage of years vary within industries and countries

intangible assets using growth accounting and estimation of a Cobb-Douglas production function with industry-level data from European countries between 1995 - 2007. They use pooled OLS, fixed effects and a system GMM estimator (with lagged levels of variables as instruments) and find output elasticities to be between 0.10 and 0.20

Roth and Thum (2013) estimate a macroeconomic growth accounting model, in which they incorporate intangible capital. Their estimation method is based on random effects estimator and a dynamic panel GMM estimator. With country-level panel data from EU between 1998 and 2005 they find that growth in intangible capital explains approximately half of labour productivity growth. Roth and Thum (2013) estimate a dynamic panel data model using lagged levels of intangible capital as instruments to attenuate possible problems of endogeneity and show that their dynamic panel data estimates are statistically significant and conclude that their results are not caused by endogenous regressors.

Marrocu et al. (2011) use firm-level balance sheet data from Bureau van Dijk's database to estimate a log-normalized Cobb-Douglas production function using identification strategies developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). They also find that intangible capital is positively linked with firm's value added with both identification strategies.

3 Data

I use the 9th vintage of the CompNet dataset. CompNet is a micro-aggregated dataset based on firm-level balance sheet data from 22 European countries (however, there is no data on intangibles from the United Kingdom). Data from individual countries comes mostly from respective national statistical agencies or central banks (CompNet, 2018). The dataset is an unbalanced panel that is aggregated over macro-sector, country, 2-digit industry-code based on NACE rev. 2 and level of technological knowledge. In addition, CompNet provides joint distributions of certain variables and transition matrices for studying firm dynamics. However, transition matrices do not contain data about intangibles and, hence, I am unavailable to link this study to firm dynamics. For more information about the dataset, the reader is encouraged to see the user guide of CompNet (CompNet, 2023).

The dataset includes statistical moments of variables related to firm characteristics and performance such as assets, employment, labour productivity and revenue. Furthermore, CompNet provides several indicators related to the use of intangibles, most importantly data of intangible fixed assets.

I run the regressions using the data aggregated over 2-digit industry codes (which are described in more detail in CompNet (2023)). As reported in section 7, results of regressions run at the level of higher aggregation are similar in magnitude, and hence, the results of this paper are not entirely driven by the choice of aggregation.

CompNet offers four samples of data: a truncated sample that only contains data of firms with at least 20 employees, an untruncated sample, an unweighted and a weighted sample. Based on CompNet (2023) the weighted sample is more descriptive of the overall population of firms in particular industries and countries rather than just the sample of firms, of which the variables are estimated. Truncated sample is offered since for some countries CompNet does not have data on smaller firms than 20 employees (for example, German data is only available in the truncated sample). In addition to different levels of aggregation, my results are of the same magnitude (and statistically significant on 5-percent level) regardless of the choice of sample (weighted or unweighted and truncated or untruncated). (CompNet, 2023).

3.1 Variable description and comparability of data

A possible complication is cross-country comparability; macro-sector coverage varies between countries in CompNet and not all macro-sectors are covered for each country. For example, CompNet is missing intangible data of real estate macro-sector in Finland and mean of intangible fixed assets for ICT macro-sector in Denmark between 2009 − 2018.

CompNet (2023) contains detailed information regarding the collection of data and definitions used by individual countries and thus I believe that the variables used in this analysis are comparable across countries as explained in more detail below. For a thorough review of cross-country comparability, the reader should consult CompNet (2018).

3.1.1 Intangibles in the 9th vintage of CompNet

9th vintage of CompNet database contains data on intangible fixed assets and intangible investments. Based on CompNet (2023), intangible fixed assets are based on firms' balance sheet data. In the 9th vintage of CompNet intangible assets are based on only acquired assets while intangibles can also be developed in-house. Since intangible assets are often produced in-house, CompNet data is missing a part of intangible assets (Corrado et al., 2022). Data on intangible investments is calculated as a difference between intangible fixed assets at time t and time $t-1$.

This way of accounting for intangible assets has certain shortcomings. Since only acquired intangibles are included in CompNet data, it is possible that intangibles (goodwill) resulting from mergers and acquisitions are drivers of intangible investments (Corrado et al., 2022). In addition, different accounting standards between countries may explain some of the variation in the data (Van Criekingen et al., 2020). However, intangibles are difficult to measure accurately (Corrado et al., 2022). Thus, I believe this imperfect measure of intangibles is still an interesting proxy of the development in Europe.

