WIFO ■ WORKING PAPERS
711/2025

Short and Medium-term Effects of Intangible Capital on Firm Growth

Firm Level Evidence from Austrian Microdata

Klaus Friesenbichler
Agnes Kügler

Short and Medium-term Effects of Intangible Capital on Firm Growth

Firm Level Evidence from Austrian Microdata

Klaus Friesenbichler, Agnes Kügler

WIFO Working Papers 711/2025
September 2025

Abstract

We study the short- and medium-term extensive and intensive margins of intangible investments in firm growth processes. The intensive and extensive margins of investment are both highly skewed and differ across sectors. Less productive firms are less likely to invest in intangibles, while incorporated firms are more likely to do so. Intangible capital only complements physical capital for a limited number of firms. Intangible investment is positively associated with short-term productivity growth, particularly among firms that consistently invest over time. The medium-term effects on productivity are limited and are largely confined to top-performing firms. We find systematic short-term effects of intangible investment on employment growth. Regular investment patterns correlate with higher employment growth over both time horizons. These results challenge the conventional assumption that intangible capital uniformly enhances firm performance. They also highlight the importance of sustained investment behavior and sectoral context.

E-Mail: klaus.friesenbichler@wifo.ac.at, agnes.kuegler@wifo.ac.at

2025/1/W/1918

Media owner (publisher), producer: Austrian Institute of Economic Research
1030 Vienna, Arsenal, Objekt 20 | Tel. (43 1) 798 26 01 0 | https://www.wifo.ac.at
Place of publishing and production: Vienna

Short and Medium-Term Effects of Intangible Capital on Firm Growth. Firm-level evidence from Austrian microdata*

This is a draft version. The final version will be published in a forthcoming issue of Empirica.

Klaus S. Friesenbichler† Agnes Kügler‡

Abstract

We study the short- and medium-term extensive and intensive margins of intangible investments in firm growth processes. The intensive and extensive margins of investment are both highly skewed and differ across sectors. Less productive firms are less likely to invest in intangibles, while incorporated firms are more likely to do so. Intangible capital only complements physical capital for a limited number of firms. Intangible investment is positively associated with short-term productivity growth, particularly among firms that consistently invest over time. The medium-term effects on productivity are limited and are largely confined to top-performing firms. We find systematic short-term effects of intangible investment on employment growth. Regular investment patterns correlate with higher employment growth over both time horizons. These results challenge the conventional assumption that intangible capital uniformly enhances firm performance. They also highlight the importance of sustained investment behavior and sectoral context.

JEL Classifications: D22, D24, D25

Keywords: intangible capital, employment, productivity, lumpy investment, firm growth, sample selection

---

* For valuable comments we thank Werner Hölzl, Andreas Reinstaller and Michael Peneder. The text was refined using AI to enhance its language. We gratefully acknowledge support by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 822781 GROWINPRO – Growth Welfare Innovation Productivity.

†† Affiliation I: Austrian Institute of Economic Research (WIFO), Arsenal Objekt 20, 1030 Vienna, Austria; Tel.: +43 1 798 26 01 296; Fax: +43 1 798 93 86; Klaus.Friesenbichler@wifo.ac.at.

Affiliation II: Supply Chain Intelligence Institute Austria (ASCII), Metternichgasse 8, 1030 Vienna, Austria

‡ Austrian Institute of Economic Research (WIFO), Arsenal Objekt 20, 1030 Vienna, Austria; Agnes.Kuegler@wifo.ac.at

Short and Medium-Term Effects of Intangible Capital on Firm Growth. Evidence from Austrian Microdata

1. Introduction

Intangible assets, such as research and development (R&D), software, and licenses, have become a defining feature of modern production systems. Their role in shaping firm performance and driving aggregate productivity is well acknowledged. However, the firm-level dynamics of intangible investment remain heterogeneous and are still insufficiently understood, particularly in small open economies lacking superstar firms.

This paper examines how intangible capital affects two distinct dimensions of firm performance: productivity growth, measured through labour productivity, and firm growth, proxied by changes in employment. This distinction is critical. Productivity growth captures improvements in the efficiency of input use, while employment growth reflects firm expansion and changes in scale. Both outcomes matter economically and politically, but they may respond differently to intangible investments, particularly over different time horizons (Corrado et al. 2013; Haskel and Westlake 2018; Roth et al. 2023; Syverson 2017; De Ridder 2024). Two empirical patterns motivate our analysis. First, sluggish aggregate productivity growth in many advanced economies has coincided with rising investments in intangible assets - a paradox that raises questions about the diffusion and effectiveness of such investments . Second, firm performance is increasingly driven by a small subset of firms, suggesting that intangible capital may contribute to divergence rather than convergence (Bloch et al., 2023; Crouzet & Eberly, 2021; Mouel & Schiersch, 2024; Roth et al., 2023).

We analyse the relationship between intangible capital and both productivity and employment growth using register data from Austrian firms between 2012 and 2017. We distinguish between the extensive margin (whether firms invest in intangibles at all) and the intensive margin (how much and how regularly they invest), assessing the effects in the short and medium term. Austria is a particularly relevant case study because, as a small open economy without dominant 'superstar' firms, it provides a representative context for evaluating the diffusion rather than the concentration of intangibles.

Our contribution to the existing literature on intangibles and productivity growth is multi-faceted.

First, make several conceptual contributions. We trace short- and medium-term effects, thereby capturing both adjustment dynamics and persistent growth patterns. We build on the observation that intangible capital often entails implementation lags, transitional costs, and temporal heterogeneity in its returns (Pozzi and Schivardi 2016; Hall et al. 2013). We distinguish between the extensive and intensive margins of intangible investment. This allows us to disentangle whether performance effects are driven by the decision to invest at all, or by the scale and persistence of investment once initiated. By focusing on both productivity and employment growth, we offer a broader understanding of how intangibles shape firm trajectories. Second, we address methodological concerns of endogeneity and sample bias and explicitly model selection into intangible investment in our empirical approach. Third, we contribute to a still limited but growing body of work focusing on small open economies, where intangible capital may play a different role than in countries dominated by superstar firms. By studying Austria, an economy without pronounced market concentration or ‘digital giants’, we offer insights into how intangible investments affect a broad population of firms in a non-concentrated, institutionally distinct context.

2. Intangible Capital and Firm Performance

Intangible capital has become a core feature of production and innovation in advanced economies. Assets such as R&D, software, design, and organisational competencies are now widely recognised as key determinants of firm competitiveness and economic dynamism (Corrado et al. 2013; Haskel and Westlake 2018). Yet, the underlying mechanisms for firm performance, particularly the time profile and interaction with different dimensions of firm growth, are complex and context-dependent. This section reviews the relevant literature on how intangible capital affects productivity and employment dynamics, and derives testable hypotheses based on theoretical considerations and empirical evidence.

2.1 Stylised Facts and Conceptual Underpinnings

The rise of intangible capital has transformed production structures across advanced economies. Aggregate figures show rising intangible intensity in national investment profiles, yet firm-level evidence points to a highly skewed distribution: only a subset of firms invests regularly or heavily in such assets (Mouel & Schiersch, 2024). Three stylised facts are particularly relevant. First, intangible investments are not evenly distributed across the business sector but are concentrated among certain firms and industries (Kaus et al., 2024; Tambe et al., 2020). Second, intangible investment tends to be lumpy, i.e. firms often invest irregularly (Kaus et al., 2024). Third, firms engaging in intangible investments are often larger, incorporated, or located closer to the productivity frontier (Roth et al. 2023; Friesenbichler et al. 2024). This suggests that both firm characteristics and strategic orientation influence the propensity and intensity of intangible investment.

Conceptually, intangible capital can affect firm performance through multiple channels. It may enhance the productivity of existing inputs by enabling better coordination, improving product quality, or facilitating innovation. At the same time, it may induce organisational restructuring or enable firms to scale up operations, thereby affecting employment dynamics. These mechanisms may unfold at different speeds and intensities, with short-term adjustment costs giving way to longer-term performance gains (Pozzi & Schivardi, 2016).

The broader economic context also matters. The nature and function of intangible capital likely differ by country context. In economies such as the United States, intangibles are often linked to the emergence of superstar firms and market concentration (Autor et al. 2020; De Loecker et al. 2020). In contrast, in smaller open economies like Austria, intangibles may play a more diffusive and incremental role (Bloch et al., 2023; Di Ubaldo & Siedschlag, 2021). Rather than being a tool for rent extraction, intangible capital in such settings acts as a potential enabler of broad-based performance improvements, though, often with delayed effects.

These theoretical and empirical insights provide the foundation for analysing how intangible investments relate to two key dimensions of firm performance: labour productivity and employment growth.

2.2 Intangible Capital and Productivity Growth

Productivity growth is widely viewed as a key channel through which intangible capital enhances firm performance. Unlike productivity levels, which reflect cross-sectional performance gaps, productivity growth captures dynamic efficiency improvements and technological adaptation over time. This distinction is particularly relevant for assessing the role of intangibles, given their complex and potentially lagged effects on firm operations.

A growing literature emphasises that intangible investments may not immediately translate into higher productivity (Castelli et al., 2024). The implementation of new organisational structures, digital systems, or innovation capabilities often requires firm-specific adjustment processes, which may temporarily disrupt operations or entail learning costs (Brynjolfsson et al., 2021; Chappell & Jaffe, 2018). Consequently, the short-run impact of intangibles on productivity growth may be negligible or even negative.

Over the medium term, however, intangible capital can enable firms to improve input coordination, reduce inefficiencies, and scale innovative outputs. These mechanisms are consistent with findings that productivity gains from intangible capital tend to materialise with delay and are stronger in firms that complement these investments with other strategic assets, such as skilled labour or digital readiness (Gozen & Ozkara, 2024; Marrocu et al., 2012; Roth et al., 2023).

Based on this reasoning, we propose the following hypotheses:

H1a**:** Productivity growth is not significantly associated with intangible investment in the short term.

H1b**:** Productivity growth is positively associated with intangible investment in the medium term.

These hypotheses reflect the expectation that adjustment costs and implementation frictions may mask the productivity-enhancing effects of intangibles in the short run, while longer time horizons allow these investments to unfold their full potential.

2.3 Intangible Capital and Employment Growth

The impact of intangible capital on employment growth is theoretically ambiguous and empirically contested. On the one hand, intangible investments, particularly those related to product innovation, digital capabilities, or organisational development, can support firm expansion, stimulate market entry, and increase the demand for skilled labour (Coad & Rao, 2008; DeStefano et al., 2023). On the other hand, some intangibles may be labour-saving or facilitate automation, especially when embedded in software or process innovations, potentially reducing employment over time. However, existing evidence does not support a labour-substituting effect of ICT at the firm level (Biagi and Falk 2017).

