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Firm-level Evidence from Austrian Microdata

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Intangible capital as a production factor. Firm-level evidence from Austrian microdata*

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JEL Classifications: D24, O30, L22, C33

Keywords: intangible capital, R&D, firm level productivity, investment, production function, Austria

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1. Introduction

Intangible assets such as research and development, licenses or software have become an acknowledged driver of economic growth (Corrado et al. 2013; Haskel and Westlake 2018; Roth, Sen, and Rammer 2022). While aggregate figures show a deepening of intangible capital, firm-level results suggest that the distribution of investment is highly skewed, with only a small fraction of firms investing in intangibles. However, the structural characteristics of the capital employed differ across countries and sectors. Firm-level evidence is still scarce, suggests highly asymmetric effects, and typically focuses on manufacturing firms or uses samples from survey data. A deeper understanding of the microeconomic dynamics underlying aggregate observations is key to shaping economic policy and informing economic theory.

The aim of this paper is to empirically investigate the importance of intangible investment in firms' production processes. Recognizing that production processes differ, we split the sample along three broad dimensions: (i) industry affiliation, (ii) firm size, and (iii) firm capabilities. These characteristics capture the core characteristics of the Austrian economy, which is dominated by SMEs, export activities and innovation. We use anonymized register data for Austria, which fully covers private sector firms with more than 10 employees and at least 10,000 Euros in sales. The descriptive statistics show that both the intensive and the extensive margin of investment are highly skewed and differ across sectors. The results of the estimated production functions suggest that the different components of intangible capital play different roles in firms' production processes, with notable differences across sectors. Research and development capital (R&D) is more important in manufacturing, IT and professional, scientific and technical activities. This is in line with previous evidence (Ortega-Argilés, Piva, and Vivarelli 2015) suggesting that R&D is more important in sectors where firms pursue more knowledge-intensive business models. The importance of software - on average - is equal to the importance of R&D but is observed in most sectors. Firm size is particularly important for small firms, where software and licenses are more important than R&D. The results for software are also strong for exporting firms. Industrial and innovation policies that seek to promote a broad-based growth pattern may wish to broaden their perspective to include the diffusion of software.

We make three contributions to the literature. First, we identify firm-level differences in the production process and contribute to the understanding of the firm-level determinants of productivity (Syverson 2011). We add to the empirical literature by providing an analysis of multiple firm environments. We consider not only the service sector, but also multiple firm characteristics such as export behavior. Previous analyses have either not considered these aspects due to lack of data availability or have not focused on them specifically, although they have controlled for them in the estimation (Marrocu, Paci, and Pontis 2012). Some of our findings differ from those in the previous literature. This may be due to the empirical approach chosen. We use register data, i.e., a complete survey of private sector firms. This eliminates possible survey bias that may arise from the chosen sampling strategy. We also provide input to industrial and innovation policy. In line with recent findings for Germany (Roth, Sen, and Rammer 2022) and policy work on Austria (Hölzl et al. 2019), our results suggest an innovation policy approach that does not focus exclusively on R&D, but also includes licenses and software. This implies a sectoral reorientation of support schemes towards "high-tech" sectors.

Third, these results are particularly relevant in the local context. Although highly relevant, the availability of micro data is novel for economic research in Austria. It allows us to put aggregate observations into a micro perspective.

1.1 Country background

Austria is a suitable setting for the study of the role of intangible assets. It is a small open economy with a relatively high level of aggregate productivity. In 2017, the country's GDP p.c. was USD 54,173 (PPP in constant prices, international dollar, base year 2017; World Bank data), which is among the highest in the European Union. However, aggregate productivity barely grew over the period (2008: 52 166 USD, (The World Bank 2021)).

The economy's investment dynamics are no exception to the internationally observed trend. Investment in intangible assets such as R&D and licenses grew at an annualized rate of 4.4 % between 2008 and 2017, according to national accounts data from Statistics Austria, the country's statistical authority. This rate is significantly higher than the annualized growth rate of investment in machinery and equipment, which was 2.8 %. Intangible investment increased from 33 % in 2008 to 38 % in 2017 as a share of gross fixed capital formation (intangible and tangible assets excluding buildings). In the same period, the R&D intensity of the Austrian corporate sector increased from 1.18 % to 1.5 %, corresponding to an annual growth of the ratio of 2.7 % ("Austrian Research and Technology Report" 2022, 218 Table A-2). This implies that non-R&D investment in intangible capital (e.g., software) has expanded rapidly.

The macroeconomic deepening of intangible capital has taken place against a background of asymmetric structural dynamics, as suggested by recent findings from the OECD's MultiProd project, which examines productivity patterns across countries. While the manufacturing sector has performed well over the period analyzed, the growth performance of the services sector has lagged. Moreover, in this study we rely on measures of within-firm performance. This is permissible because firm entry and exit have been found to be negligible for aggregate productivity dynamics (Peneder and Prettner 2021). It has been argued that these asymmetries are driven by asymmetric firm capabilities and technology diffusion, especially with respect to ICT (Hölzl et al. 2019).

2. A short review of the literature

By economic standards, the study of the knowledge economy has a long history. Fritz Machlup (1962) laid the foundations for modern research in his seminal work on the production and distribution of knowledge in the US. He showed, for example, that between 1959 and 1990 the proportion of the US labor force engaged in the knowledge economy increased from 11 % to 32 %. The discussion soon shifted from labor to capital inputs. Especially in recent decades, the composition of the capital stock has changed and physical investment has lost its relative importance to intangible investment (Carol Corrado, Haltiwanger, and Sichel 2005; Carol Corrado, Hulten, and Sichel 2009; C. A. Corrado and Hulten 2010; Machlup 1962).

This observation led to a surge in growth accounting studies attributing a growth-enhancing effect to intangibles, with notable differences across countries and sectors. The closer observations are to the technology frontier, the more they benefit from intangible capital (Roth, Sen, and Rammer 2022; Fukao et al. 2009; Van Ark et al. 2009; Crass, Licht, and Peters 2015). It is also worth noting that productivity is not the direct result of investing in R&D and ICT per se, but rather the result of an innovation and structural transformation process that relies on intangible capital stocks (Corrado and Hulten 2010; Haskel and Westlake 2018; Freeman and Soete 1990).

Another strand of literature, based on firm-level data, considers intangible capital as a factor of production and links it to firms' productivity levels.

Using a panel of European firms, Battisti, Belloc, and Del Gatto (2015) find that intangibles promote technology adoption and allow for more efficient use of given technologies, as reflected in higher TFP levels. Similar results have been found for the Indian software industry (De and Dutta 2007). Another study based on accounting information on intangibles has found a contribution in Italian firms using different types of production functions (Bontempi and Mairesse 2015), although there are notable differences across industries. Such heterogeneity is also found in a study on Ireland, a small open economy. The positive effect of knowledge-based capital on firm productivity is particularly pronounced in manufacturing and smaller firms (Di Ubaldo and Siedschlag 2021).