There are two similar definitions for intangible assets used in CompNet data. First, for 9 countries (Belgium, Czech Republic, Finland, France, Italy, the Netherlands, Poland, Romania and Spain) intangible assets are based on yearly average intangible fixed assets capitalized in the firms' balance sheets. Second, 12 countries (Croatia, Denmark, Germany, Hungary, Latvia, Lithuania, Malta, Portugal, Slovakia, Slovenia, Sweden, Switzerland) use definition "intangible fixed assets at a particular point in time". (CompNet, 2023).

Some firms do not invest in intangibles at all; approximately for 0,6% (108 observations out of 18 067) of all observations the logarithm of intangible assets is negative. These observations are dropped from the sample. However, a few alternative transformations are explored that do not drastically change the results. These alternative transformations are reported in Section 7.

3.1.2 Measure of output

I use the mean of real value added as the measure of output per industry, which based on CompNet (2023) is calculated as deflated value of difference between nominal revenue and nominal intermediate inputs. Furthermore, this measure of value added only includes positive values. CompNet dataset also includes measure of value added where negative values are not censored, but since variables are log-normalized, my results would not differ even if the uncensored variable was used.

3.1.3 Tangible assets

Countries also vary in their definition of capital; the first definition is tangible fixed assets and intangible fixed assets from firm's balance sheets and the second definition is "tangible fixed assets at a particular point in time" (CompNet, 2023, p. 126). Based on CompNet (2023), 6 countries (Czech Republic, France, Italy, the Netherlands, Poland and Estonia) use the first definition and 13 countries (Croatia, Denmark, Finland, Germany, Latvia, Lithuania, Malta, Portugal, Romania, Slovakia, Slovenia, Sweden and Switzerland) use the second best definition.

Hence, for the countries that use the first definition, tangible assets are measured by subtracting mean of intangible fixed assets from mean of capital. For the countries that use the second definition, tangible assets are measured by simply using the mean of capital. Subtracting intangible assets from capital produced 133 negative observations (69 observations from France, 14 from Italy, 46 from the Netherlands and 4 from Poland). Mean of real capital was zero for 26 observations, all of which were from France. These negative observations are dropped from the sample.

3.1.4 Labor

As a measure of labor, I use the mean of number of employees. 9th vintage of CompNet also includes data on full-time-equivalent (FTE) number of employees but, for example, on 2-digit industry level FTE-variable is missing over 8000 observations compared to less than 500 missing observations of headcount variable. Hence, I use the mean of headcount even though number of full-time-equivalent employees might be more harmonized and comparable between countries (CompNet, 2023).