Short-run dynamics are often shaped by implementation demands and transitional restructuring. Firms investing in new systems or innovation capabilities may initially require additional labour, for instance to s to manage projects, integrate IT systems, or transfer knowledge efficiently (Hall et al. 2013; Demirkan et al. 2022; Capozza and Divella 2019). Moreover, firms investing in intangibles are frequently in a growth phase, during which employment and output increase in parallel (Corrado et al. 2018; Yang et al. 2018).

In contrast, medium-term effects may differ. As intangible investments mature and integration is completed, firms may realise productivity gains that reduce labour demand per unit of output, especially if intangibles replace routine tasks or support more scalable business models (Autor et al. 2020; Autor and Dorn 2013; Frey and Osborne 2017). This can be particularly relevant in service industries or digital-intensive sectors, where intangible capital often complements technology-driven substitution effects.

Empirical findings reflect this ambiguity. Some studies document positive employment effects of innovation and intangible investment (Harrison et al., 2014), while others find no impact or even negative effects, especially in routine-intensive jobs (Evangelista & Savona, 2003). Sectoral and temporal heterogeneity, as well as the type and intensity of intangible investment, appear to mediate these outcomes.

We therefore expect the relationship between intangible investment and employment growth to be time-sensitive and potentially non-monotonic:

H2a: Employment growth is positively associated with intangible investment in the short term.

H2b: Employment growth is negatively associated with intangible investment in the medium term.

These hypotheses reflect the idea that intangibles may initially support firm expansion and job creation, but could lead to rationalisation or labour-saving reorganisation in the longer run.

3. Intangible Investments in Austria

9We use Austria as a case study to examine the effects of intangible capital in advanced, small, open economies. The findings are therefore not confined to the national context but are likely to hold broader relevance for similar institutional and structural environments (Kügler et al., 2023). Austria provides a particularly suitable setting for testing our hypotheses: it is a developed economy where intangible capital plays an increasingly important role, yet it lacks dominant superstar firms and features a diversified, SME-driven business structure.

National accounts data from Statistics Austria show that investments in intangible assets, such as R&D and licenses, grew at an annualised rate of 4.4% between 2008 and 2017. This growth rate substantially outpaced investment in machinery and equipment, which increased by 2.8% per year over the same period. The share of intangible assets in gross capital formation (excluding buildings) rose from 33% in 2008 to 38% in 2017, underscoring a structural shift toward knowledge-based assets.

This trend has unfolded against a backdrop of asymmetric structural dynamics, as highlighted by recent OECD analyses of productivity growth. While Austria's manufacturing sector recovered relatively strongly from the global financial crisis in 2008/09, many service industries have continued to lag in terms of performance (Peneder & Prettner, 2021). Firm entry and exit have played only a marginal role in aggregate productivity dynamics. Instead, performance is shaped primarily by stable firm-specific characteristics, especially in a business landscape dominated by small and medium-sized enterprises (SMEs), with a few globally competitive niche firms at the frontier. In this context, intangible capital in Austria is better understood as a production enabler rather than a source of market power. Unlike in economies characterised by 'digital champions' or large-scale 'superstar firms' (Crouzet et al., 2022; Crouzet & Eberly, 2021), intangibles in Austria tend to support incremental productivity improvements and organisational adaptation. As such, they provide a valuable lens for understanding the diffusion and impact of intangible investments in non-concentrated, open market environments (K. Friesenbichler et al., 2025).

4. Data and Indicators

Our main data source is the "Structural Business Statistics" ("Leistungs- und Strukturerhebung") of Statistics Austria. These establishment-level, registry data are the basis for official statistics and allows for a productivity dynamics analysis in Austria.[1] The sampling includes enterprises conducting market-based activities and report a sales revenue of at least 10,000 Euros and a minimum of ten employees. In 2017, the dataset covered approximately 72.8% of the total "persons employed" in Austria. This does not consider self-employment or non-market activities such as the public sector. A multitude of types of firms are considered. Included are public limited companies, foreign legal types of firms, charitable foundations or funds (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. Approximately 18% of the firms in the sample are incorporated, meaning they have limited liability (see Annex for more descriptive statistics). Structural Business Statistics are a viable

[1] Offical datasets are also less exposed to survey bias (K. S. Friesenbichler et al., 2014, 2018; Warner, 1965).

source for studying firm growth dynamics and have previously been applied to firm growth questions (Falk, 2014) and production function estimations (K. Friesenbichler et al., 2025).

In addition, we merged information on R&D to the micro data. R&D figures were provided by Statistic Austria ("F&E Erhebung"), and are a crucial component of intangible investments. This data is obtained from full primary statistical surveys among approximately 10,000 institutions that conduct R&D in all sectors of the national economy whose participation is compulsory. This dataset effectively covers all entities engaged in R&D activities in Austria. The data comprise information on persons employed in R&D, expenditure on R&D, the financing of said expenditure, and the nature and orientation 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 & Jaffe, 2018; Roth et al., 2023).

To obtain real values, all nominal figures are deflated with producer price indices at the NACE Rev. 2 2-digit 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. The deflators are obtained from the national accounts' statistics by Eurostat.

4.1 Intangible Investments

There is a long debate about the adequate measurement of knowledge and its role in economic performance (Freeman & Soete, 1990; Machlup, 1962; Sichel, 2024), which is still ongoing and differs by the level of analysis (Martin & Baybutt, 2021; Van Criekingen et al., 2021). We apply a 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; Iqbal et al. 2021).

We define investments into intangible capital as (i) expenditures for internal R&D, (ii) expenditures for external R&D, (iii) investments into software, which includes the purchase of both packaged and individual software, including one-off licence payments for software use, (iv) investments into licenses, which includes concessions, copyrights, patents, licences, trademarks and similar rights, such as utility models, land use and mining rights (K. Friesenbichler et al., 2025). Goodwill is not included.

Our approach is accountancy-based. It provides a complete survey of the population of the Austrian corporate sector, but also has limitations. Especially, it does not explicitly take into account ‘softer factors’ that are typically collected in surveys such as the Community Innovation Survey (e.g. in Roth, Sen and Rammer (2023)). These aspects include organisational capital, like training, advertising and marketing activities, organisational learning, structures and cultures, which may be the source of firm-specific competitive advantages (Bloch et al., 2023). The inclusion of these factors could potentially affect the sample of enterprises active in intangible capital. Thus, depending on the definition of intangible capital used, either a higher proportion of firms could be identified as having intangible capital, since a larger number of firms invest in training and similar initiatives, but not necessarily in R&D. Alternatively, the treatment group would be smaller if the definition of intangible capital required investment in both R&D and other "soft" measures at the same time.

The original sample covers the period 2008 to 2017. However, our analysis requires the estimation of capital stocks, which draws on a proxy of initial capital, depreciation rates, and firm-specific investments that accumulate over time (see Annex for a detailed variable description). The longer this process takes the lower the possible bias of the capital stock estimates becomes. Hence, we restrict the period analyzed to the five years between 2012 to 2017. The subsample used consists of 21,225 firms, of which 4,217 are assigned to manufacturing and 17,007 to the service sector. The number of observations may slightly vary in the subsequent analyses due to differences in the data availability.

We validate the data by computing the shares of intangible investments in total investments. The investment dynamics broadly conform to the macroeconomic intangible capital deepening. In 2012, the (unweighted) mean of intangible investments as a share of total investments amounted to 5.8% and rose to 9.8% by 2017. The (unweighted) annual mean growth rate of intangible capital is 1.8% in real terms.

4.2 Labour Productivity Growth

The first measure of firm performance is labour productivity, defined as gross value added per full-time employee. This indicator can be linked to a canonical Cobb-Douglas production function (Syverson, 2011) which is augmented with intangible capital (Griliches, 1979, 2007). This approach has previously been employed in the analysis of intangible capital as a production factor (K. Friesenbichler et al., 2025; Roth et al., 2023), from which labour productivity growth can easily be derived (Di Ubaldo & Siedschlag, 2021).

4.3 Employment Growth

Another indicator used is employment growth, defined as the logarithmic change of firm specific employment from one year to another. Employment is a production factor and a measure of firm size. Hence, these regressions do not capture increases in efficiency performance, but in firm growth (Daunfeldt et al., 2014; Delmar et al., 2003; K. Friesenbichler & Hölzl, 2020; K. S. Friesenbichler & Hoelzl, 2022; Hölzl, 2013).

5. Descriptive Statistics

5.1 Extensive and Intensive Investment Margins

Descriptive statistics of intangible show a great degree of firm and sector heterogeneity. These can be categorized into two dimensions (Table 1):

- The extensive margin to which intangible investments are made. In other words, we ask how many firms invest into intangibles at least once.
    - We further split this group into firms that invest continuously (i.e. every year) into intangibles and provide information about the share of years in the sample in which they invest.
- Firms that invest in intangibles also differ by investment intensities, i.e. the intensive margin.

We find that most firms do not invest in intangible capital. A total of 31.1% of the firms in the sample report intangible investments after 2012, which differs vastly across Nace Rev. 2 one-digit level sectors. A higher share of investing firms indicates that intangible investors are more ubiquitous. The highest fractions of firms investing into intangibles are found in in "Financial and insurance activities" (K), Information and Communication (J), Electricity (D), and Manufacturing (C). The data shows fewer investors in Accommodation and food service activities (I) and Administrative and support service activities (N).

A lower frequency indicator suggests that investment tends to be lumpy, meaning it is concentrated over time (Cooper & Haltiwanger, 2006; Doms & Dunne, 1998). The frequency of firms investing in intangibles and the share of firms with sustained investment patterns largely mirror the proportion of firms that have invested in at least one year. However, notable sectoral differences emerge. For instance, in the `Financial and insurance activities´ sector, 59.3% of firms have invested in intangible capital at least once. On average, these firms invest in roughly every second year (44.5% of the observed years). In contrast, only 20% of firms in `Accommodation and food service´ activities have invested in intangibles, and their investment behaviour is even more sporadic, with intangible assets reported in only 11.7% of the observed years on average. Across all sectors, firms that invest continuously in intangible capital represent a clear minority. Even in `Financial and insurance activities´, the most investment-active sector, only about 7% of firms report intangible investment in every year, a pattern that is broadly representative of other industries.

Table 1 about here

The intensive margins also differ across sectors. The highest mean intensities are recorded for Professional, scientific and technical activities (M) and Information and communication (J), while the intensities in Construction (F), Administrative and support service activities (N) or Water supply (E) are almost negligible.

5.2 Successful and Unsuccessful Up- and Downsizers

We next explore how employment and labour productivity growth are related, and how intangible investments have developed. We follow Baily, Bartelsman, and Haltiwanger (1996) and use median employment growth rates in the medium-term to broadly bin firms into two categories: upsizers and downsizers. We then split the sample into firms that outperform the market and exhibit a productivity growth above the sample median, and into firms that do not. This leads to four quadrants: (1) successful upsizers, (2) unsuccessful upsizers, (3) successful downsizers, and (4) unsuccessful downsizers (see Table 2).