Furthermore, Roth, Sen, and Rammer (2022) use data from the German Community Innovation Survey (CIS) for the period 2006 to 2018 and find a highly significant and positive relationship between intangible capital and output. This positive effect of intangibles on firms' productivity levels is driven by non-R&D intangibles, especially software & databases, training, and advertising & marketing in both goods and services. The impact of non-R&D intangibles on firm-level productivity is stronger in services, and R&D only affects productivity in high-tech manufacturing.

Intangible investment can also explain the dispersion of profitability (Görzig and Gornig 2013) and market value (Piekkola 2016) across firms, which translates into regional productivity differentials (Dettori, Marrocu, and Paci 2012). Finally, the low level of firm-level investment in intangibles in lagging economies such as Russia (Shakina, Barajas, and Molodchik 2017) or catching-up economies such as Slovenia (Verbič and Polanec 2014) is used to explain the lower level of productivity compared to firms in advanced economies.

3. Data

Our main data source is the Structural Business Statistics (SBS) of Statistics Austria. These micro-level register data are the basis for official statistics and allow an analysis of productivity dynamics in Austria. The sample comprises firms that carry out market-oriented activities and report a turnover of at least EUR 10 000 and at least ten employees. It thus covers all larger firms, apart from micro-enterprises, whose economic size is estimated in Austria. In 2017, the dataset covered approximately 72.8 % of the total number of "persons employed" in Austria. This does not consider self-employment or non-market activities, such as the public sector. A variety of types of firms are covered. Included are public limited companies, foreign legal types of firms, charitable foundations or fund (legally defined, also under province law), sole traders (registered or unregistered), European economic interest groups, companies under civil law, cooperatives (Austrian and European), limited liability companies, limited partnerships, general partnerships, European companies (SE), other legal forms, savings banks, mutual insurance associations, and associations.

In addition, we have merged information on R&D with the micro data. R&D figures are provided by Statistic Austria ("F&E Erhebung") and are an important component of intangible investment. These data are obtained from complete primary statistical surveys of about 10,000 enterprises and institutions performing R&D in all sectors of the economy whose participation is compulsory. They include information on R&D personnel, R&D expenditure, the financing of this expenditure and the nature and direction of R&D activities. The R&D survey is based on international (EU, OECD) standards and guidelines. In particular, the use of register data differs from other approaches that use smaller, survey-based samples (Chappell and Jaffe 2018; Roth, Sen, and Rammer 2022).[1]

[1] To obtain real values, all nominal figures are deflated with producer price indices at the NACE two-digit industry level using 2010 as the reference year. NACE, the "Nomenclature générale des Activités économiques dans les Communautés Européennes", is the statisticial classification of the European Community; Revision 2). The deflators are obtained from the national accounts' statistics by Eurostat.

There is a long history of measuring knowledge and its role in economic activity (Machlup 1962; Freeman and Soete 1990), which is still ongoing and differs depending on the level of analysis (Van Criekingen, Bloch, and Eklund 2021; Martin and Baybutt 2021).

We use a firm-level definition of intangible investments at the firm-level which incorporates expenditures on computerized information, innovation and economic competencies (Corrado and Hulten 2010; Van Ark et al. 2009; Brynjolfsson and Hitt 2000; Griliches 1981). We define investment in intangible capital as (1) expenditure on internal R&D, (2) expenditure on external R&D, (3) investment in software and (4) investment in licenses.

Our approach is accountancy-based. While it provides a complete survey of the population of the Austrian corporate sector, it also has limitations. It does not explicitly take into account 'softer factors' that are typically collected in surveys such as the Community Innovation Survey (e.g., Roth, Sen, and Rammer 2022). Such aspects include organizational capital including organizational learning, structures and cultures which may be the source of firm-specific competitive advantages.

The final sample covers the period from 2008 to 2017 and consists of 20,776 enterprises for which all required data are available, of which 4,955 are in manufacturing (Section C) and 15,821 in services. The number of observations may vary due to differences in the estimation techniques used.

4. Descriptive statistics

To validate whether our firm-level data support the observed aggregate investment dynamics, we calculate the average shares of intangible investments made between 2008 and 2017. In Table 1, intangible investments are also broken down into investments in R&D, software and licenses to illustrate the average business focus in different NACE Rev. 2 industries in Austria. In our sample, tangible investments account for most investments (86 %), while R&D investments account for 7 %, licenses for 4 % and software for 3.2 %. However, the composition of investments differs considerably between industries. Overall, with 0.5 % of total investment, the lowest shares of intangible investment are found in real estate (L, 0.5 %), administrative and support service activities (N, 1.1 %) and "Accommodation and food service activities"(I, 1.7 %). The highest shares of intangible investment in total investment are found in "Professional, scientific and technical activities" (M) - almost half (48.6 %) of total investment is intangible - and in "Information and communication" (J, 41.9 %).

While "Professional, scientific and technical activities" (M) and "Manufacturing" (C) show the largest shares of investments in R&D (38.4 % and 25 % respectively), the focus in "Information and communication" (J) and "Transportation and storage" (H) lies more on licenses rather than investments in R&D (18.5 %: 9.8 % and 10.2 %: 0.1 %, respectively). Investments in software is most important in "Information and communication" (J) (13.5 %) and "Financial and insurance activities" (K) (9 %).

Table 1 about here

In a next step, we use the data to examine how many firms invest in intangibles at least once between 2008 and 2017, i.e., we focus on the extensive margin at which intangible investments are made. Second, we identify those firms that continuously invest in intangibles and provide information on the share of years in the sample in which they invest as a proxy for the regularity of investment. Third, we assume that firms that invest in intangibles also differ in their investment intensity. To analyze the intensive margin, we look at the share of intangible investment in a firm's value added.

Table 2 shows how many firms invest in intangibles at least once during the analysis period. We find that most firms do not invest in intangibles at all, which supports the findings of Arrighetti, Landini, and Lasagni (2014). Between 2008 and 2017, only 30.5 % of the firms in the sample report investing in intangibles at least once, which varies widely across the NACE Rev. 2 1-digit level sections. A higher share of investing firms is an indication that investors in intangibles are more ubiquitous. The highest proportions of firms investing in intangibles are found in "Financial and insurance activities" (K), "Information and Communication" (J), "Electricity, gas, steam and air conditioning supply" (D), and "Manufacturing" (C). The data shows fewer investors in "Accommodation and food service activities" (I) and "Administrative and support service activities" (N).

Both the frequency of firms investing in immaterial goods and the share of firms that permanently invest in immaterial goods are roughly the same as the shares of firms that invested at least in one year. However, there are notable differences in some industries. For example, 59.3 % of firms in "Financial and insurance activities" invested in intangibles at least once during the sample period. However, the frequency varies. On average, firms invest almost every second year (investments are recorded in 44.5 % of the years observed). Only 7 % of firms in this sector invest every year. A similar picture emerges for the average coverage of years with intangible investment, which serves as a proxy for the continuity of intangible investment.