4 Descriptive statistics

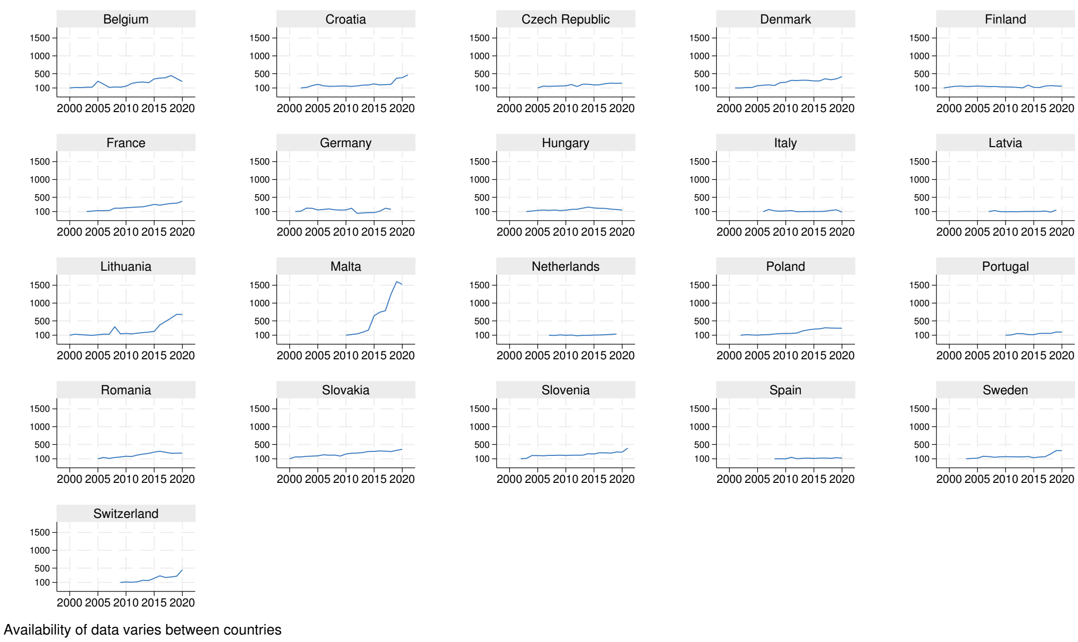

Figure 1: Time-series of aggregate intangible assets by country

Time-series graph of index of the aggregate intangible assets by country is reported in Figure (1) along with mean of intangibles and value added in Tables (1) and (2), respectively. In addition, Table (3) includes the mean number of firms, of which the

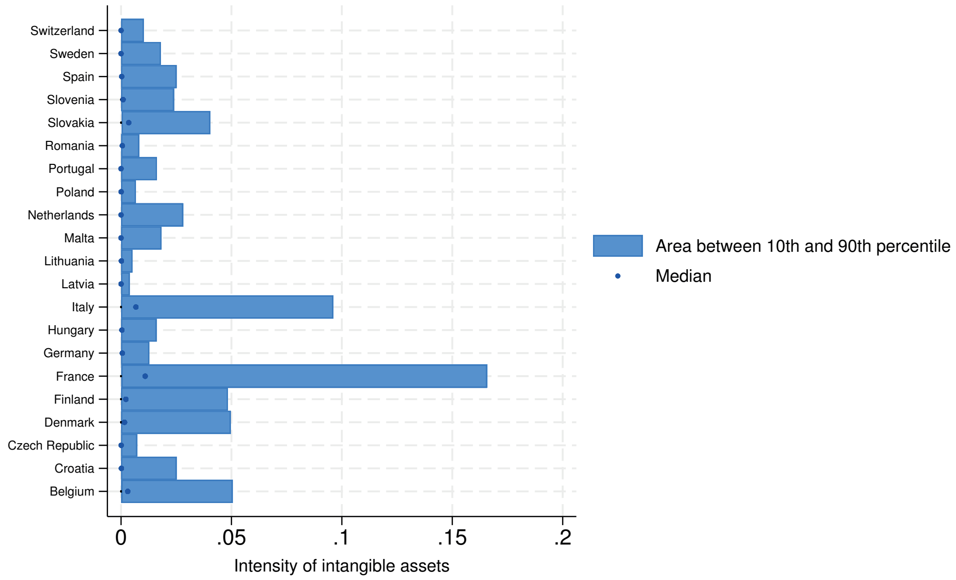

Figure 2: Intensity of intangible assets, measured by intangible assets / nominal revenue

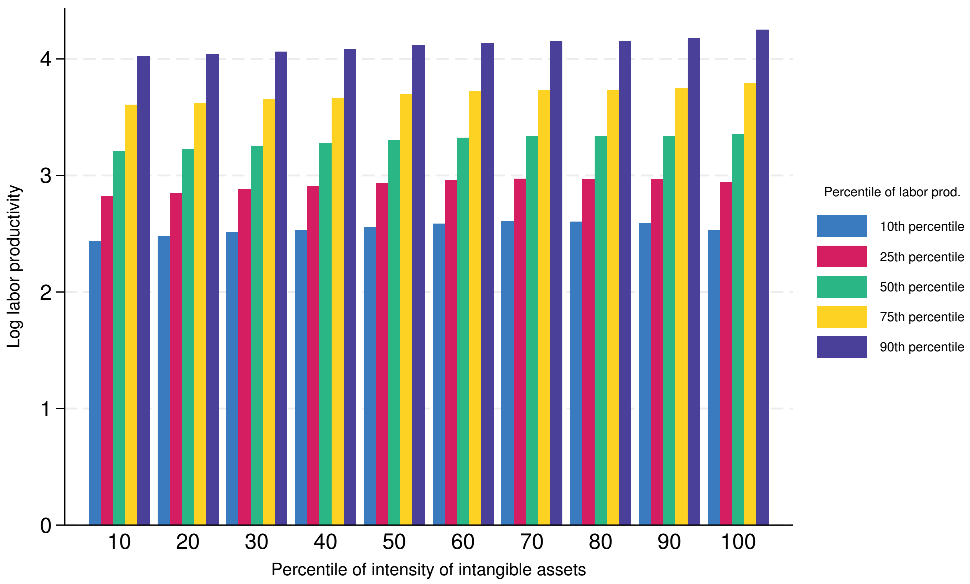

Figure 3: Productivity percentiles by intangible asset intensity measured by intangible assets / nominal revenue