Table 2 about here

The picture obtained shows that the number of firms are rather equally distributed across the extremes. Both successful upsizers and unsuccessful downsizers make for 21% of the sample. With 29% each, the segments of successful downsizers and unsuccessful upsizers are also equally distributed. In all categories, the mean shares of intangible investments in total investments have increased, with downsizing firms showing larger starting values and larger rises in absolute percentage points. The intangible capital stock has increased in upsizing firms and decreased in downsizing firms, though. This indicates a positive relationship between employment growth and intangible capital stocks.[2]

The sample can be used to compute the contribution of each category to aggregate developments within the private sector. We use information on growth rates provided in Table 2, which we jointly interpret with the number of observations, the mean firm size and labour productivity levels. Both aggregate labour productivity (approximately 49m Euros) and employment (approximately 38k) have increased in absolute terms in the period observed. These figures show net effects, i.e., the difference between firms increasing and decreasing productivity or employment.

Successful downsizers pose the biggest contribution to aggregate labour productivity growth. This group accounts for three times the net effect, while successful upsizers account for twice the net effect. The biggest growth dampening effect is observed in the group of the unsuccessful upsizers. Their aggregate productivity reductions account for 2.5 times of the net productivity gains. Unsuccessful downsizers account for productivity losses amounting to 1.5 of the net productivity gains.

[2] We also implement this illustration with total factor productivity growth instead of labour productivity growth. The picture obtained remains qualitatively unchanged,

The biggest positive contributor to aggregate employment growth is the group of unsuccessful upsizers whose absolute contribution amounts to 1.4 times the net effect. The increase in labour in successfully upsizing firms amounts to the aggregate net effect. The employment reduction attributed to successful downsizers amounts to approximately 80% of the net effect. Unsuccessful downsizers made for 50%.

6. Regression Analysis

6.1 Estimation Strategy

We draw on three estimation approaches: (i) panel estimations to study the average effect of intangibles on all firms, (ii) a Heckman estimator controls for sample selection related to the propensity to invest in intangible capital which particularly affects productivity growth (the first stage results are presented in the Annex). Finally, we depart from the yearly panel data representation and concentrate on the structural change in the medium term. We employ (iii) quantile regressions to investigate the nonlinear effects across the growth distribution.[3]

(i) Panel Estimations

We implement a panel regression model to estimate the short-term effects of intangible investment on firm performance growth, with $\Delta\ln(Y_{ijt})$ indicating logarithmic growth rates of labour productivity and firm size:

$$\Delta\ln(Y_{ijt}) = \beta_0 + \beta_1(INV_{ij}) + \beta_2(PERM_{ij}) + \beta_3(Z_{ijt}) + \mu_j + \mu_t + u_{ijt}. \tag{4}$$

[3] The distribution of firm size typically follows a power law (Bacilieri et al., 2023; Segarra & Teruel, 2012). Weighted regressions would be dominated by a few large firms, which is why unweighted data was used instead.

INV is a time invariant binary variable taking on the value of one if a company has at least once invested into intangible capital during the period of observation and zero otherwise. The variable PERM equals one if a firm invests in intangibles every year of the sample and zero otherwise. The variable is employed for the identification of high-frequency investors and constitutes a subset of INV. Thus, this specification explores only behavioural (i.e. binary) variables, and does not consider investments into intangibles in absolute terms.

Z denotes a set of control variables at the firm level, specifically the lagged change of the share of subsidies in the firm's capital stock (Δ SUB $_{t-1}$) and, whether a firm is incorporated (CORP), which serves as a proxy for growth ambitions and debt acquisition capacity. In addition, we use the firm specific lagged distance to the productivity frontier (Distance $_{t-1}$) to model catching-up mechanisms. The frontier is defined as the industry-specific productivity level of the 95th percentile of labour or total factor productivity, respectively.

In the employment regressions, we also include the out-of-sample employment level of 2008 (EMP, $_{t0}$) as an explanatory variable to control for a firm's `starting value'. We include this variables as small firms are more likely to grow at a high rate in comparison to large firms. Moreover, we control for the lagged changes of the tangible capital stock (Δ CAP $_{t-1}$). μ denotes fixed effects at the year (t) and sector (j). We use heteroskedasticity and autocorrelation consistent standard errors (Holtz-Eakin et al., 1988; Newey & West, 1986).

In addition to the extensive margin, we ask about the intensive margin of intangible investments. Hence, we replace the behavioural variables with changes in intangible capital stock (ΔINT $_{t-1}$), as well as the frequency (FREQU) with which firms invest in intangible capital. The latter is expressed as a percentage of the number of years during which investments are recorded, out of the total number of years that have been observed (see regression (6).

$$\Delta\ln\left(Y_{ijt}\right) = \beta_0 + \beta_1 \Delta\ln\left(INT_{ijt-1}\right) + \beta_2\left(FREQU_{ij}\right) + \beta_3\left(Z_{ijt}\right) + \mu_j + \mu_t + u_{ijt}. \qquad (5)$$

The amount of investment in intangible capital (INT) is potentially endogenous, i.e. the estimated coefficients are biased if investment is correlated with the error term. Endogeneity can arise from unobservable variable bias, which can affect both investment in intangibles and productivity. For example, a management strategy may increase both performance and the intangible capital stock, but independently of each other. Endogeneity can also arise from reverse causality. For example, low-performing capital-constrained firms may invest less in intangibles, and firms with better financial performance would be better able to invest in intangibles. Altogehter, the primary concern is that the error term is correlated with investment (Chappell & Jaffe, 2018). To address this issue, we utilize only lagged investment in intangibles, ensuring that the right-hand side of the equation consists of at least predetermined variables.

The frequency indicator is defined as a time-invariant share: the number of years in which a firm reports investments into intangible capital as a percentage of the number of years in which data for the given firm are not missing in the sample.

(ii) Heckman Selection Model

The presumed productivity effects of intangible investment may not be distributed at random, i.e. some firms may be more likely to invest in intangibles than others. This could be due to underinvestment or because not all business models require intangible capital. Standard procedures will be biased if unobservables affect both the investment decision and potential productivity growth. Therefore, we also implement Heckman's sample selection estimation procedure (Heckman, 1979). In the first stage, we want to explain the extensive investment margin and use the binary variable INV on the left-hand-side of the probit regression

$$Prob(INV = 1|X) = \Phi(X\gamma). \tag{6}$$

INV takes on the value of one if a firm has invested at least once into intangible capital, and zero otherwise. γ is a vector of unknown paramenters and Φ is the cumulative distribution function of the normal distribution. X is a vector of explanatory variables. We use a sectoral taxonomy proposed by the OECD (Calvino et al., 2018) as an exogenous determinant of the selection. It captures the business environment affecting the likelihood to invest in intangibles (see Friesenbichler and Peneder 2016 for a similar identification approach). The taxonomy is based on a set of indicators to classify 36 ISIC Rev. 4 sectors over the period 2001-2015, including the share of investment in tangible ICT capital and software, the share of purchases of intermediate ICT goods and services, the number of robots per hundred employees, the share of ICT specialists in total employment, and the share of turnover from online sales. Four different groups of sectors are defined: low, medium-low, medium-high and high ICT-intensive sectors[4].

The second stage is shown in equation (4):

$$E[y|Z, INV = 1] = Z\beta + \rho\sigma_u\lambda(X\gamma), \tag{7}$$

Self-selection of high productive firms into the group of investors into intangible assets is addressed by incorporating a transformation of these predicted firm probabilities as an additional explanatory variable, i.e. the inverse Mills ratio λ. ρ is the correlation between unobserved determinants of investing in intangibles and unobserved determinants of productivity υ, and σ_u is the standard deviation of the error term. Additionlly we use a set of explanatory variables analogous to equation (2).

[4] The coefficients of these variables are significant in the selection equation (see Appendix).

(iii) Quantile Regressions

We examine the medium-term effect over a five-year period on the distribution of the performance outcome. We implement simultaneous quantile regressions to capture nonlinearities suggested by the literature (Chappell & Jaffe, 2018). Low-growth and high-growth firms are also often of special interest to policymakers. Hence, this method has become common in the empirical analysis of firm performance (Coad & Rao, 2008; Di Cintio et al., 2017; Hölzl, 2009; Leoncini et al., 2019; Mathew, 2017; Ramdani & Witteloostuijn, 2010) and is likely to be relevant in the present context.

Quantile regressions draw on the entire conditional distribution of the dependent variable. Hence, the method paints a more `complete´ picture of the relationship between variables. The q^{th} conditional quantile of Y given Z is

$$Q_{Y|Z}(q) = inf\{y: F_{Y|Z}(y) \geq q\}, \tag{8}$$

where F denotes the conditional cumulative distribution function of Y given Z. Further, it is assumed that the q^{th} conditional quantile is given as a linear function of the explanatory variables Z ($Q_{Y|Z}(q) = Z\beta_q$). Quantile regressions have comparable efficiency to OLS estimators for Gaussian linear models, while substantially outperforming OLS over a wide class of non-Gaussian error distributions. The method splits the sample into a number (q) of quantiles. The coefficients are conditional on the location on the q^{th} quantile of the distribution and can be interpreted in a similar fashion as in an OLS regression. Using quantile regressions reduce the issue of sample selection. We restrict the sample to the period between 2012 and 2017 to compute within-firm growth rates. Using the same set of explanatory variables as in equation (2), we estimate the quantile regression model (5) using 1,000 bootstrapped replications. We choose the 20^{th}, 40^{th}, 60^{th} and 80^{th} percentiles. While the panel estimators from above uncover short term effects, the quantile regressions focus on structural changes and, thus, can be interpreted as medium term effect.

6.2 Results for Labour Productivity Growth

The first specification, column (1) in Table 3, regresses labour productivity growth on the extensive margin of investment (equation (1)). There is no significant effect of the dummy variable capturing whether a firm has ever invested in intangible capital. However, firms that permanently invest in intangibles have significantly higher annual productivity growth rates.

The second column examines the intensive margin of intangible investment as expressed in equation (2). The results show that the coefficient of changes of the intangible capital stock is positive but insignificant. The coefficient measuring the frequency with which firms invest in intangibles is positive and weakly significant.

The third column presents the results of the second stage of the Heckman regression, when controlling for sample selection (as depicted in equation (4)), i.e. accounting for the fact that firms ever invest in intangibles in a first stage regression. The coefficient on intangible capital growth and the frequency which firms invest in intangibles now turn highly significant.