The intensive margins also differ between industries. The highest mean intensities are recorded for "Professional, scientific and technical activities" (M) and "Information and communication" (J), while the intensities in "Construction" (F), "Accomodation and food service activities" (I), and "Real estate activities" (L) are almost negligible.

Table 2 about here

5. Estimating production functions

5.1 Specification and estimation methods

To uncover differences in the importance of intangible capital in production processes across industries, we estimate augmented Cobb-Douglas production functions. Recognizing the extensive and growing discussion on the estimation of total factor productivity (Ackerberg, Caves, and Frazer 2015; Levinsohn and Petrin 2003; Olley and Pakes 1996; Wooldridge 2009; Syverson 2011), we follow Kaus et al. (2021) and specify the following production function:

$$Y_{it} = LAB_{it}^{\beta l} * TANG_{it}^{\beta 2} * RD_{it}^{\beta 3} * SOFT_{it}^{\beta 4} * LIC_{it}^{\beta 5} * A_{it} \tag{1}$$

where Y is the output of firm i in year t measured as gross value added. The labor stock is denoted by L, TANG is tangible capital, and intangible capital is subdivided into research and development (RD), software (SOFT), and licenses (LIC). A is the error term and denotes the total factor productivity (TFP) of a firm. After logarithmizing the production function, we obtain the following estimation equation:

$$y_{it} = \beta_0 + \beta_l \cdot lab_{it} + \beta_2 \cdot tang_{it} + \beta_3\, rd_{it} + \beta_4\, soft_{it} + \beta_5\, lic_{it} + \omega_{it} + u_{it} \tag{2}$$

where lower-case letters denote logarithmic terms. TFP comprises of ln(A_{it})= $\beta_0 + \omega_{it} + u_{it}$. The term u_{it} is a stochastic residual. The term ω_{it} is a firm-specific productivity component which is observed by the firm yet unobserved by the econometrician. This is the source of endogeneity because firm-specific productivity is the basis for input choice. When productivity shocks occur in profit-maximizing firms, they expand their output, which in turn requires additional inputs. The productivity shock is not observed empirically but affects the choice of inputs. This leads to a simultaneity problem in the estimation of the production function, which causes a bias in ordinary least squares estimations.

There is a large literature discussing endogeneity issues in estimating production functions that attempt to resolve the correlation between unobservable productivity shocks and input levels. Several control function approaches that exploit the panel structure of the data have addressed identification issues (Ackerberg, Caves, and Frazer 2015; Rovigatti and Mollissi 2018). Cognizant of this literature, we split the sample into a broadly defined manufacturing and service sector and implemented three widely used estimators:

- We use an Olley-Pakes (OP) estimator in which we use total firm-level investment as a proxy variable (Olley and Pakes 1996).
- We implement a Levinsohn-Petrin (LP) estimator using energy, a component of intermediate goods, as a time-varying proxy for unobservable productivity (Levinsohn and Petrin 2003)
- We again use energy as a proxy variable to implement a generalized method of moments (GMM) estimator proposed by Wooldridge (2009). The two-equation system has been argued to address identification issues and lead to more efficient estimators and simple inference. To obtain accurate standard errors and test statistics, we implement the bootstrapping with 10,000 replications.

In the case of the Olley-Pakes and Levinsohn-Petrin estimators, we use a correction proposed by Ackerberg et al. (2015) that addresses possible functional dependence problems between investment or intermediate inputs and labor inputs. In all specifications, we include both year and two-digit NACE Rev. 2 dummies to control for time and industry fixed effects.[2]

[2] We do not include firm- fixed effects as this would violate the necessary monotonicity assumption of the used proxy-variable estimation approach (Ackerberg, Caves, and Frazer 2015).

5.2 Variable definitions

We explain gross value added by the firm-specific labor stock, tangible and intangible capital. In particular, the capital stock variables are not directly included in the data, so we compute proxies. The data do not include capital stock, but they do include investment, which allows us to compute a proxy for firm-specific capital stock. We compute proxies for both tangible (i.e., material or physical) and the components of intangible (i.e., immaterial) capital stocks, which we use to estimate the production function in a stepwise approach.

First, we use OECD STAN information on capital per employee at the NACE Rev. 2 2-digit level for the year 2008. Second, we multiply this industry-level capital intensity by the firm-specific employment information (number of persons employed in full-time equivalents) to obtain a firm-specific initial capital stock for our starting year 2008.

Third, we add annual investments and subtract depreciation to obtain the annual capital stock of the following years. The depreciation rates are obtained from the OECD and are allowed to vary across NACE Rev. 2 2-digit industries and by asset class (see below). We adjust the depreciation rates at the industry level of tangible and intangible capital to account for the observation that intangible capital is typically depreciated faster than physical investment (Corrado, Hulten, and Sichel 2009). Hence, we use the initial year's capital stock as described above and divide the capital stock into a tangible (s) and an intangible (1-s) part. We start with the total industry-level depreciation rate (δ)and draw on pooled information from the microdata to compute the annual average share of intangible investments in total investments, so that δ=(1-s)*0,2+s* δ_t. The depreciation rate for intangible capital is assumed to be constant at 20 %. The remainder of the depreciation rate at the industry level is then attributed to the time-varying deprecation of tangible capital (δ_t).

Thus, the following variables are included in our production function estimation: The labor stock was calculated as the number of employees in full-time equivalents, from which R&D

employees were subtracted. This is done to avoid double counting, as the cost of R&D personnel is already included in R&D expenditure, which is a component of intangible capital formation. Investments in tangible capital are defined as investments in land and buildings (including own construction) and in machinery and equipment (including transport, low-value or second-hand equipment). Capital stock is calculated as described above. Investment in R&D includes both intramural and extramural R&D expenditure. Analogous to the calculation of physical capital, we use the long-run share of R&D investment in total investment to compute the firm-specific value of the R&D capital stock in the starting year 2008. We then use R&D investments in subsequent years to compute the annual R&D capital stock of firms, assuming an annual depreciation rate of 20 %. Investments in software include the purchase of both packaged and individual software, including one-time license payments for software use. System software is not included. Investments into licenses covers concessions, copyrights, patents, licenses, trademarks and similar rights, such as utility models, land use rights and mining rights. Goodwill is not included. Again, we use the long run fraction of software investments and investments in licenses in total investments to compute the firm specific values of the software capital stock and capital stock of licenses in the starting year 2008, respectively. Next, we use the software investments and investments into licenses in subsequent years to compute the annual capital stocks of software and licenses, assuming for both stocks an annual depreciation rate of 20 %

6. Results

6.1 Production functions across sectors

We analyze different production functions for broadly defined sectors to account for differences in terms of the sectoral technology base, regulations, and demand conditions (Malerba 2002), the tradability of goods and services (Sachs and Larraine 1993), which eventually lead to different performance patterns (Peneder 2009).