measure of intangibles is calculated at the 2-digit industry level of aggregation. Figure (2) diplays the area between 10th and 90th percentile of intensity of intangible assets, which describes the dispersion in intangible assets between firms.

Figure (3) includes graph of productivity percentiles by percentile of intensity of intangible assets (measured by dividing intangible assets by nominal revenue). This preliminary evidence would suggest that the use of intangibles is most beneficial to firms that already have higher productivity. However, further research, preferably using firm-level data, would be required to confirm the finding of Figure (3).

Table 1: Table of aggregate intangible assets by country and macro-sector

	Macro sector 0-9 following NACE Rev. 2 classification (section)								
	1	2	3	4	5	6	7	8	9
Country name									
Belgium	7378	132	2015	505	124	3688	22	4428	332
Croatia	278	19	312	80	52	437	9	24	10
Czech Republic	1068	44	194	94	8	1413	7	93	33
Denmark	3482	130	1686	542	78	2295	86	1436	216
Finland	3277	161	903	194	170	1360		224	186
France	41801	2809	38759	7389	2964	76790	3859	17448	8830
Germany	141678	396	13603	6669	411	29265	149	37968	1278
Hungary	2130	26	390	172	12	2325	9	102	44
Italy	28010	1520	12226	3682	1809	79368	158	1540	1962
Latvia	17	2	22	15	1	43	1	4	3
Lithuania	53	13	42	17	2	150	3	8	10
Malta	13	1	77	4	6	126	.	248	3
Netherlands	28389	3566	13827	3134	621	25968		2669	3463
Poland	1961	158	1281	203	35	5296	15	208	151
Portugal	852	48	732	2668	81	2077	6	194	98
Romania	305	16	254	23	14	432		29	8
Slovakia	719	30	155	137	5	1057	11	80	28
Slovenia	611	18	114	25	9	383	1	24	9
Spain	8356	927	7470	10174	778	13750	850	1488	1405
Sweden	5803	142	1923	674	108	2697	132	562	307
Switzerland	16362	80	15629	1397	209	3502	47	8943	1200

Note: unit of observation is million euros.

4.1 Intangibles in Finland

Development of intangible assets in Finland by macro-sector is shown in Figure (4). As we can notice from Figure (4), intangible assets in Finland are concentrated on manufacturing and ICT macro-sectors. Moreover, the amount of intangible capital in ICT macro-sector has declined since 2006. As is shown in the Appendix, this development is mostly driven by decline in telecommunications (2-digit industry 61); during 2020 the aggregate value of intangible assets in telecommunications in Finland was less than third to that in 2006.

Furthermore, from Herfindahl-Hirschmann index (HHI) we can observe the concentration of intangible assets. The development of HHI is reported in Figure (4) for Finland, Sweden and Denmark. We can note that concentration in Finland has increased since

Table 2: Table of aggregate value added by country and macro-sector

	Macro sector 0-9 following NACE Rev. 2 classification (section)								
	1	2	3	4	5	6	7	8	9
Country name									
Belgium	71871	10524	36370	22195	3153	23268	1134	14783	13591
Croatia	7221	3002	4735	2591	1280	3176	327	1526	599
Czech Republic	30379	2872	8709	3426	632	4895	358	2140	2025
Denmark	26829	5456	13252	9874	1420	10518	1308	7161	3229
Finland	25524	4088	8812	4191	933	7339		2790	2803
France	376885	81578	191172	113849	21911	134181	24853	89441	48931
Germany	539881	51878	205706	72659	22124	112038	21969	82808	63728
Hungary	16667	1625	4769	3241	646	4341	351	2043	1677
Italy	168760	14777	56359	34076	8059	56230	710	13020	21840
Latvia	1318	410	7924	1249	128	373	141	135	252
Lithuania	2287	720	1363	999	104	591	68	265	292
Malta	593	86	437	271	223	290	29	214	213
Netherlands	67333	20242	45346	33220	3464	28925		17032	17440
Poland	58040	6938	18969	6971	1195	11385	2401	5222	3984
Portugal	14355	3644	8695	3941	1768	5218	226	1990	3644
Romania	11678	2004	10160	2601	591	4425		853	819
Slovakia	10218	802	12672	1298	156	1911	237	1029	590
Slovenia	6353	747	2012	1017	294	1002	38	503	364
Spain	84690	21157	62810	27639	14735	44178	1735	18895	31733
Sweden	100441	15178	115925	33456	4196	37376	9112	16612	11161
Switzerland	65276	12721	48425	12900	4915	15980	1671	18981	10281