Table 3 about here

Next, we use quantile regressions (equation (5)) based on the 5-year productivity growth between 2012 and 2017 in columns (4) to (7). Increases in the intangible capital stock are positively associated with higher productivity growth in the highest quantile, although the coefficient is only weakly significant. At the same time, the coefficients on investment frequency are highly significant at higher growth rates and negatively associated with labour productivity growth. This suggests that the deepening of intangible capital is growth-enhancing and lumpy. Capital deepening is ultimately more important for labour productivity growth than continuous investment.

6.3 Results for Employment Growth

Employment growth is the second dimension we examine. The short-term results show a highly significant positive relationship between both the intensive and the extensive margin of intangible investments and employment growth (see columns (1) and (2) in Table 4). Investments into intangible capital are likely to be complementary with employment growth.

In the medium term, this relationship also holds for the extensive margin (columns (3)-(6)). Firms that have at least invested once in intangibles also have higher employment growth. This relationship is fairly stable across growth intensities. Moreover, firms that invest into intangibles each year experience significantly higher employment growth.

The picture for the five-year period changes slightly when the intensive margin is examined (columns (7)-(10)). The coefficients of the lagged changes of the intangible capital stock are insignificant. Hence, intangible capital stock growth is not systematically related to employment growth in the medium run. However, investment frequency is positively correlated with employment growth. We find that firms that invest in intangible capital regularly also have significantly higher employment growth.

Table 4 about here

6.4 Further Results, Robustness Checks, Limitations

The control variables largely perform as anticipated. In particular, changes in the tangible capital stock show strong, consistently positive effects on labour productivity and employment growth - considerably more pronounced than those of intangible capital. The greater performance improvements among firms farther from the productivity frontier point to a clear catching-up dynamic. Public subsidies (received by about 22% of the firms in the sample), by contrast, exhibit no statistically significant effect. Incorporation is positively associated with growth, particularly in high-growth firms, indicating its role as a proxy for access to finance and organisational maturity. Time and sector fixed effects are mostly significant, lending additional support to the validity of our specifications.

The selection equation of the Heckman model (see Appendix, Table 5) supports that firms in low-ICT intensity sectors are significantly less likely to invest in intangibles. The probability of investment is also lower for firms farther from the frontier, those with minimal tangible investment, and those lacking incorporation. Once these factors are accounted for, incorporation status becomes insignificant in the outcome equation, suggesting that its main influence operates through the selection mechanism. To validate our results, we estimated fixed-effects models controlling for unobserved time-invariant heterogeneity, such as managerial practices, internal culture, or informal networks (see Annex Table 6). The core findings hold across all robustness checks, including pooled OLS models with clustered standard errors. These results strengthen confidence in the consistency of our estimates.

Nonetheless, some limitations remain. While our findings underscore the significance of intangible capital, they suggest that its role is more facilitative than causal. Intangibles appear to support rather than directly drive growth, consistent with the view that their relevance depends on firm strategy and sectoral context (Chappell & Jaffe, 2018). Similarly, we do not have information on intra-firm processes or the strategic orientation of firms (see also Anderson and Eshima 2013). Due to a lack of data, we did not consider organisational capital such as training and education. Moreover, in our analysis micro-enterprises and some very small firms are underrepresented, although the dataset is complete for entities engaged in R&D activities in Austria. Nevertheless, the results provide a robust picture of the impact of intangible investment on productivity and employment dynamics in Austrian firms.

We conceptualise intangible capital not as a production input per se (K. Friesenbichler et al., 2025)), but as a facilitator of dynamic efficiency. Accordingly, we exclude it from the production function and assess its effects on productivity as a residual outcome (Crass & Peters, 2014). This framework is particularly suitable for small open economies like Austria, where the production role of intangibles is less tied to market power and more to incremental performance improvements across a wide range of firms. In such settings, the diffusion of intangible practices, rather than their concentration in superstar firms, may be the more relevant empirical phenomenon (Di Ubaldo and Siedschlag 2021; Bloch, Eklund, and Piekkola 2023).

Finally, to examine autocorrelation, we estimated autoregressive models with year and industry fixed effects. The AR(1) coefficients for labour productivity (-0.39), TFP (-0.43), and employment growth (-0.27) are negative, aligning with established findings on firm dynamics (Coad & Hölzl, 2009). In light of this, we chose not to include lagged dependent variables in the main specifications.

7. Discussion and Conclusion

This study examines the role of intangible capital investment in shaping firm performance, using registry data from Austrian firms between 2010 and 2018. Drawing on comprehensive firm-level information, we analyse how intangible assets relate to labour productivity and employment growth over different time horizons and across sectors with varying ICT intensity (see also Hölzl et al., 2019, 2025).

Our descriptive analysis indicates the expected heterogeneity in intangible investment across firms and sectors. Intangible investment is uneven and lumpy, and only a small share of firms engage in it at all. Firms that do invest in intangibles tend to simultaneously invest more heavily in tangible capital, suggesting complementary investment strategies. This selective engagement may reflect not only barriers or missed opportunities but also differing business models; some firms simply may not require intangible capital for their operations.

Investment intensity is particularly pronounced in certain service and manufacturing sectors, where intangible investment represents a substantial share of value added. Still, the share of investing firms - the extensive margin - varies markedly across sectors and shows only a weak correlation with investment intensity. These sectoral patterns underscore the importance of distinguishing between how many firms invest and how much they invest.

Unlike much of the existing literature, our analysis explicitly addresses potential sample selection bias in the econometric estimations. This is particularly relevant given that many influential studies (especially those focused on the United States) rely on data from "superstar firms" (Hall 2018; De Loecker, Eeckhout, and Unger 2020; Autor et al. 2020; Tambe et al. 2020; Ayyagari, Demirguc-Kunt, and Maksimovic 2024). In contrast, our context is that of a small open economy, where such dominant firms are largely absent, and where intangible capital may serve different functions.

We further explore how intangible capital relates to productivity and employment outcomes by categorising firms according to their growth trajectories. Firms that reduce employment but achieve above-median productivity gains -the "successful downsizers"- make the largest contribution to aggregate productivity growth. Interestingly, these firms tend to reduce their intangible capital stock, though not as sharply as their unsuccessful counterparts. This pattern suggests that labour reallocation, rather than intangible investment alone, may drive productivity gains in this segment of the firm population.

This mixed picture leads us to examine the impact of the extensive and intensive margins of intangible investment on productivity growth across growth intensities. In a regression analysis, we empirically examine whether and how the intensity and frequency of investment in intangibles (the intensive margin) and their ubiquity (the extensive margin) are related to firm productivity and employment growth. This links our study to the policy debate. Not only are employment and productivity growth objectives that policymakers try to achieve simultaneously, there is also a debate about possible trade-offs related to labour-saving technological change.

Our findings complicate the narrative of intangible capital as a straightforward growth driver. Regarding labour productivity, we find no support for the hypothesis that intangible investment lacks short-term impact. On the contrary, firms that invest consistently in intangible assets exhibit significantly higher productivity growth in the short term. This suggests that intangible capital can deliver immediate performance benefits, particularly when embedded in sustained strategic behaviour. However, medium-term effects are less robust. We observe only weakly significant productivity gains at the upper end of the conditional distribution, which provides limited support for the notion that intangible assets deliver broad-based, cumulative advantages over time.

The relationship between intangible capital and employment growth similarly departs from theoretical expectations. While the average association between intangible investment and employment is modest, we find that firms engaging in frequent intangible investment experience significantly higher employment growt, both in the short and medium term. This finding directly contradicts the hypothesis that intangible capital substitutes for labour in the medium run. Rather, it suggests that intangible-intensive firms may be expanding their workforce to scale or support new organisational routines, particularly in high-ICT intensity sectors. This roughly supports recent findings that intangible capital accumulation is positively, but only weakly linked to employment growth (Stehrer, 2024).

These results point to two overarching insights. First, the performance effects of intangible investment are contingent- on time, frequency, and sectoral context. Intangible capital appears to function less as an isolated input and more as an enabler of firm-specific trajectories. Second, investment behaviour matters. It is not simply the presence of intangible assets that drives growth, but the persistence and strategic integration of such investments into firm operations.

For policymakers, these findings signal the importance of designing support instruments that go beyond one-off incentives. Facilitating long-term investment behaviour, strengthening organisational capabilities, and tailoring interventions to sectoral absorptive capacities are likely more effective paths to fostering inclusive and sustainable firm growth in an increasingly intangible-driven economy.

Literature

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411–2451.

Anderson, B. S., & Eshima, Y. (2013). The influence of firm age and intangible resources on the relationship between entrepreneurial orientation and firm growth among Japanese SMEs. *Journal of Business Venturing*, *28*(3), 413–429. https://doi.org/10.1016/j.jbusvent.2011.10.001

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020a). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), 645–709.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020b). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), 645–709.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553–1597.

Ayyagari, M., Demirguc-Kunt, A., & Maksimovic, V. (2024). The Rise of Star Firms: Intangible Capital and Competition. *The Review of Financial Studies*, *37*(3), 882–849.

Bacilieri, A., Borsos, A., Astudillo-Estevez, P., & Lafond, F. (2023). Firm-level production networks: What do we (really) know? *INET Working Paper*, 33.

Baily, M. N., Bartelsman, E. J. B., & Haltiwanger, J. (1996). Downsizing and Productivity. *Small Business Economics*, *8*(4), 259–278.

Biagi, F., & Falk, M. (2017). The impact of ICT and e-commerce on employment in Europe. *Journal of Policy Modeling*, *39*(1), 1–18. https://doi.org/10.1016/j.jpolmod.2016.12.004

Bloch, C., Eklund, C., & Piekkola, H. (2023). Innovative competences, the financial crisis and firm-level productivity in Denmark and Finland. *Economics of Innovation and New Technology*, *32*(2), 198–212. https://doi.org/10.1080/10438599.2021.1895496

Brynjolfsson, E., & Hitt, L. M. (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

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, *13*(1), 333–372.

Calvino, F., Criscuolo, C., Marcolin, L., & Squicciarni, M. (2018). *A taxonomy of digital intensive sectors* (OECD Science, Technology and Industry Working Papers No. 2018/14). OECD. https://doi.org/10.1787/f404736a-en

Capozza, C., & Divella, M. (2019). Human capital and firms' innovation: Evidence from emerging economies. *Economics of Innovation and New Technology*, *28*(7), 741–757.

Castelli, C., Comincioli, N., Ferrante, C., & Pontarollo, N. (2024). Tangible, intangible assets and labour productivity growth. *Journal of Economic Studies*, *51*(9), 272–289.

Chappell, N., & Jaffe, A. (2018). Intangible investment and firm performance. *Review of Industrial Organization*, *52*(4), 509–559.

Coad, A., & Hölzl, W. (2009). On the autocorrelation of growth rates. *Journal of Industry, Competition and Trade*, 9(2), 139–166.