We split the sample into a capital-intensive, manufacturing sector on the one hand and a service sector on the other hand. The sample split is based on the NACE classification. The capital intensive sector consists of the sections C-E (Manufacturing, Electricity, gas, steam and air conditioning supply, and Water supply; sewerage, waste management and remediation activities). The service sector consists of the sections F-N. Section S is not included due to the low number of observations.

The results show that the hierarchy of coefficients remains largely stable across specifications in both sectors. The highest coefficients are observed for labor, followed by physical capital and R&D. While the coefficients for software are not robust, the results point to a notable role of licenses in firms' production processes, especially in the services sector.

The magnitude of these coefficients is broadly consistent with evidence for Germany implementing a similar specification (Kaus, Slavtchev, and Zimmermann 2020). However, their size is substantially larger than the coefficients estimated for intangible capital in Italy (Bontempi and Mairesse 2015).

There are differences between manufacturing and services in the OL and LP estimations: the coefficients on labor are larger in manufacturing than in services, while the opposite is true for physical capital. The coefficients on R&D capital stock are comparable in the OL and LP specifications, while they are slightly higher in manufacturing in the Wooldridge estimators. The coefficients on software and licenses tend to be higher in manufacturing than in services, supporting recent results for Ireland documenting a larger effect of intangibles in manufacturing (Di Ubaldo and Siedschlag 2021).

Table 3 about here

This pattern differs from the survey-based results for Germany (Roth, Sen, and Rammer 2022). Only software, training, and advertising and marketing, which are not considered here, are reported as significant. The coefficients for R&D and licenses are reported as largely insignificant. Roth et al. (2022) base their estimates on gross output, while we use value added. However, these differences are not due to the estimation approach (see Appendix for robustness checks). It seems that either the production functions themselves or the underlying sample shape the differences. Roth et al. (2022) use rich survey data from the Mannheim Innovation Panel, while we rely on a complete survey of firms, thus eliminating a possible sampling bias.

6.2 Size, exports, and continuous innovation

Austria's firm demography is dominated by SMEs, and economic activity is generally driven by exports and innovation. Therefore, we examine the production functions of these groups separately to control for relevant dimensions of firm heterogeneity. We split the sample according to the following characteristics, which capture (see Table 4):

- Firm size
- Export activity
- Continuity of intangible investment

The approach proposed by Woodridge (2009) is our preferred method of estimating production functions, as it is more efficient than a two-stage procedure. Therefore, in the following we focus on the results based on this estimator.

<u>Firm size</u>

Firm size, which is arguably endogenous, reflects sunk costs and the growth process (Sutton 1991; 1997; Henrekson and Johansson 2010), survival probabilities, innovation and access to finance (Amorim Varum and Rocha 2012; Beck and Demirguc-Kunt 2006; Friesenbichler and Peneder 2016). To uncover the estimated coefficients by firm size, we use the means of full-time equivalents to group firms into three size categories. We compute time-invariant average employment levels across years. We define small firms as those with fewer than 50 employees, medium firms as those with between 50 and 249 employees, and large firms as those with more than 250 employees.

We find inverted U relationships for the coefficients of labor, R&D, and software. The smallest coefficients are found in small firms and the highest coefficients in medium firms. The coefficients for labor increase strongly from small firms to medium and large firms. Licenses are relevant for SMEs, while the coefficient is statistically insignificant for large firms. Unlike intangibles, tangible capital follows a U-shaped relationship, with the highest coefficient for large firms. This may indicate economies of scale.

Table 4 about here

Exporting firms

Export activity is driven by selection mechanisms, i.e., more capable or productive firms self-select into export markets. We define firms as exporters that have exported at least once in the observation period and firms that have not. Exporting firms have been associated with higher firm productivity and higher markups (Feenstra 2015; De Loecker and Warzynski 2012). Although production functions cannot explain how exporting firms achieve higher productivity or market power, it is likely that intangible capital is one of the underlying drivers.

In our sample, export information is only available for manufacturing firms, which is why the number of observations in this subsample is smaller than in the other subsamples. Most observations (86 %) in manufacturing report exports.

The coefficient of labor is higher, and the coefficient of physical capital is lower for exporting firms than for firms that focus on the domestic market. There are significant differences in intangible capital stocks. On average, non-exporting firms have a higher coefficient for R&D. This may be due to highly specialized R&D firms serving the local rather than the international market. Similar results have recently been documented for the growth patterns of firms in frontier economies (Friesenbichler and Hoelzl 2022). In contrast, exporting firms show significant effects for software and licenses, both of which are insignificant in the subsample of non-exporting firms. This pattern is broadly consistent with a recent paper for Ireland, which finds that exporters invest more in knowledge-based capital (Di Ubaldo and Siedschlag 2021).

Continuous investments into intangible capital

At the technological frontier, Austria's economy is also driven by innovation and the capabilities of firms and the degree to which innovation is embedded in their business model. More innovative firms differ from their non-innovative counterparts in their ability to optimize their operations, routine activities, administration and basic governance. This flexibility and their agility allow them to execute a given production program more efficiently (Barney 2001; Winter 2003). Their dynamic capabilities, i.e. the ability of firms to adapt to change, may also be reflected in intangible capital (Teece 2018).

To capture innovativeness, we split the sample into firms that invested in intangibles in each year of the observation period and firms that did not. Firms that invest in intangibles on a regular basis are more likely to pursue a firm strategy in which innovation and absorptive capacity are key to firm performance (Cohen and Levinthal 1990; Cassiman and Veugelers 2006; Ortega-

Argilés, Piva, and Vivarelli 2015). Overall, only 8.1 % of the firms in the sample are continuous investors.

The results indicate that labor is more, and tangible capital less important in the production function of firms that permanently invest into intangibles. Considering that innovation is mainly driven by people and not by machines, this result is also quite plausible. Within the category of intangible capital, there are notable differences in all three categories, with the coefficients being higher in the category of continuous investors in intangible capital. The differences are particularly pronounced for software and to a lesser extent for R&D expenditure.

6.3 Robustness checks and additional results

To support the findings of the previous results, we conduct several robustness checks (see Annex).

We estimate the size-class production function not only for the whole private sector, but also separately for broad manufacturing and services. The results for manufacturing show that the largest coefficients are obtained for labor and tangible goods, and that these increase with firm size. The next largest coefficients are found for software, where the highest coefficient is found for medium-sized enterprises. The coefficients for R&D are positive and significant and do not vary much across size classes. However, licenses are important for SMEs. Their coefficient becomes insignificant for large firms. The picture across size classes is different for services. Labor is the most important production input. Tangible capital, R&D and software seem to be almost equally important for small enterprises. Medium-sized enterprises have higher coefficients for R&D and software than for tangible goods and licenses. For large enterprises in services, the coefficient for tangible goods is significantly higher than that for R&D, while the coefficients for royalties and software are hardly significant.