Note: unit of observation is million euros.

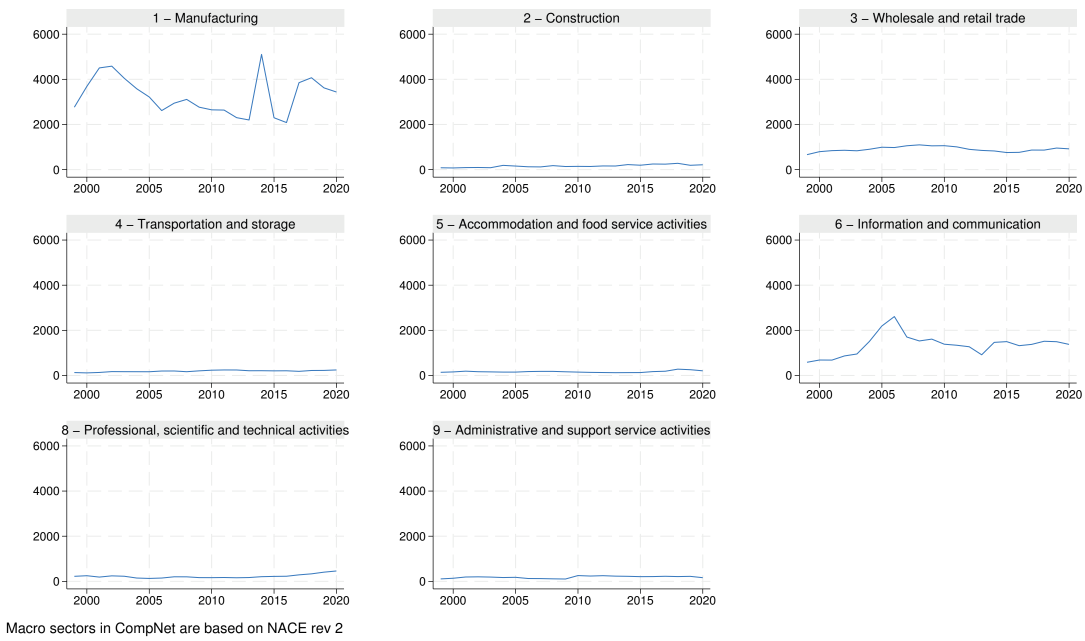

Figure 4: Aggregate intangibles in Finland by macro sector. Unit of observation is million euros

Table 3: Number of firms per observation of intangible assets at the 2-digit industry level of aggregation

Country name	Mean number of firms per observation
Belgium	98.7
Croatia	101.0
Czech Republic	225.3
Denmark	185.4
Finland	150.6
France	1472.1
Germany	.
Hungary	240.9
Italy	1040.6
Latvia	82.3
Lithuania	104.2
Malta	28.9
Netherlands	579.7
Poland	570.6
Portugal	321.9
Romania	257.6
Slovakia	84.4
Slovenia	65.4
Spain	442.8
Sweden	277.2
Switzerland	132.0
Total	326.2