Coad, A., & Rao, R. (2008). Innovation and Firm Growth in High-Tech Sectors: A Quantile Regression Approach. *Research Policy*, *37*(4), 633–648.

Cooper, R. W., & Haltiwanger, J. C. (2006). On the nature of capital adjustment costs. *The Review of Economic Studies*, *73*(3), 611–633.

Corrado, C. A., & Hulten, C. R. (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, C., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2013). Innovation and intangible investment in Europe, Japan, and the United States. *Oxford Review of Economic Policy*, *29*(2), 261–286. https://doi.org/10.1093/oxrep/grt017

Corrado, C., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2018). Intangible investment in the EU and US before and since the Great Recession and its contribution to productivity growth. *Journal of Infrastructure, Policy and Development*, *2*(1), 11–36. http://dx.doi.org/10.24294/jipd.v2i1.205

Corrado, C., Hulten, C., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth*, *55*(3), 661–685. https://doi.org/10.1111/j.1475-4991.2009.00343.x

Crass, D., & Peters, B. (2014). Intangible assets and firm-level productivity. *ZEW-Centre for European Economic Research Discussion Paper*, *14–120*.

Crouzet, N., & Eberly, J. (2021). Intangibles, markups, and the measurement of productivity growth. *Journal of Monetary Economics*, *124*, 92–109.

Crouzet, N., Eberly, J. C., Eisfeldt, A. L., & Papanikolaou, D. (2022). The Economics of Intangible Capital. *Journal of Economic Perspectives*, *36*(3), 29–52. https://doi.org/10.1257/jep.36.3.29

Daunfeldt, S.-O., Elert, N., & Johansson, D. (2014). The Economic Contribution of High-Growth Firms: Do Policy Implications Depend on the Choice of Growth Indicator? *Journal of Industry, Competition and Trade*, *14*(3), 337–365. https://doi.org/10.1007/s10842-013-0168-7

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications*. *The Quarterly Journal of Economics*, *135*(2), 561–644. https://doi.org/10.1093/qje/qjz041

De Ridder, M. (2024). Market power and innovation in the intangible economy. *American Economic Review*, *114*(1), 199–251.

Delmar, F., Davidsson, P., & Gartner, W. B. (2003). Arriving at the high-growth firm. *Journal of Business Venturing*, *18*(2), 189–216.

Demirkan, I., Srinivasan, R., & Nand, A. (2022). Innovation in SMEs: The role of employee training in German SMEs. *Journal of Small Business and Enterprise Development*, *29*(3), 421–440.

DeStefano, T., Kneller, R., & Timmis, J. (2023). Cloud Computing and Firm Growth. *Review of Economics and Statistics*, *Online First*, 1–47. https://doi.org/10.1162/rest_a_01393

Di Cintio, M., Ghosh, S., & Grassi, E. (2017). Firm growth, R&D expenditures and exports: An empirical analysis of Italian SMEs. *Research Policy*, *46*(4), 836–852.

Di Ubaldo, M., & Siedschlag, I. (2021). Investment in Knowledge-Based Capital and Productivity: Firm-Level Evidence from a Small Open Economy†. *Review of Income and Wealth*, *67*(2), 363–393. https://doi.org/10.1111/roiw.12464

Doms, M., & Dunne, T. (1998). Capital Adjustment Patterns in Manufacturing Plants. *Review of Economic Dynamics*, *1*(2), 409–429. https://doi.org/10.1006/redy.1998.0011

Evangelista, R., & Savona, M. (2003). Innovation, employment and skills in services. Firm and sectoral evidence. *Structural Change and Economic Dynamics*, *14*(4), 449–474.

Falk, M. (2014). The impact of new goods and service products on firm growth: Evidence from Austrian-linked firm-level data. *Economics of Innovation and New Technology*, *23*(4), 378–397. https://doi.org/10.1080/10438599.2013.871165

Freeman, C., & Soete, L. (1990). Information technology, and the global economy. In *In The information society: Evolving landscapes* (pp. 278–294). Springer.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280.

Friesenbichler, K., & Hölzl, W. (2020). High-growth firm shares in Austrian regions: The role of economic structures. *Regional Studies*, *54*(11), 1585–1595. https://doi.org/10.1080/00343404.2020.1742316

Friesenbichler, K., Kügler, A., & Schieber-Knöbl, J. (2025). Intangible capital as a production factor. Firm level evidence from Austrian microdata. *Applied Economics*, *57*(43), 6948–6962.

Friesenbichler, K., & Peneder, M. (2016). Innovation, competition and productivity. *Economics of Transition*, *24*(3), 535–580.

Friesenbichler, K. S., Clarke, G., & Wong, M. (2014). Price competition and market transparency: Evidence from a random response technique. *Empirica*, *41*(1), 5–21.

Friesenbichler, K. S., & Hoelzl, W. (2022). Firm-growth and Functional Strategic Domains: Exploratory evidence for differences between frontier and catching-up economies. *Journal of Economics and Business*, *119*, 106033. https://doi.org/10.1016/j.jeconbus.2021.106033

Friesenbichler, K. S., Selenko, E., & Clarke, G. (2018). Perceptions of corruption: An empirical study controlling for survey bias. *Journal of Interdisciplinary Economics*, *30*(1), 55–77.

Gozen, S., & Ozkara, Y. (2024). Intangible Capital Meets Skilled Labor: The Implications for Productivity Dynamics. *Available at SSRN 4922684*.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 92–116.

Griliches, Z. (1981). Market value, R&D, and patents. *Economics Letters*, *7*(2), 183–187.

Griliches, Z. (2007). *R&D and productivity: The econometric evidence*. University of Chicago Press.

Hall, B. H., Lotti, F., & Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*, *22*(3), 300–328.

Hall, R. (2018). *New Evidence on the Markup of Prices over Marginal Costs and the Role of Mega-Firms in the US Economy* (No. w24574; NBER Working Paper, p. w24574). National Bureau of Economic Research. https://doi.org/10.3386/w24574

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, *35*, 29–43.

Haskel, J., & Westlake, S. (2018). *Capitalism without capital: The rise of the intangible economy*. Princeton University Press.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153. https://doi.org/10.2307/1912352

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371–1395.

Hölzl, W. (2009). Is the R&D behaviour of fast-growing SMEs different? Evidence from CIS III data for 16 countries. *Small Business Economics*, *33*(1), 59–75. https://doi.org/10.1007/s11187-009-9182-x

Hölzl, W. (2013). Persistence, survival, and growth: A closer look at 20 years of fast-growing firms in Austria. *Industrial and Corporate Change*, *23*(1), 199–231.

Hölzl, W., Bärenthaler-Sieber, S., Bock-Schappelwein, J., Friesenbichler, K., Kügler, A., Reinstaller, A., Reschenhofer, P., Dachs, B., & Risak, M. (2019). *Digitalisation in Austria: State of Play and Reform Needs*. European Union. https://ec.europa.eu/docsroom/documents/37267/attachments/1/translations/en/renditions/native

Hölzl, W., Friesenbichler, K., Kügler, A., & Meyer, B. (2025). Herausforderungen und Determinanten der Wettbewerbsfähigkeit in Zeiten globaler Unsicherheit Ergebnisse der WIFO-Industriebefragung 2025. *WIFO Monatsberichte*, *98*(7), 373–382.

Iqbal, A., Rajgopal, S., Srivastava, A., & Zhao, R. (2021). Value of Internally Generated Intangible Capital. *Management Science*, *forthcoming*, 54. https://doi.org/10.2139/ssrn.3917998

Kaus, W., Slavtchev, V., & Zimmermann, M. (2024). Intangible capital and productivity: Firm-level evidence from German manufacturing. *Oxford Economic Papers*, *76*(4), 970–996. https://doi.org/10.1093/oep/gpad051

Kügler, A., Reinstaller, A., & Friesenbichler, K. S. (2023). Can value chain integration explain the diverging economic performance within the EU? *Journal of Industrial and Business Economics*, *50*(1), 25–47. https://doi.org/10.1007/s40812-022-00236-y

Leoncini, R., Marzucchi, A., Montresor, S., Rentocchini, F., & Rizzo, U. (2019). 'Better late than never': The interplay between green technology and age for firm growth. *Small Business Economics*, *52*(4), 891–904.

Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, *70*(2), 317–341. https://doi.org/10.1111/1467-937X.00246

Machlup, F. (1962). *The production and distribution of knowledge in the United States* (Vol. 278). Princeton university press.

Marrocu, E., Paci, R., & Pontis, M. (2012). Intangible capital and firms' productivity. *Industrial and Corporate Change*, *21*(2), 377–402.

Martin, J., & Baybutt, C. (2021). The F words: Why surveying businesses about intangibles is so hard. *Paper Prepared for the IARIW-ESCoE Conference*, 41.

Mathew, N. (2017). Drivers of firm growth: Micro-evidence from Indian manufacturing. *Journal of Evolutionary Economics*, *27*(3), 585–611.

Mouel, M. L., & Schiersch, A. (2024). Intangible capital and productivity divergence. *Review of Income and Wealth*, *70*(3), 605–638. https://doi.org/10.1111/roiw.12653

Newey, W. A., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *NBER Working Paper Series*, *55*, 14.

Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *94*(6), 1263–1297.

Peneder, M., & Prettner, C. (2021). *Entwicklung der Produktivität österreichischer Unternehmen von 2008 bis 2018. Auswertung von Mikrodaten für Österreich im Rahmen von Multiprod 2.0*. WIFO. http://www.wifo.ac.at/wwa/pubid/67450

Pozzi, A., & Schivardi, F. (2016). Demand or productivity: What determines firm growth? *The RAND Journal of Economics*, *47*(3), 608–630.

Ramdani, D., & Witteloostuijn, A. van. (2010). The impact of board independence and CEO duality on firm performance: A quantile regression analysis for Indonesia, Malaysia, South Korea and Thailand. *British Journal of Management*, *21*(3), 607–627.

Roth, F., Sen, A., & Rammer, C. (2023). The role of intangibles in firm-level productivity–evidence from Germany. *Industry and Innovation*, *30*(2), 263–285.

Segarra, A., & Teruel, M. (2012). An appraisal of firm size distribution: Does sample size matter? *Journal of Economic Behavior & Organization*, *82*(1), 314–328. https://doi.org/10.1016/j.jebo.2012.02.012

Sichel, D. E. (2024). Intangibles: How far we have come and the road ahead. *Review of Income and Wealth*, *forthcoming*, roiw.12706. https://doi.org/10.1111/roiw.12706

Stehrer, R. (2024). The impact of ICT and intangible capital accumulation on employment growth and labour income shares. *Structural Change and Economic Dynamics*, *70*, 211–220. https://doi.org/10.1016/j.strueco.2024.02.003

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature*, *49*(2), 326–365. https://doi.org/10.1257/jel.49.2.326

Syverson, C. (2017). Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives*, *31*(2), 165–186. https://doi.org/10.1257/jep.31.2.165

Tambe, P., Hitt, L., Rock, D., & Brynjolfsson, E. (2020). *Digital capital and superstar firms*. National Bureau of Economic Research.