Instead of value added we use gross output as the outcome variable (y_{it}), also include and, therefore, intermediate inputs (inter) on the LHS of the equation. This is consistent with the approach implemented by Roth et al. (2022), which leads to the following estimated equation:

$$y_{it} = \beta_0 + \beta_l \cdot \mathrm{lab}_{it} + \beta_2 \cdot \mathrm{tang}_{it} + \beta_3\ \mathrm{int}_{it} + \beta_4\ \mathrm{inter}_{it} + \omega_{it} + u_{it} \qquad (3)$$

The estimation of gross output is implemented for the size class split, for continuous and non-continuous investors in intangible assets, and for exporting firms. The results are qualitatively similar to those above.[3]

7. Conclusions

Intangibles are a central part of the transformation of advanced economies into knowledge economies (Haskel and Westlake 2018; Roth, Sen, and Rammer 2022). Evidence from aggregate data suggests that intangibles account for up to a quarter of labor productivity growth in advanced economies (Van Ark et al. 2009). Using Austrian register data, we first find a significantly low extensive margin: Only 30.5 % invest in intangible capital. Second, the intensive margin of intangible investment also varies considerably across industries. For example, R&D expenditures are concentrated in manufacturing, information and communication, and professional, scientific and technical activities. The largest investment in licenses occurs in transport and storage.

Differences across activities in the use of intangible capital suggest that intangibles play different roles in production processes. We therefore estimate firm-level production functions that explain firm-level gross value added by full-time equivalent employment and both intangible (R&D, software, and licenses) and tangible (i.e., physical) capital. We examine the

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[3] We only show the results based on Wooldridge's (2009) estimation approach since Ackerberg, Caves and Frazer (2015) recommend that their approach is only tob e used with value-added production functions, not gross output functions.

role of different types of capital in firms' production processes across (i) broadly defined sectors, (ii) size classes, (iii) export activity, and (iv) the continuity of investment in intangible capital. The uncovered coefficients indicate that, in addition to labor and physical capital, research and development is an important factor of production for firms in both the manufacturing and the service sectors. Similarly, the results for firms that continuously invest in intangibles also indicate higher effects of intangible inputs on value added or output. Thus, the results suggest that the effect of intangibles depends on the knowledge of the business model itself.

From the perspective of SME policy and export promotion, licenses and software investments can offer opportunities for technological upgrading in almost all industries and thus a broader firm base (see also Hölzl et al. 2019). This also supports the broad approach of Austria's generous R&D funding system consisting of direct and indirect funding schemes (Falk 2007). Given the rather small extensive margin of intangible investors, policy makers should focus on broadening the target firms.

Overall, this suggests an industrial policy approach that should include non-R&D intangible assets to strengthen the competitiveness of a small open economy with a strong SME base like Austria. However, it should be kept in mind that there are natural limits to the use of knowledge capital. In a highly developed economy, many, but not all, business concepts require intangible capital. The proportion of knowledge-intensive firms that can benefit from intangible capital depends on economic structures, such as the demographics and dynamics of firms.

Literature

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica* 83 (6): 2411–51. https://doi.org/10.3982/ECTA13408.

Amorim Varum, Celeste, and Vera Catarina Rocha. 2012. "The Effect of Crises on Firm Exit and the Moderating Effect of Firm Size." *Economics Letters* 114 (1): 94–97. https://doi.org/10.1016/j.econlet.2011.09.015.

Arrighetti, Alessandro, Fabio Landini, and Andrea Lasagni. 2014. "Intangible Assets and Firm Heterogeneity: Evidence from Italy." *Research Policy* 43 (1): 202–13.

"Austrian Research and Technology Report." 2022. Vienna. Forthcoming on https://www.bmvit.gv.at/en/innovation/publications/index.html.

Barney, J. B. 2001. "Resource-Based Theories of Competitive Advantage: A Ten-Year Retrospective on the Resource-Based View." *Journal of Management* 27 (6): 643–50. https://doi.org/10.1177/014920630102700602.

Battisti, Michele, Filippo Belloc, and Massimo Del Gatto. 2015. "Unbundling Technology Adoption and TFP at the Firm Level: Do Intangibles Matter?" *24* 2: 390–414.

Beck, Thorsten, and Asli Demirguc-Kunt. 2006. "Small and Medium-Size Enterprises: Access to Finance as a Growth Constraint." *Journal of Banking & Finance* 30 (11): 2931–43. https://doi.org/10.1016/j.jbankfin.2006.05.009.

Bontempi, Maria Elena, and Jacques Mairesse. 2015. "Intangible Capital and Productivity at the Firm Level: A Panel Data Assessment." *Economics of Innovation and New Technology* 24 (1–2): 22–51. https://doi.org/10.1080/10438599.2014.897859.

Brynjolfsson, Erik, and Lorin M Hitt. 2000. "Beyond Computation: Information Technology, Organizational Transformation and Business Performance." *Journal of Economic Perspectives* 14 (4): 23–48. https://doi.org/10.1257/jep.14.4.23.

Cassiman, Bruno, and Reinhilde Veugelers. 2006. "In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition." *Management Science* 52 (1): 68–82.

Chappell, Nathan, and Adam B Jaffe. 2018. "Intangible Investment and Firm Performance." *Review of Industrial Organization* 52 (4): 509–59.

Cohen, Wesley M, and Daniel A Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35 (1): 128–52.

Corrado, C., J. Haskel, C. Jona-Lasinio, and M. Iommi. 2013. "Innovation and Intangible Investment in Europe, Japan, and the United States." *Oxford Review of Economic Policy* 29 (2): 261–86. https://doi.org/10.1093/oxrep/grt017.

Corrado, Carol A, and Charles R Hulten. 2010. "How Do You Measure a 'Technological Revolution'?" *American Economic Review* 100 (2): 99–104. https://doi.org/10.1257/aer.100.2.99.

Corrado, Carol, John Haltiwanger, and Daniel Sichel. 2005. *Measuring Capital in the New Economy*. Chicago: University of Chicago Press. https://doi.org/10.7208/chicago/9780226116174.001.0001.

Corrado, Carol, Charles Hulten, and Daniel Sichel. 2009. "Intangible Capital and U.S. Economic Growth." *Review of Income and Wealth* 55 (3): 661–85. https://doi.org/10.1111/j.1475-4991.2009.00343.x.

Crass, Dirk, Georg Licht, and Bettina Peters. 2015. "Intangible Assets and Investments at the Sector Level – Empirical Evidence for Germany." *In: Bounfour, A., Miyagawa, T. (Eds) Intangibles, Market Failure and Innovation Performance.*, 57–111. https://doi.org/10.1007/978-3-319-07533-4_4.

De Loecker, Jan, and Frederic Warzynski. 2012. "Mark-Ups and Firm-Level Export Status." *American Economic Review* 102 (6): 2437–71.

De, Supriyo, and Dilip Dutta. 2007. "Impact of Intangible Capital on Productivity and Growth: Lessons from the Indian Information Technology Software Industry." *Economic Record* 83: S73–86.