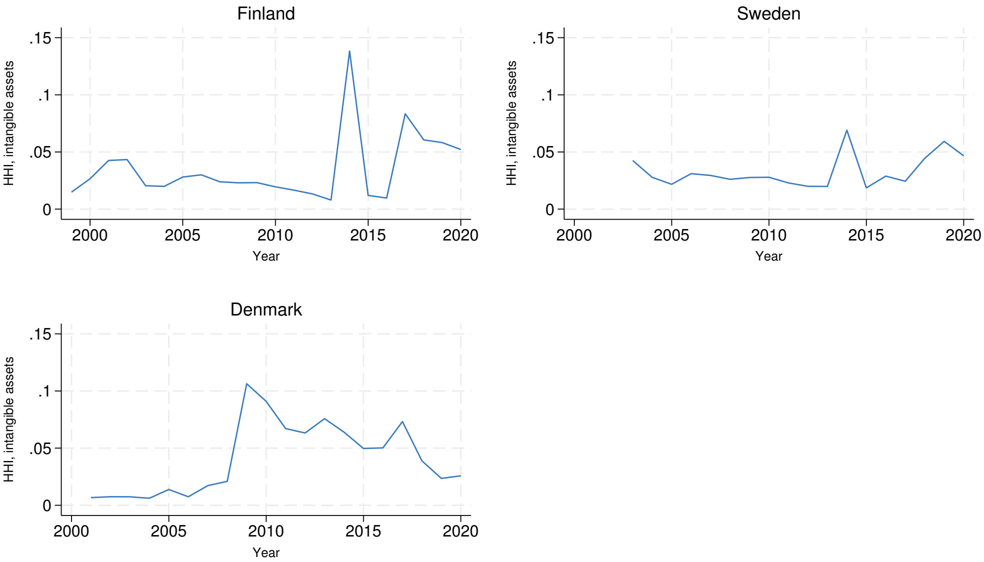

Figure 5: Time-series of Herfindahl-Hirschman index of intangible assets

2015 and was slightly higher than in Denmark during 2020 but approximately equal to concentration of intangible assets in Sweden.

5 Econometric model

In line with the earlier literature, I consider the classical Cobb-Douglas production function augmented with intangible capital variable INT_{cit} (for example, Marrocu et al. (2011); Niebel et al. (2017); Roth and Thum (2013)) given in equation (1). Equation (1) includes the total factor productivity (TFP) term A_{cit}, tangible capital K_{cit}, labor and exponential error term $\exp(\epsilon_{cit})$. As the data is aggregated at the level of 2-digit industry, subscript i represents industry, c country and t time (year).

$$Y_{cit} = A_{cit} K_{cit}^{\beta_K} INT_{cit}^{\beta_{INT}} L_{cit}^{\beta_L} \exp(\epsilon_{cit}) \tag{1}$$

Corrado et al. (2017) model the change in total factor productivity of an industry by fixed effects. I use a similar approach and model the TFP-term using equation (3) (including an error term).

$$a_{cit} = \gamma_c + \gamma_i + \gamma_t \tag{2}$$

Furthermore, I take logarithms of equation (1) to obtain the equation that then estimated.

$$y_{cit} = \beta_K k_{cit} + \beta_{INT} int_{cit} + \beta_L l_{cit} + \gamma_c + \gamma_i + \gamma_t + \epsilon_{cit} \tag{3}$$

There are a few reasons why estimating the coefficients of equation (3) is complex. First, simultaneous causality may pose a problem. It is possible that firms with higher productivity use more intangible assets and, equivalently, that greater usage of intangible assets leads to higher productivity. Second, it is possible that firms observe (at least partially) the shock in value added (captured here by the variable ϵ_{cit} in equations (1) and (3)) before choosing usage of capital and labor (see Ackerberg et al. (2015)).

Equation (2) is estimated using first differences[2] and fixed effects. In addition, coefficients are estimated using a pooled OLS that is reported for reference. In theory, problems with possible endogeneity of regressors could be solved with appropriate instrumental variables, but the difficult availability of suitable instruments prevent such identification strategy to be used in this study.

I believe that the most plausible result is produced by the fixed effects model since it allows to control for unobserved time-invariant heterogeneity between different countries

[2] *Note*: first differences is estimated as $y_{cit} - y_{cit-1} = \beta_K(k_{cit} - k_{cit-1}) + \beta_{INT}(int_{cit} - int_{cit-1}) + \beta_L(l_{cit} - l_{cit-1}), +\epsilon_{cit} - \epsilon_{cit-1}$

and industries and is more efficient than the first differences model. For example, as noted by Van Criekingen et al. (2020) countries' accounting standards differ, which I am able to control for with either country fixed effects or first differences.