Van Ark, B., Hao, J. X., Corrado, C., & Hulten, C. (2009). Measuring intangible capital and its contribution to economic growth in Europe. *EIB Papers*, *14*(1), 62–93.

Van Criekingen, K., Bloch, C., & Eklund, C. (2021). Measuring intangible assets—A review of the state of the art. *Journal of Economic Surveys*, *in press*.

Warner, S. L. (1965). Randomized Response: A Survey Technique for Eliminating Evasive Answer Bias. *Journal of the American Statistical Association*, *60*(309), 63–69. https://doi.org/10.1080/01621459.1965.10480775

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, *104*(3), 112–114. https://doi.org/10.1016/j.econlet.2009.04.026

Yang, S., Zhou, Y., & Song, L. (2018). Determinants of intangible investment and its impacts on firms' productivity: Evidence from Chinese private manufacturing firms. *China & World Economy*, *26*(6), 1–26.

Tables and Figures

Table 1: Intangible investment share and ubiquity of investors at the sector level

Nace Rev. 2, 1-digit	Sector	Mean int. inv. as a share of VA	Share of immaterial investors	Share of perm. Immat. investors	Mean coverage of years with immat. 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%

Source: STAT data, own calculations.

Note: This table uses Nace Rev. 2 1-digit sectors 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. Sector "S" (Other service activies) excluded due to small sample size.

Table 2: Employment and labour productivity dynamics

	Successful upsizer	**Unsuccessful upsizer**	**Successful downsizer**	**Unsuccessful downsizer**
	$\Delta LP > \Delta LP_{p50}$	$\Delta LP < \Delta LP_{p50}$	$\Delta LP > \Delta LP_{p50}$	$\Delta LP < \Delta LP_{p50}$
	$\Delta EMP > \Delta EMP_{p50}$	$\Delta EMP > \Delta EMP_{p50}$	$\Delta EMP < \Delta EMP_{p50}$	$\Delta EMP > \Delta EMP_{p50}$
Δ LP	5.4%	-6.1%	6.1%	-5.2%
Δ Emp.	5.1%	6.0%	-4.3%	-3.1%
Share of firms	21.4%	28.7%	28.6%	21.3%
Share Int. Inv. in total inv., t	9.0%	8.6%	11.0%	10.9%
Share int. Inv. in total inv. $_{t-1}$	5.4%	5.5%	6.0%	6.5%
Δ int. capital stock	3.2%	1.5%	-0.6%	-3.2%

Source: STAT data, own calculations. Illustration adapted from Baily et al. (1996).
Note: ΔLP, ΔEMP and Δ immat. cap. are firm-specific. LP denotes labour productivity, EMP employment, and "Immat. cap." the immaterial capital stock. The subscripts are dropped to shorten the description. ** p<0.01, * p<0.05, + p<0.1.

Table 3: Labour productivity growth – regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	N-W	N-W	HECK	QUANT p20	QUANT p40	QUANT p60	QUANT p80
INV	0.0000						
	(0.001)						
PERM.	0.0072**						
	(0.002)						
Δ INT $_{t-1}$		0.0001	0.0011**	-0.0001	0.0011	0.0016	0.0039*
		(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)
FREQU		0.0006*	0.0055**	0.0033+	-0.0004	-0.0043**	-0.0075**
		(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δ CAP $_{t-1}$	0.0128**	0.0152**	0.0197**	0.0112+	0.0189*	0.0397**	0.0504**
	(0.003)	(0.002)	(0.004)	(0.006)	(0.008)	(0.007)	(0.009)
Δ SUB $_{t-1}$	-0.0066	-0.0062	-0.0180	0.0615	-0.0213	-0.0106	-0.0942
	(0.006)	(0.005)	(0.022)	(0.074)	(0.067)	(0.058)	(0.162)
CORP	0.0006	0.0008	0.0024	-0.0041	0.0101	0.0106	0.0213*
	(0.001)	(0.001)	(0.003)	(0.008)	(0.007)	(0.007)	(0.010)
Distance $_{t-1}$	0.2427**	0.2545**	0.2423**	0.8347**	0.6524**	0.6149**	0.6764**
	(0.003)	(0.003)	(0.006)	(0.023)	(0.021)	(0.017)	(0.021)
Sector effects	Y	Y	Y	Y	Y	Y	Y
Time effects	Y	Y	Y	n.a.	n.a.	n.a.	n.a.
Constant	0.0051	-0.0148**	-0.5516**	-0.6762**	-0.4398**	-0.2923**	-0.1040
	(0.004)	(0.003)	(0.023)	(0.039)	(0.026)	(0.033)	(0.072)
Obs.	100,075	139,802	100,074	15,785	15,785	15,785	15,785

Source: STAT data, own calculations.
Note: Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. ** p<0.01, * p<0.05, + p<0.1.

Table 4: Employment growth - regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NW	NW	QUANT p20	QUANT p40	QUANT p60	QUANT p80	QUANT p20	QUANT p40	QUANT p60	QUANT p80
INV	0.0100**		0.0560**	0.0396**	0.0411**	0.0540**				
	(0.001)		(0.007)	(0.005)	(0.005)	(0.007)				
PERM	0.0216**		0.0871**	0.0475**	0.0509**	0.0602**				
	(0.003)		(0.012)	(0.011)	(0.010)	(0.011)				
Δ INT_{t-1}		0.0047**					-0.0006	-0.0001	0.0007	0.0021
		(0.000)					(0.002)	(0.001)	(0.001)	(0.001)
FREQU		0.0033**					0.0153**	0.0105**	0.0100**	0.0118**
		(0.000)					(0.002)	(0.002)	(0.002)	(0.002)
Δ CAP_{t-1}	0.0633**	0.0473**	0.0195+	0.0442**	0.0771**	0.1312**	0.0205*	0.0442**	0.0767**	0.1321**
	(0.011)	(0.009)	(0.011)	(0.008)	(0.011)	(0.012)	(0.010)	(0.008)	(0.010)	(0.012)
Δ SUB_{t-1}	-0.0398	-0.0484+	0.1277	0.0325	0.1501	0.4265*	0.1239	0.0322	0.1501	0.4080*
	(0.025)	(0.027)	(0.125)	(0.152)	(0.138)	(0.199)	(0.121)	(0.151)	(0.149)	(0.205)
CORP	0.0047**	0.0070**	-0.0025	0.0067	0.0186**	0.0354**	-0.0013	0.0070	0.0192**	0.0367**
	(0.001)	(0.001)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)
EMP, t_0	-0.0108**	-0.0109**	-0.0484**	-0.0327**	-0.0418**	-0.0554**	-0.0479**	-0.0330**	-0.0414**	-0.0548**
	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)
Constant	0.0273**	0.0229	-0.0829*	-0.0221	0.1530**	0.3278**	-0.0898*	-0.0222	0.1447**	0.3288**
	(0.003)	(0.000)	(0.038)	(0.029)	(0.038)	(0.036)	(0.039)	(0.029)	(0.039)	(0.034)
Sector effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time effects	Y	Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Obs.	97,592	137,008	15,322	15,322	15,322	15,322	15,322	15,322	15,322	15,322

Source: STAT data, own calculations.

Note: Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. EMP, t_0 is an out-of-sample level of employment (FTE) at the base year. ** p<0.01, * p<0.05, + p<0.1.

Annex

Variable definitions

We explain gross value added by the firm specific labour stock, tangible, and intangible capital. In particular, the capital stock variables are not directly included in the data, which is why we compute proxies.

Labour stock. The labour stock was computed as the number of employees in full time equivalents, from which the R&D employees were deducted. This is to avoid double-counting, because the costs of R&D employees are already considered in R&D expenditures, which are a component of the intangible capital stock formation.

Tangible capital stock. The data does not contain capital stocks, but investments that allowed us to compute a proxy for the firm-specific capital stock.[1] We compute proxies for both material and immaterial capital stocks which we use to estimate an AKL production function in a stepwise approach. First, we used OECD STAN information on capital per employees at the Nace Rev. 2 2-digit level for the base year 2008. Second, we multiply the industry-level capital intensity by the enterprise-specific employment information (number of persons employed in full time equivalents) to obtain an enterprise specific initial capital stock. Third, we add annual investments and deduct depreciation to obtain the annual capital stocks of the subsequent years. Investments into tangible capital are defined as investments in land and buildings (including self-construction) and machinery and equipment (including transport, low-value, or used equipment). The depreciation rates were obtained from the OECD and allowed to vary across Nace Rev. 2 2-digit industries and by asset class (see below).[2]

---

[1] The chosen approach resembles the procedure by the OECD's Multiprod project (https://www.oecd.org/sti/ind/multiprod.htm, accessed on 15 June 2025).

[2] The data contain a variable on firm-specific depreciation, whose sectoral aggregates are consistent with the sectoral depreciation rates based on the OECD data (ρ=0.98).

Intangible capital stock. We implement the definition of intangible investments described above. The capital stocks were then computed analogously to tangible capital.

Depreciation rates. We adjust the sectoral depreciation rates of both tangible and intangible capital to consider the observation that intangible capital is typically depreciated faster than physical investments (Corrado, Hulten, and Sichel 2009). Hence, we use the capital stock of the base year as described above and split the capital stock into a tangible (s) and an intangible part (1-s). We use the overall sectoral deprecation rate (δ) as the starting point and draw on pooled information from the microdata at the sector level to compute the mean intensity of intangible investments in total investments. The depreciation rate for intangible capital was assumed to be 20%, and the was in the remainder of the sectoral depreciation rate is then attributed to the deprecation of tangible capital (δ_t) so that $\delta=(1-s)*0{,}2+s*\delta_t$.

Total factor productivity

Besides labour productivity, an additional dimension of firm performance is total factor productivity, which is a measure of overall efficiency. While the labour productivity regressions used previously controlled for changes in the capital stock, TFP is a firm-specific performance indicator that captures both capital and employment in the calculation of the productivity score. Recognising the extensive and growing discussion on the estimation of total factor productivity (Ackerberg et al., 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996; Syverson, 2011; Wooldridge, 2009). We specify the following production function:

$$Y_{it} = L_{it}^{\beta l} * K_{it}^{\beta 2} * A_{it} \tag{4}$$

where Y is the output of firm i in year t measured as gross value added. The labor stock is denoted by L, K is tangible capital. A denotes the total factor productivity (TFP) of a firm. Defining the variables L and K, we exclude R&D employees in full time equivalents from total employment, and only consider tangible capital stocks. After logarithmizing the production function, we obtain the following estimation equation:

$$y_{it} = \beta_0 + \beta_l \cdot l_{it} + \beta_2 \cdot k_{it} + \omega_{it} + u_{it} \qquad (5)$$

where lower-case letters denote logarithmic terms, where $\ln(A_{it}) = \beta_0 + \omega_{it} + u_{it}$. The intercept β_0 measures the mean efficiency level across firms. The term u_{it} is an i.i.d. component, representing unexpected deviations from the mean (e.g. due to unexpected delays, measurement errors, etc.).