Dettori, Barbara, Emanuela Marrocu, and Raffaele Paci. 2012. "Total Factor Productivity, Intangible Assets and Spatial Dependence in the European Regions." *Regional Studies* 46 (10): 1401–16.

Di Ubaldo, Mattia, and Iulia Siedschlag. 2021. "Investment in Knowledge-Based Capital and Productivity: Firm-Level Evidence from a Small Open Economy†." *Review of Income and Wealth* 67 (2): 363–93. https://doi.org/10.1111/roiw.12464.

Falk, Rahel. 2007. "Measuring the Effects of Public Support Schemes on Firms' Innovation Activities." *Research Policy* 36 (5): 665–79. https://doi.org/10.1016/j.respol.2007.01.005.

Feenstra, Robert C. 2015. *Advanced International Trade: Theory and Evidence*. Princeton university press.

Freeman, Christopher, and Luc Soete. 1990. "Information Technology, and the Global Economy." In *In The Information Society: Evolving Landscapes*, 278–94. New York: Springer.

Friesenbichler, Klaus, and Michael Peneder. 2016. "Innovation, Competition and Productivity." *Economics of Transition* 24 (3): 535–80.

Friesenbichler, Klaus S., and Werner Hoelzl. 2022. "Firm-Growth and Functional Strategic Domains: Exploratory Evidence for Differences between Frontier and Catching-up Economies." *Journal of Economics and Business* 119 (March): 106033. https://doi.org/10.1016/j.jeconbus.2021.106033.

Fukao, Kyoji, Tsutomu Miyagawa, Kentaro Mukai, Yukio Shinoda, and Konomi Tonogi. 2009. "Intangible Investment in Japan: Measurement and Contribution to Economic Growth." *Review of Income and Wealth* 55 (3): 717–36. https://doi.org/10.1111/j.1475-4991.2009.00345.x.

Görzig, Bernd, and Martin Gornig. 2013. "Intangibles, Can They Explain the Dispersion in Return Rates?" *Review of Income and Wealth* 59 (4): 648–64. https://doi.org/10.1111/j.1475-4991.2012.00525.x.

Griliches, Zvi. 1981. "Market Value, R&D, and Patents." *Economics Letters* 7 (2): 183–87.

Haskel, Jonathan, and Stian Westlake. 2018. *Capitalism without Capital: The Rise of the Intangible Economy*. Princeton University Press.

Henrekson, Magnus, and Dan Johansson. 2010. "Gazelles as Job Creators: A Survey and Interpretation of the Evidence." *Small Business Economics* 35 (2): 227–44.

Hölzl, Werner, Susanne Bärenthaler-Sieber, Julia Bock-Schappelwein, Klaus Friesenbichler, Agnes Kügler, Andreas Reinstaller, Peter Reschenhofer, Bernhard Dachs, and Martin Risak. 2019. *Digitalisation in Austria: State of Play and Reform Needs*. Luxembourg: European Union. https://ec.europa.eu/docsroom/documents/37267/attachments/1/translations/en/renditions/native.

Kaus, Wolfhard, Viktor Slavtchev, and Markus Zimmermann. 2020. "Intangible Capital and Productivity. Firm-Level Evidence from German Manufacturing." *IWH Discussion Papers* 1/2020: 53.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies* 70 (2): 317–41. https://doi.org/10.1111/1467-937X.00246.

Machlup, Fritz. 1962. *The Production and Distribution of Knowledge in the United States*. Vol. 278. Princeton university press.

Malerba, Franco. 2002. "Sectoral Systems of Innovation and Production." *Research Policy* 31 (2): 247–64.

Marrocu, Emanuela, Raffaele Paci, and Marco Pontis. 2012. "Intangible Capital and Firms Productivity." *Industrial and Corporate Change* 21 (2): 377–402. https://doi.org/10.1093/icc/dtr042.

Martin, Josh, and Cain Baybutt. 2021. "The F Words: Why Surveying Businesses about Intangibles Is so Hard." *Paper Prepared for the IARIW-ESCoE Conference*, November, 41.

Olley, G Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 94 (6): 1263–97.

Ortega-Argilés, Raquel, Mariacristina Piva, and Marco Vivarelli. 2015. "Productivity Gains from R&D Investment: Are High-Tech Sectors Still Ahead?" *Economics of Innovation and New Technology* 24 (3): 204–22. https://doi.org/10.2139/ssrn.1933332.

Peneder, Michael. 2009. *Sectoral Growth Drivers and Competitiveness in the European Union*. Office for Official Publications of the European Communities.

Peneder, Michael, and Catherine Prettner. 2021. *Entwicklung Der Produktivität Österreichischer Unternehmen von 2008 Bis 2018. Auswertung von Mikrodaten Für Österreich Im Rahmen von Multiprod 2.0*. Wien: WIFO. http://www.wifo.ac.at/wwa/pubid/67450.

Piekkola, Hannu. 2016. "Intangible Investment and Market Valuation." *Review of Income and Wealth* 62 (1): 28–51. https://doi.org/10.1111/roiw.12149.

Roth, Felix, Ali Sen, and Christian Rammer. 2022. "The Role of Intangibles in Firm-Level Productivity – Evidence from Germany." *Industry and Innovation*, October, 1–23. https://doi.org/10.1080/13662716.2022.2138280.

Rovigatti, Gabriele, and Vincenzo Mollissi. 2018. "Theory and Practice of Total-Factor Productivity Estimation: The Control Function Approach Using Stata." *The Stata Journal* 18 (3): 618–62.

Sachs, Jeffrey, and Felipe B. Larraine. 1993. "Chapter 21: Tradable and Nontradable Goods." In *Macroeconomics in the Global Economy*, 657–88. Englewood Cliffs: Prentice Hall.

Shakina, Elena, Angel Barajas, and Mariya Molodchik. 2017. "Bridging the Gap in Competitiveness of Russian Companies with Intangible Bricks." *Measuring Business Excellence* 21 (1): 86–100.

Sutton, John. 1991. *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution of Concentration*. MIT press.

———. 1997. "Gibrat's Legacy." *Journal of Economic Literature* 35 (1): 40–59.

Syverson, Chad. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49 (2): 326–65. https://doi.org/10.1257/jel.49.2.326.

Teece, David J. 2018. “Business Models and Dynamic Capabilities.” *Long Range Planning* 51 (1): 40–49.

The World Bank. 2021. “GDP per Capita, PPP (Constant 2017 International $) - Austria | Data.” 2021. https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD?locations=AT.

Van Ark, Bart, Janet X. Hao, Carol Corrado, and Charles Hulten. 2009. “Measuring Intangible Capital and Its Contribution to Economic Growth in Europe.” *EIB Papers* 14 (1): 62–93.

Van Criekingen, Kristof, Carter Bloch, and Carita Eklund. 2021. “Measuring Intangible Assets—A Review of the State of the Art.” *Journal of Economic Surveys* in press (November).