While I believe that the most reliable results are those from the fixed effects, it requires certain assumptions. Fixed effects cannot be used to control for unobserved heterogeneity if the unobserved heterogeneity varies over time. Time-variant unobserved heterogeneity could arise, for example, if accounting practices that vary between countries also change over time. In addition, validity of the fixed effects relies on the strict exogeneity assumption which would not hold if firms' usage of capital and labor was correlated with shocks that happened during previous years.

In conclusion, due to issues specified above, I do not encourage readers to make a causal interpretation but rather interpret the coefficient estimates as descriptive work of an interesting phenomenon, for which little cross-country firm-level data is available.

6 Results

Table 4: Main regression results

	(1) Pooled OLS	(2) Fixed Effects	(3) First Differences
Intangible assets	0.351***	0.0889***	
	(0.0338)	(0.0153)	
Tangible assets	0.144**	0.176***	
	(0.0393)	(0.0290)	
Labour (headcount)	0.470***	0.653***	
	(0.0959)	(0.0436)	
Difference in tangible assets			0.0198**
			(0.00512)
Difference in tangible assets			0.0862**
			(0.0248)
Difference in labour (headcount)			0.775***
			(0.0399)
Constant	3.284***	3.521***	0.0113**
	(0.308)	(0.149)	(0.00386)
Observations	13487	13487	12073
Adjusted R^2	0.728	0.909	0.300

Standard errors in parentheses are two-way clustered on country and industry -level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results to pooled OLS, fixed effects and first differences are reported in Table (4)[3]. Coefficient on intangible assets is statistically significant on 1-percent level in each model. Since the statistical model is a log-log regression, the coefficients can be interpreted as output elasticities. Interestingly, relative values of the coefficients change drastically between pooled OLS and fixed effects since in pooled OLS coefficient on intangible assets is approximately double to that of tangible assets compared to the fixed effects model where coefficient on intangible assets is approximately half of coefficient on tangible assets.

6.1 Extensions

In addition to the results reported above I run a number of robustness checks. Most importantly, GMM-estimators were tried to solve possible problems of endogeneity. However, Sargan's overidentifying restrictions test rejected the null hypothesis and implied that my instruments were not valid unless a large number of instruments was chosen. This choice of instruments would have been problematic since a large number of instruments will overfit the model and weaken the test statistic (Roodman, 2009).

Pooled OLS, fixed effects and first differences regressions were run on all samples (all four different combinations of truncation and weighting). Coefficients on intangible assets estimated with fixed effects were statistically significant on 1-percent level and of same magnitude with all possible samples choices. Lowest coefficient value on intangible assets (0.0642 with standard error of 0.0152) was obtained using the untruncated and weighted sample. Highest coefficient value of intangible assets (0.0982 with standard error of 0.0154) with fixed effects specification was obtained using the truncated (at 20 employees) and unweighted sample.

Equivalent regressions to those shown in Table (4) were also run on macro-sector data. Coefficient values were of similar magnitude. Intangible assets' coefficient value of an equivalent fixed effects regression was 0.0781 (standard error 0.0344, statistically significant on 10-percent level). Coefficient value of a pooled OLS regression was 0.366 (0.0382 standard error, statistically significant 1-percent level).

Finally, it was mentioned earlier that a few (72) observations of intangible assets became negative after the log-transformation. Whilst this is a relatively small number of observations compared to the whole sample, dropping these observations could lead to sample selection. Hence, I also estimated the fixed effects model using $\log(1 + INT_{cit})$ and $\text{arcsinh}(INT_{cit})$. Coefficient of intangible assets was of similar magnitude in all pos-

[3]CompNet require users of their data to include the following footnote: The user must be aware that small differences in data collection rules and procedures across countries may exist and are out of CompNet's control. Nevertheless comparability issues appear to be limited.

sible log-transformations with differences arising earliest in the third decimal (for more discussion on similar topic see Chen and Roth (2024)).