The term ω_{it} is the firm-level productivity. It might be crucial for both firm selection and a firm's input demand decision. This leads to a simultaneity problem in the estimation of the production function, which causes a bias in ordinary least squares estimations.

We address this issue by using energy as a proxy variable to implement a generalised method of moments 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 a bootstrapping with 10,000 replications.

Deriving labour productivity growth from a Cobb-Douglas function

Labour productivity growth can be dereived from a Cobb-Douglas production function in several steps. Let us first define a production function:

$$Y_t \ = A(t) * \ LAB_t^{\beta} * TANG_t^{a} * INT_t^{\gamma} * \ A_t \qquad \text{(A1)}$$

Y represents the output of firm i in year t. A is the total factor productivity. The labour stock is denoted by LAB, tangible capital by TANG, and intangible capital by INT. The output elasticities are α, β and γ.

Next, we define labour productivity as the produced output per unit of labour:

$$\frac{Y_t}{L_t} = A(t) * \ LAB_t^{(\beta-1)} * TANG_t^{a} * INT_t^{\gamma} * \ A_t \qquad \text{(A2)}$$

Taking the natural logarithm leads to the following equation:

$$\ln(\frac{Y_t}{L_t}) = \ln\big(A(t)\big) \quad + a\ln(TANG(t)) \quad + \gamma \ln(INT(t)) \quad + (\beta-1)\ln(LAB(t)) \qquad \text{(A3)}$$

This equation is differentiated with respect to time:

$$\frac{d}{t} ln(\frac{Y_t}{L_t}) = \frac{d}{t}[\ln\big(A(t)\big)] \quad + a\frac{d}{t}[\ln(TANG(t))] \quad + \gamma\frac{d}{t}[\ln\big(INT(t)\big)] \quad + (\beta-1)\frac{d}{t}\ln[(LAB(t))] \qquad \text{(A4)}$$

Finally, we rearrange the terms to isolate the growth rate and, for simplicity, we change the notation, so that prime denotes the derivatives with respect to time:

$$\text{LP } Growth \ = A'(t)/A(t) + aTANG'(t)/TANG(t) \quad + \gamma(INT'/INT(t) + (\beta-1)\ (LAB'(t)/LAB(t) \qquad \text{(A5)}$$

Additional descriptive statistics

	Mean	Median	Std.Dev.
LP, nat. log	4.26	4.21	0.55
TFP, nat. log	2.74	2.72	0.59
Emp., nat. log	3.03	2.94	1.16
LP, nat. log, t_0	4.29	4.25	0.54
TFP, nat. log, t_0	2.78	2.75	0.61
Emp., nat. log, t_0	3.21	3.09	1.18
ΔLP, nat. log	0.04	0.03	0.42
ΔTFP, nat. log	0.03	0.03	0.43
ΔEmp., nat. log	0.08	0.05	0.41
Immat. Invest / Total Invest	0.07	0.00	0.19
Immat. Investor, Dummy	0.61	0.00	0.49
Capital stock, nat. log.	7.84	7.71	1.55
Material capital stock, nat. log	7.88	7.73	1.63
Intangible capital stock, nat. log	2.14	0.00	2.64

Source: STAT data, own calculations.

Note: Sample composition varies across subsamples

Sample selection regressions

Table 5: Heckman regression results incl. first stage

	INV HECK, 1st stage	LP HECK, 2nd stage	INV HECK,1st stage	TFP HECK, 2nd stage
Δ INT, t-1	0.0147**	0.0011**	0.0141**	-0.0001
	(0.002)	(0.000)	(0.002)	(0.000)
FREQU		0.0055**		0.0047*
		(0.002)		(0.002)
Δ CAP, t-1	0.3320**	0.0197**		
	(0.032)	(0.004)		
Δ SUB, t-1	0.0226	-0.0180	0.0366	0.0002
	(0.053)	(0.022)	(0.047)	(0.043)
CORP	0.1498**	0.0024	0.1860**	0.0028
	(0.016)	(0.003)	(0.017)	(0.002)
Distance, t-1	-0.2547**	0.2423**	-0.1451**	0.2388**
	(0.032)	(0.006)	(0.032)	(0.006)
Sector effects	Y	Y	Y	Y
Time effects	Y	Y	Y	Y
ICT, med. low	0.5536**		0.8821**	
	(0.026)		(0.051)	
ICT, med. high	0.2418**		1.7750**	
	(0.017)		(0.242)	
ICT, high	0.4623**		0.7406**	
	(0.018)		(0.093)	
Constant	-0.0540**	-0.5516**	-1.0802**	-0.1850**
	(0.010)	(0.023)	(0.043)	(0.016)

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. ** p<0.01, * p<0.05, + p<0.1.

Robustness checks

Table 6: LP growth, panel, fixed effects at the firm level

	(1) Panel, FE	(2) Panel, FE	(3) Panel, FE	(4) Panel, FE
INVEST_INT, dummy		0.00		
		(0.002)		
PERM_INT, dummy		n.a.		
Δ CAP, t-1	0.00*	0.00	0.00+	0.00+
	(0.002)	(0.003)	(0.002)	(0.002)
Distance, t-1	1.01**	1.12**	1.01**	1.01**
	(0.008)	(0.010)	(0.008)	(0.008)
Δ SUB, t-1	0.00	-0.00	0.00	0.00
	(0.006)	(0.005)	(0.007)	(0.007)
CORP	0.01	0.01	0.01	0.01
	(0.011)	(0.012)	(0.011)	(0.011)
Δ INT, t-1			0.00	0.00
			(0.000)	(0.000)
FREQU			0.00	0.01**
			(0.000)	(0.003)
FREQU, squared				-0.00**
				(0.001)
Constant	-0.57**	-0.52**	-0.57**	-0.57**
	(0.051)	(0.059)	(0.051)	(0.051)
Observations	139,802	100,075	139,802	139,802
R-squared	0.231	0.255	0.231	0.231

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 7: LP growth, OLS, panel, s.e. clustered at the firm level

	(1) Panel. Clust. S.e.	(2) Panel. Clust. S.e.	(3) Panel. Clust. S.e.	(4) Panel. Clust. S.e.
INVEST_INT, dummy		0.00		
		(0.001)		
PERM_INT, dummy		0.01**		
		(0.002)		
Δ CAP, t-1	0.02**	0.01**	0.02**	0.01**
	(0.003)	(0.003)	(0.003)	(0.003)
Distance, t-1	0.25**	0.24**	0.25**	0.25**
	(0.003)	(0.004)	(0.003)	(0.003)
Δ SUB, t-1	-0.01	-0.01	-0.01	-0.01
	(0.005)	(0.005)	(0.005)	(0.005)
CORP	0.00	0.00	0.00	0.00
	(0.001)	(0.001)	(0.001)	(0.001)
Δ INT, t-1			0.00	0.00
			(0.000)	(0.000)
FREQU			0.00*	0.01**
			(0.000)	(0.002)
FREQU, squared				-0.00**
				(0.001)
Constant	-0.01**	0.01	-0.01**	-0.01**
	(0.003)	(0.003)	(0.003)	(0.004)
Observations	139,802	100,075	139,802	139,802
R-squared	0.063	0.060	0.063	0.063

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 8: LP growth, OLS, cross section, s.e. clustered at the firm level

	(1)	(2)	(3)	(4)
	OLS, cl.	OLS, cl.	OLS, cl.	OLS, cl.
INVEST_INT, dummy		-0.01		
		(0.009)		
PERM_INT, dummy		-0.00		
		(0.017)		
∆ CAP, t-1	0.03**	0.03**	0.03**	0.03**
	(0.008)	(0.008)	(0.008)	(0.008)
Distance, t-1	0.69**	0.69**	0.69**	0.69**
	(0.026)	(0.026)	(0.026)	(0.026)
∆ SUB, t-1	-0.03	-0.03	-0.03	-0.03
	(0.071)	(0.072)	(0.070)	(0.071)
CORP	0.01	0.02	0.02	0.02
	(0.017)	(0.017)	(0.017)	(0.017)
∆ INT, t-1			0.00+	0.00*
			(0.001)	(0.001)
FREQU			-0.00	0.01
			(0.003)	(0.007)
FREQU, squared				-0.00
				(0.002)
Constant	-0.51**	-0.51**	-0.50**	-0.50**
	(0.019)	(0.019)	(0.017)	(0.017)
Observations	15,510	15,510	15,510	15,510
R-squared	0.200	0.200	0.200	0.200

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. ∆ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, ∆ CAP the growth rate of tangible capital. ∆ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include industry effects (NACE Rev. 2, 2-digit). Standard errors are clustered at the firm level. ** p<0.01, * p<0.05, + p<0.1

Table 9: Employment growth, panel, fixed effects at the firm level

	(1)	(2)	(3)	(4)
	Panel, FE	Panel, FE	Panel, FE	Panel, FE
INVEST_INT, dummy		-0.00+		
		(0.002)		
PERM_INT, dummy		-		
Δ CAP, t-1	0.04**	0.05**	0.04**	0.04**
	(0.013)	(0.014)	(0.012)	(0.012)
Emp., base year	-	-	-	-
Δ SUB, t-1	-0.06+	-0.05	-0.05+	-0.05+
	(0.034)	(0.035)	(0.033)	(0.033)
CORP	0.04**	0.04**	0.04**	0.04**
	(0.012)	(0.012)	(0.012)	(0.012)
Δ INT, t-1			0.00**	0.00**
			(0.000)	(0.000)
FREQU			-0.00	-0.02**
			(0.000)	(0.003)
FREQU, squared				0.01**
				(0.001)
Constant	0.01	-0.09	0.01	0.01
	(0.071)	(0.077)	(0.071)	(0.071)
Observations	137,008	97,592	137,008	137,008
R-squared	0.014	0.018	0.017	0.017

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 10: Employment growth, OLS, panel, s.e. clustered at the firm level