Verbič, Miroslav, and Sašo Polanec. 2014. “Innovativeness and Intangibles in Transition: The Case of Slovenia.” *Economic Research-Ekonomska Istraživanja* 27 (1): 67–85. https://doi.org/10.1080/1331677X.2014.947109.

Winter, Sidney G. 2003. “Understanding Dynamic Capabilities.” *Strategic Management Journal* 24 (10): 991–95. https://doi.org/10.1002/smj.318.

Wooldridge, Jeffrey M. 2009. “On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables.” *Economics Letters* 104 (3): 112–14. https://doi.org/10.1016/j.econlet.2009.04.026.

Tables

Table 1 Composition of investments in Austria, total and across sectors

	Section	Obs.	Licenses	R&D	Software	Tangible
Manufacturing	C	54,749	1.8%	25.0%	1.7%	71.5%
Electricity, gas, steam and air conditioning supply	D	3278	3.3%	0.6%	1.4%	94.7%
Water supply; sewerage, waste man. and remediation act.	E	4873	1.3%	0.7%	0.8%	97.2%
Construction	F	49,426	0.6%	3.0%	1.5%	95.0%
Wholesale and retail trade; rep. of motor vehicles and -cycles	G	79,765	3.2%	6.1%	2.6%	88.1%
Transportation and storage	H	18,025	10.2%	0.1%	1.3%	88.3%
Accommodation and food service activities	I	28,013	1.0%	0.0%	0.7%	98.3%
Information and communication	J	14,619	18.5%	9.8%	13.5%	58.1%
Financial and insurance activities	K	10,955	0.9%	1.0%	9.0%	89.0%
Real estate activities	L	23,340	0.4%	0.0%	0.1%	99.5%
Professional, scientific and technical activities	M	42,063	5.0%	38.4%	5.2%	51.4%
Administrative and support service activities	N	19,514	0.3%	0.1%	0.8%	98.9%
Total sample			**4%**	**7%**	**3.2%**	**86%**

Source: STAT data, own calculations.
Note: This table uses NACE Rev. 2 1-digit sections to shows the means of the sectoral investment composition. Data covers 2008 to 2017.

Table 2: Intangible investment share and ubiquity of investors at the sector level

NACE Rev. 2, 1-digit	Section	Mean int. inv. as a share of VA	Share of immaterial investors	Share of perm. int. investors	Mean coverage of years with int. inv. In %
Manufacturing	C	5.6%	44.8%	15.7%	32.6%
Electricity, gas, steam and air conditioning supply	D	2.1%	48.5%	10.6%	35.5%
Water supply; sewerage, waste man. and remediation act.	E	0.7%	29.8%	5.7%	19.1%
Construction	F	0.4%	23.6%	5.1%	15.3%
Wholesale and retail trade; rep. of motor vehicles and -cycles	G	1.3%	26.7%	6.6%	17.7%
Transportation and storage	H	4.0%	25.1%	6.0%	16.2%
Accommodation and food service activities	I	0.4%	19.7%	4.6%	11.7%
Information and communication	J	10.1%	46.5%	18.5%	37.1%
Financial and insurance activities	K	1.0%	59.3%	7.0%	44.4%
Real estate activities	L	0.6%	23.8%	2.6%	18.9%
Professional, scientific and technical activities	M	10.5%	36.3%	11.7%	28.1%
Administrative and support service activities	N	0.7%	23.9%	6.1%	16.0%
Total sample		3,4%	31,1%	8,6%	21,9%

Source: STAT data, own calculations.

Note: This table uses NACE Rev. 2 1-digit sections to shows the sectoral means of (i) intangible investments as a share of value added, (ii) the share firms that at least once invested into intangible capital, (iii) the share of firms that permanently (i.e., every year) invest in intangible capital), and the average coverage of years reported in which investments into intangible capital was made. Section "S" (Other service activities) excluded due to small sample size. Data covers 2008 to 2017.

Table 3: Cobb-Douglas production functions across sectors

	(1)	(2)	(3)	(4)	(5)	(6)
		Manufacturing			Services	
	OP	LP	WDRD	OP	LP	WDRD
Labor	0.85**	0.84**	0.64**	0.72**	0.71**	0.63**
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.003)
Tangible Capital	0.11**	0.10**	0.13**	0.14**	0.13**	0.13**
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.005)
R&D	0.04**	0.03**	0.13**	0.04**	0.03**	0.16**
	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.011)
Software	0.00**	-0.01**	0.17**	-0.00**	-0.01**	0.14**
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.007)
Licenses	0.01**	-0.00**	0.08**	0.02**	0.01**	0.06**
	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.007)
Industry fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	40,285	40,285	34,575	124,128	116,804	98,780
Number of groups	4,955	4,955	4,955	15,821	14,976	14,976

Source: STAT; own calculations.
Note: This table shows the production functions estimated separately at the sectoral level across different estimation methods: Levinsohn-Petrin (LP), Olley-Pakes (OP), and the Wooldridge (WDRD) approach. The manufacturing sector is defined widely, including the capital intensive sections C-E. The service sector includes the sections F-N (Section L "Real estate activities" is excluded). Data covers 2008 to 2017. Standard errors in parentheses. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 4: Cobb-Douglas production functions across firm size classes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Small	Medium	Large	No Export	Export	No Continuous investor	Continuous investor
Labor	0.54**	0.80**	0.76**	0.62**	0.76**	0.64**	0.70**
	(0.003)	(0.006)	(0.010)	(0.023)	(0.006)	(0.003)	(0.007)
Tangible Capital	0.15**	0.10**	0.25**	0.33**	0.20**	0.15**	0.07**
	(0.005)	(0.009)	(0.029)	(0.067)	(0.015)	(0.005)	(0.011)
R&D	0.13**	0.16**	0.13**	0.26*	0.12**	0.13**	0.18**
	(0.012)	(0.011)	(0.016)	(0.118)	(0.011)	(0.009)	(0.015)
Software	0.12**	0.19**	0.10**	0.05	0.15**	0.12**	0.27**
	(0.007)	(0.013)	(0.025)	(0.047)	(0.014)	(0.007)	(0.021)
Licenses	0.06**	0.06**	0.01	0.05	0.06**	0.06**	0.08**
	(0.007)	(0.010)	(0.017)	(0.065)	(0.011)	(0.006)	(0.014)
Year effects	Y	Y	Y	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y	Y	Y	Y
Observations	96,062	30,256	7,252	2,298	28,521	119,109	14,461
Number of groups	14,882	3,899	894	617	3,829	16,945	2,730

Source: STAT; own calculations.