6.2 Finnish data

Table 5: Main regression results based on Finnish data

	(1)	(2)	(3)
	Pooled OLS	Fixed Effects	First Differences
Intangible assets	0.165***	0.0542	
	(0.0386)	(0.0297)	
Tangible assets	0.170***	0.169*	
	(0.0318)	(0.0733)	
Labour (headcount)	0.719***	0.809***	
	(0.0955)	(0.0964)	
Difference in intangible assets			0.0266
			(0.0179)
Difference in tangible assets			0.0920
			(0.0561)
Difference in labour (headcount)			0.909***
			(0.190)
Constant	3.031***	3.296***	0.000590
	(0.287)	(0.537)	(0.00392)
Observations	1039	1038	965
Adjusted R^2	0.850	0.948	0.429

Standard errors in parentheses are clustered on industry-level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regression results using only Finnish data are reported in Table (5). We can note that coefficient on intangible assets in the fixed effects model is statistically significant only on 10-percent level. We can also note that the coefficient of intangibles is lower than in the main results in all models but first differences. Whilst this evidence is inconclusive, it would suggest that intangibles contribute relatively less to labour productivity in Finland.

7 Discussion

The results found in this paper are similar in sign and significance to those found in the relevant literature. Yet, coefficients reported in Table (4) are relatively small compared to similar studies. For example, Niebel et al. (2017) estimate output elasticity of intangible assets to be between 0.10 and 0.2. Roth and Thum (2013) estimate output elasticity of intangibles to be 0.29 with random effects. However, since CompNet contains only those intangible assets that are capitalized in firm's balance sheets, fewer types of assets are counted into intangibles than in other studies.

Estimating production function coefficients using cross-country analysis with industry and country fixed effects has well known limitations that are discussed in Section 5. The other limitation of this study is the dataset; not all intangible assets are accounted for. While there are logical reasons (for example, as noted by CompNet staff in our discussions related to measuring intangibles, firms may have incentives to give excessive valuations to intangibles produced in-house) to count only acquired intangibles from intangibles capitalized in balance sheets, CompNet data on intangibles is missing a substantial part of assets generally accounted into intangibles (for discussion about what should be counted into intangibles see Corrado et al. (2005)).

8 Conclusions

The aim of this paper was to study effects of intangible assets on productivity. Using a large panel dataset with 21 European countries, I estimate a Cobb-Douglas production function and find output elasticity to be – while positive and statistically significant – somewhat smaller than in previous studies, which could be explained by the fact that intangibles produced in-house are not included in this study. Nevertheless, further studies, preferably using firm-level data or instrumental variable methods, are required to understand intangibles more thoroughly.

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Appendix

Figure (6) shows the development of intangibles in ICT macro sector in Finland by the 2-digit industry codes. We can note that most of the intangible assets in ICT macro sector have been in telecommunications and that the decline of intangibles in ICT is mostly explained by telecommunications.

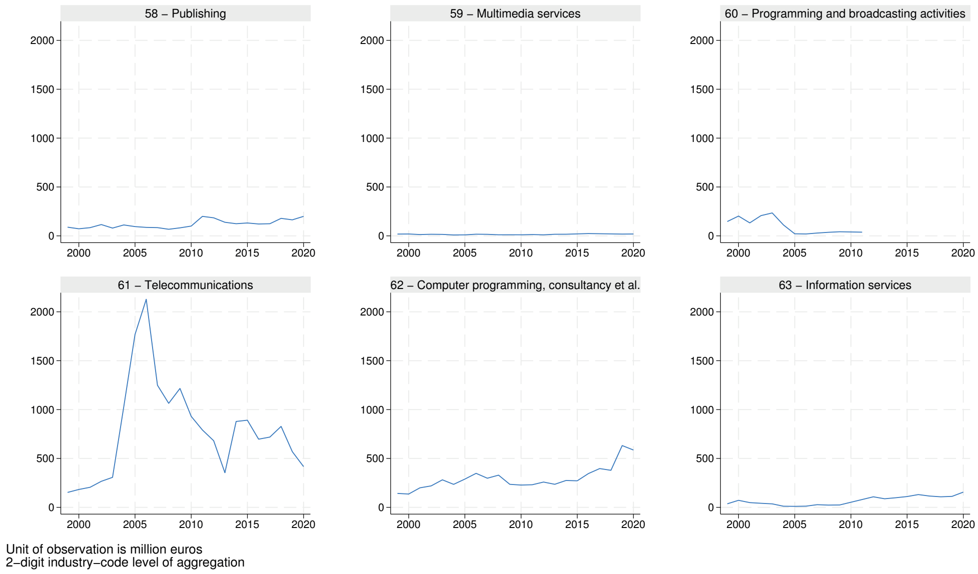

Figure 6: Breakdown of development of intangibles in Finnish ICT macro-sector

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