	(1)	(2)	(3)	(4)
	Panel. Clust. S.e.	Panel. Clust. S.e.	Panel. Clust. S.e.	Panel. Clust. S.e.
INVEST_INT, dummy		0.01**		
		(0.001)		
PERM_INT, dummy		0.02**		
		(0.003)		
Δ CAP, t-1	0.05**	0.06**	0.05**	0.05**
	(0.011)	(0.012)	(0.011)	(0.011)
Emp., base year	-0.01**	-0.01**	-0.01**	-0.01**
	(0.000)	(0.001)	(0.001)	(0.001)
Δ SUB, t-1	-0.05+	-0.04	-0.05+	-0.05+
	(0.029)	(0.026)	(0.029)	(0.029)
CORP	0.01**	0.00**	0.01**	0.01**
	(0.001)	(0.001)	(0.001)	(0.001)
Δ INT, t-1			0.00**	0.00**
			(0.000)	(0.000)
FREQU			0.00**	0.01**
			(0.000)	(0.002)
FREQU, squared				-0.00
				(0.001)
Constant	0.01	0.03	0.02	0.03
	(.)	(426.266)	(289.947)	(479.737)
Observations	137,008	97,592	137,008	137,008
R-squared	0.015	0.020	0.019	0.019

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** p<0.01, * p<0.05, + p<0.1

Table 11: Employment growth, OLS, cross section, s.e. clustered at the firm level

	(1)	(2)	(3)	(4)
	OLS, cl.	OLS, cl.	OLS, cl.	OLS, cl.
INVEST_INT, dummy		0.08**		
		(0.008)		
PERM_INT, dummy		0.10**		
		(0.013)		
Δ CAP, t-1	0.05**	0.04*	0.04*	0.04*
	(0.017)	(0.016)	(0.016)	(0.016)
Emp., base year	-0.06**	-0.07**	-0.07**	-0.07**
	(0.005)	(0.006)	(0.006)	(0.006)
Δ SUB, t-1	0.35*	0.36**	0.36**	0.36**
	(0.137)	(0.131)	(0.132)	(0.132)
CORP	0.02*	0.02**	0.02**	0.02**
	(0.007)	(0.007)	(0.007)	(0.007)
Δ INT, t-1			0.00	0.00
			(0.002)	(0.002)
FREQU			0.02**	0.02+
			(0.002)	(0.008)
FREQU, squared				0.00
				(0.003)
Constant	0.43**	0.39**	0.39**	0.39**
	(0.026)	(0.027)	(0.026)	(0.027)
Observations	15,079	15,079	15,079	15,079
R-squared	0.102	0.113	0.113	0.113

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include industry effects (NACE Rev. 2, 2-digit). Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Total factor productivity growth

Following the literature on total factor productivity (TFP) (Ackerberg et al., 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996; Syverson, 2011; Wooldridge, 2009), we specify the following production function:

$$Y_{it} = LAB_{it}^{\beta l} * TANG_{it}^{\beta 2} * A_{it} \tag{1}$$

Here, Y represents the output of firm i in year t, which is measured as gross value added. Labour stock is denoted by \`L´ and tangible capital by \`TANG´[1]. \`A´ denotes total factor productivity, the indicator of interest. Let lowercase letters denote logarithmic terms. TFP comprises of ln(A_{it})= β_0 +ω_{it}+u_{it}. The term u_{it} is a stochastic residual. The term ω_{it} is a firm-specific productivity component which is only known to the firm. This is the source of endogeneity because firm-specific productivity forms the basis for input choice. When productivity shocks occur in profit-maximising firms, they increase their output, which requires additional inputs. Although the productivity shock is not observed empirically, it affects the choice of inputs. This leads to a simultaneity problem when estimating the production function, causing bias in ordinary least squares estimations. However, the approach suggested by Ackerberg et al. (2015) resolves these empirical issues. Please see the Annex for a more detailed description.

Results for total factor productivity growth

---

[1] Intangible capital was not considered in the production function in order to explore its effects in the subsequent regression analysis. Including information on intangible capital in the production function would result in a total factor productivity (TFP) measure that already accounted for intangibles. This would be a production function approach, as opposed to the regression analysis chosen here.

The regressions using TFP growth as performance variable are presented in Table 12. The results show that firms that invest in intangibles each year have slightly higher productivity growth rates. However, this coefficient is only marginally significant. There is no evidence for the effect of the intensive margin in the contemporaneous results (column (1)). Overall, the picture that emerges is similar to that for labour productivity growth.

In column (2), the coefficient of the growth of the intangible capital stock is small, but negative and significant. It becomes insignificant in the Heckman specification, though (column (3)). In contrast, the impact of the frequency with which firms invest in intangibles is significantly positive when controlling for sample selection.

The quantile regressions examine the role of intangibles in the medium-term growth of TFP, as illustrated in columns (4) through (7). The findings reveal a positive and statistically significant correlation between intangible capital growth and TFP growth for firms demonstrating medium to high performance growth. The magnitude of the coefficients increases with higher firm productivity growth rates. A significant and increasingly negative relationship is also found between the frequency of investment and TFP growth; that is, investments that are more concentrated over time are more conducive to TFP growth at higher growth rates.

Table 12: TFP growth - regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	N-W	N-W	HECK	QUANT p20	QUANT p40	QUANT p60	QUANT p80
INV	-0.0002						
	(0.001)						
PERM	0.0039+						
	(0.002)						
Δ INT $_{t-1}$		-0.0007**	-0.0001	0.0007	0.0027*	0.0043**	0.0073**
		(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)
FREQU		0.0004	0.0047*	-0.0014	-0.0043**	-0.0059**	-0.0080**
		(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δ SUB $_{t-1}$	-0.0045	-0.0040	0.0002	0.2237*	0.1009	0.1155	0.0803
	(0.005)	(0.005)	(0.043)	(0.088)	(0.081)	(0.074)	(0.105)
CORP	0.0013	0.0032**	0.0028	-0.0009	0.0118+	0.0128*	0.0199*
	(0.001)	(0.001)	(0.002)	(0.009)	(0.006)	(0.006)	(0.008)
Distance $_{t-1}$	0.2429**	0.2541**	0.2388**	0.7950**	0.6599**	0.6259**	0.6914**
	(0.003)	(0.003)	(0.006)	(0.022)	(0.018)	(0.016)	(0.019)
Sector effects	Y	Y	Y	Y	Y	Y	Y
Time effects	Y	Y	Y	n.a.	n.a.	n.a.	n.a.
Constant	-0.1014**	-0.1049	-0.1850**	-0.6224**	-0.4281**	-0.2882**	-0.1638**
	(0.037)	(0.154)	(0.016)	(0.028)	(0.031)	(0.039)	(0.041)
Obs.	99,564	138,567	100,543	15,774	15,774	15,774	15,774

Source: STAT data, own calculations.

Note:Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. ** p<0.01, * p<0.05, + p<0.1.

Table 13: TFP growth, panel, fixed effects at the firm level

	(1)	(2)	(3)	(4)
	Panel, FE	Panel, FE	Panel, FE	Panel, FE
INVEST_INT, dummy		0.00*		
		(0.002)		
PERM_INT, dummy		n.a.		
Distance, t-1	0.96**	1.05**	0.96**	0.96**
	(0.008)	(0.010)	(0.008)	(0.008)
∆ SUB, t-1	0.00	-0.00	0.00	0.00
	(0.005)	(0.006)	(0.005)	(0.005)
CORP	0.01	0.01	0.01	0.01
	(0.012)	(0.013)	(0.012)	(0.012)
∆ INT, t-1			-0.00*	-0.00*
			(0.000)	(0.000)
FREQU			0.00**	0.02**
			(0.000)	(0.003)
FREQU, squared				-0.01**
				(0.001)
Constant	-0.39**	-0.40**	-0.39**	-0.39**
	(0.040)	(0.059)	(0.040)	(0.040)
Observations	138,567	99,564	138,567	138,567
R-squared	0.295	0.276	0.295	0.296

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. ∆ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, ∆ CAP the growth rate of tangible capital. ∆ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** p<0.01, * p<0.05, + p<0.1

Table 14: TFP growth, OLS, panel, s.e. clustered at the firm level

VARIABLES	(1) Panel. Clust. S.e.	(2) Panel. Clust. S.e.	(3) Panel. Clust. S.e.	(4) Panel. Clust. S.e.
INVEST_INT, dummy		-0.00		
		(0.001)		
PERM_INT, dummy		0.00+		
		(0.002)		
Distance, t-1	0.25**	0.24**	0.25**	0.25**
	(0.003)	(0.004)	(0.003)	(0.003)
Δ SUB, t-1	-0.00	-0.00	-0.00	-0.00
	(0.005)	(0.005)	(0.005)	(0.005)
CORP	0.00**	0.00	0.00**	0.00**
	(0.001)	(0.001)	(0.001)	(0.001)
Δ INT, t-1			-0.00**	-0.00**
			(0.000)	(0.000)
FREQU			0.00	0.01**
			(0.000)	(0.002)
FREQU, squared				-0.00**
				(0.001)
Constant	-0.10	-0.10	-0.10	-0.11
	(0.088)	(0.081)	(0.087)	(0.088)
Observations	138,567	99,564	138,567	138,567
R-squared	0.147	0.092	0.147	0.147

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017. PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include time and industry (NACE Rev. 2, 2-digit) effects. Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 15: TFP growth, OLS, cross section, s.e. clustered at the firm level

	TFP	TFP	TFP	TFP
	OLS, cl.	OLS, cl.	OLS, cl.	OLS, cl.
INVEST_INT, dummy		-0.01		
		(0.010)		
PERM_INT, dummy		-0.01		
		(0.020)		
Distance, t-1	0.67**	0.67**	0.67**	0.67**
	(0.025)	(0.025)	(0.025)	(0.025)
Δ SUB, t-1	0.09	0.08	0.08	0.08
	(0.084)	(0.084)	(0.083)	(0.083)
CORP	0.02	0.02	0.02	0.02
	(0.017)	(0.017)	(0.017)	(0.017)
Δ INT, t-1			0.01**	0.01**
			(0.001)	(0.001)
FREQU			-0.01+	-0.01
			(0.003)	(0.008)
FREQU, squared				0.00
				(0.002)
Constant	-0.57**	-0.57**	-0.56**	-0.56**
	(0.016)	(0.016)	(0.016)	(0.016)
Observations	15,460	15,460	15,460	15,460
R-squared	0.205	0.205	0.206	0.206

Source: STAT data, own calculations.

Note: INV is a binary variable indicating whether a firm has at least one invested in intangible capital between 2012 and 2017 PERM is a subset of INV. It is binary variable indicating whether a firm has invested into intangible capital each year of the sample.. Δ INT is the growth rates of intangible capital, FREQU the frequency (in percent of all years) with which firms invest into intangible capital, Δ CAP the growth rate of tangible capital. Δ SUB is the change in the share of subsidies that firms receive. CORP denotes incorporated companies. All specifications include industry effects (NACE Rev. 2, 2-digit). Standard errors are clustered at the firm level. ** $p<0.01$, * $p<0.05$, + $p<0.1$