Note: This table shows the production functions estimations across firm size classes. Small firms are firms which across their active years employed fewer than 50 people in full time equivalents, medium sized firms between 50 and 249, and large firms more than 250. Exporting firms are defined as firms that at least once report export activities in the observation period. Steady investors are defined as firms that invest into intangible capital in each year of the observation period. Section L "Real estate activities" is excluded. Data covers 2008 to 2017. Standard errors in parentheses. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Annex

Table 5: Cobb-Douglas production functions across firm size classes and broadly defined sector affiliation, value added based

	(1)	(2)	(3)	(4)	(5)	(6)
		Manufacturing			Services	
	Small	Medium	Large	Small	Medium	Large
Labor	0.52**	0.78**	0.84**	0.55**	0.81**	0.73**
	(0.007)	(0.012)	(0.017)	(0.004)	(0.008)	(0.013)
Tangible Capital	0.12**	0.17**	0.22**	0.15**	0.09**	0.32**
	(0.015)	(0.023)	(0.039)	(0.006)	(0.010)	(0.042)
R&D	0.09**	0.11**	0.10**	0.14**	0.18**	0.08*
	(0.022)	(0.015)	(0.020)	(0.015)	(0.017)	(0.034)
Software	0.12**	0.23**	0.17**	0.12**	0.17**	0.06+
	(0.017)	(0.025)	(0.042)	(0.008)	(0.016)	(0.033)
Licenses	0.07**	0.08**	0.03	0.06**	0.05**	-0.04+
	(0.017)	(0.017)	(0.024)	(0.008)	(0.013)	(0.024)
Year effects	Y	Y	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y	Y	Y
Observations	19,854	10,890	3,831	76,069	19,307	3,404
Number of groups	3,041	1,442	472	12,007	2,529	440

Source: STAT; own calculations.
Note: This table shows the production functions estimations across firm size classes. Small firms are firms which across their active years employed fewer than 50 people in full time equivalents, medium sized firms between 50 and 249, and large firms more than 250. Section L "Real estate activities" is not considered. Data covers 2008 to 2017. Standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1

Table 6: Cobb-Douglas production functions across estimation methods and broadly defined sectors, gross output based

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Services	Man.	Total	Services	Man.	Total	Services	Man.
VARIABLES	OP	OP	OP	LP	LP	LP	WDRG	WDRD	WDRD
Labor	0.19**	0.19**	0.19**	0.20**	0.21**	0.20**	0.20**	0.20**	0.20**
	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.009)	(0.001)	(0.002)	(0.002)
Intermediates	0.70**	0.69**	0.73**	0.70**	0.69**	0.73**	0.71**	0.70**	0.73**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)
Tangible capital	0.03**	0.03+	0.04**	0.03**	0.04**	0.02**	0.03**	0.03**	0.01*
	(0.006)	(0.015)	(0.006)	(0.004)	(0.008)	(0.001)	(0.002)	(0.003)	(0.005)
R&D	0.03*	0.02	0.00	0.03**	0.01	0.02**	0.03**	0.03**	0.03**
	(0.012)	(0.019)	(0.006)	(0.005)	(0.007)	(0.002)	(0.005)	(0.007)	(0.004)
Software	0.04**	0.03*	0.02**	0.02*	0.01	0.01**	0.04**	0.04**	0.03**
	(0.014)	(0.014)	(0.005)	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
Licenses	0.03**	0.02**	0.00+	0.02**	0.01	0.01**	0.02**	0.02**	0.01*
	(0.005)	(0.006)	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	171,478	130,822	40,656	164,092	123,436	40,656	140,484	105,093	35,119
Number of groups	21,132	16,482	4,965	20,288	15,637	4,965	20,288	15,637	4,965

Source: STAT; own calculations.
Note: This table shows the production functions estimations using the Levinsohn-Petrin (LP), Olley-Pakes (OP), and the Wooldridge (WDRD) approach. The estimations are implemented for the entire sample, the broadly defined service, and the broadly defined manufacturing sector. Section L "Real estate activities" is considered, which does not qualitatively alter the results. Data covers 2008 to 2017. Standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1

Table 7: Cobb-Douglas production functions across firm size classes and broadly defined sector affiliation, gross output based

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Total			Manufacturing			Services	
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Labor	0.15**	0.24**	0.25**	0.16**	0.23**	0.26**	0.14**	0.26**	0.26**
	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)	(0.007)	(0.002)	(0.005)	(0.011)
Intermediates	0.71**	0.70**	0.64**	0.72**	0.73**	0.73**	0.71**	0.67**	0.57**
	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.007)
Tangible capital	0.03**	0.00	0.02	0.00	0.03**	0.05**	0.04**	0.00	-0.00
	(0.003)	(0.006)	(0.016)	(0.006)	(0.009)	(0.015)	(0.003)	(0.007)	(0.028)
R&D	0.02*	0.04**	0.05**	0.02**	0.02**	0.03**	0.01	0.04**	0.02
	(0.007)	(0.007)	(0.010)	(0.009)	(0.006)	(0.007)	(0.009)	(0.012)	(0.025)
Software	0.04**	0.04**	0.01	0.03**	0.05**	0.02	0.05**	0.03**	0.03
	(0.004)	(0.009)	(0.014)	(0.007)	(0.010)	(0.016)	(0.005)	(0.011)	(0.024)
Licenses	0.02**	0.01	-0.01	0.02*	0.01	-0.01	0.03**	0.00	-0.00
	(0.004)	(0.007)	(0.011)	(0.007)	(0.007)	(0.009)	(0.005)	(0.009)	(0.020)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	101,866	31,235	7,383	20,199	11,061	3,859	81,490	20,100	3,503
Number of groups	15,460	3,935	893	3,067	1,431	467	12,600	2,589	448

Source: STAT; own calculations.
Note: This table shows the production functions estimations using the Wooldridge (2009) approach across firm size classes. Small firms are firms which employed fewer than 50 people in full time equivalents across their active years, medium sized firms between 50 and 249, and large firms more than 250. Section L "Real estate activities" is not considered. Data covers 2008 to 2017. Standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1

Table 8: Cobb-Douglas production functions across firm size classes and broadly defined sector affiliation, gross output based

	(1) No cont. investor	(2) Cont. investor	(3) No export	(4) Export
Labor	0.20**	0.18**	0.29**	0.22**
	(0.001)	(0.005)	(0.012)	(0.002)
Intermediates	0.71**	0.72**	0.58**	0.72**
	(0.001)	(0.003)	(0.006)	(0.001)
Tangible capital	0.03**	0.01	0.05	0.05**
	(0.003)	(0.007)	(0.034)	(0.006)
R&D	0.03**	0.03**	0.14*	0.02**
	(0.005)	(0.010)	(0.060)	(0.004)
Software	0.03**	0.10**	0.02	0.03**
	(0.004)	(0.014)	(0.024)	(0.005)
Licenses	0.02**	0.03**	0.02	0.00
Year effects	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y
Observations	125,574	14,910	2,326	28,942
Number of groups	17,539	2,749	617	3,835

Source: STAT; own calculations.
Note: This table shows the production functions estimations using the Wooldridge (2009) approach across exporting and investment behavior. Exporting firms are defined as firms that at least once report export activities in the observation period. Steady investors are defined as firms that invest into intangible capital in each year of the observation period. Section L "Real estate activities" is not considered. Data covers 2008 to 2017. Standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1