Unveiling the J-curve: How Intangibles Drive Productivity Mismeasurement*

Gert Bijnens
National Bank of Belgium

Jozef Konings
Nazarbayev University GSB
KU Leuven
and CEPR

Aaron Putseys
KU Leuven

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Abstract

This paper explores the impact of intangible investment on productivity mismeasurement using data from Belgian firms over 2002-2019. We employ microdata of business-to-business firm-level transactions to construct a measure of intangible investment at the firm level. Using a difference-in-differences event-study design leveraging lumpy investment, we find that intangibles lead to a 7-year cumulative TFP underestimation of 3 percent. However, these results are driven by the smaller firms, younger firms, and low capital-intensive firms in our sample. We find that these firms require a longer adjustment process to implement intangible investment within the firm by showing that training endeavors, the recruitment of new skilled workers, and the share of skill-intensive investment increases after the event. Finally, we show that the Solow Paradox can be explained by the complementarity between ICT and intangible assets: when ICT investment spikes are combined with large increases in intangibles, we find that ICT investments lead to an underestimation of true productivity growth. In all, our results provide additional insights on how new technologies, such as AI, drive productivity mismeasurement at the firm level.

JEL Codes: E01, E22, E23, O32

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Gert Bijnens: gert.bijnens@nbb.be, Jozef Konings: joep.konings@nu.edu.kz, joep.konings@kuleuven.be. Aaron Putseys: aaron.putseys@kuleuven.be (corresponding author).

1 Introduction

Intangible assets have become increasingly important in the production of firms (De Ridder, 2024). These assets range from software and databases to training and organizational capital, and are being adopted across many sectors of the economy. This new form of capital is, unlike tangible capital, by definition difficult to see or touch, making it hard to measure (Eisfeldt and Papanikolaou, 2014; Haskel and Westlake, 2017; Crouzet and Eberly, 2018). As a consequence, this has raised concerns that total factor productivity growth is mismeasured, especially when for many developed countries productivity growth has been stagnant for several years already.

An emerging literature studies firms adopting intangible assets. The literature focuses predominantly on software or R&D, and measures adoption through balance sheet data, surveys, or tries to infer the true value using a plethora of techniques (Brynjolfsson, 1993; Dewan and Min, 1997; Griffith et al., 2003, 2004; Bloom et al., 2012; Tambe and Hitt, 2012; Doraszelski and Jaumandreu, 2013; Crouzet and Eberly, 2018; Bloom et al., 2019; Dhyne et al., 2021; Rubens, 2023). Although these papers give insightful contributions, they fail to capture the full extend of intangible assets.[1] However, capturing intangibles in all its aspects is important, since correctly accounting for intangibles enables us to map the dynamics of productivity mismeasurement, which can give us additional insights on how new technologies can contribute to a productivity paradox (Brynjolfsson et al., 2021).[2]

There are as yet no empirical studies that directly examine what happens to firms' productivity mismeasurement when they decide to invest in intangibles, most likely due to the lack of a comprehensive measure of intangible investment. However, studying this adjustment process is critical to our understanding of how new technologies and intangibles in general impact the measurement of productivity growth. While the theoretical literature models intangibles as triggering a J-curve

[1] There are some papers, however, that try to capture intangibles in all its aspects. Brynjolfsson et al. (2021) uses the q-theory of investment to recover the amount of intangibles correlated with observable software, R&D, and computer intangible assets. Enache and Srivastava (2018) develop a method to estimate intangible expenditures that are reported together with SG&A expenditures. Iqbal et al. (2025) estimate intangible capital by running a regression of R&D or MainSG&A on current revenues and a series of future revenues, which identifies the investment portions and the useful lives of intangible expenditures.

[2] Brynjolfsson et al. (2021) show using aggregate data that intangible-related productivity growth mismeasurement follows a J-curve: at first, total factor productivity growth will initially be underestimated because capital and labor are used to accumulate unmeasured intangible capital stocks. Later, measured productivity growth overestimates true productivity growth because the capital service flows from those hidden intangible stocks generate measurable output.

of productivity mismeasurement (see, e.g., Brynjolfsson et al. (2021)), this need not translate to a firm-level J-curve. Further, our data also allows us to examine which firms drive productivity mismeasurement. Firm can differ in their experience with intangibles, and hence require a longer adjustment period. We show this by examining the impact of intangible investment spikes on training hours, the ratio of ICT investment over total tangible investment, and the entrance of new skilled employees within the firm. In the example of AI, we know that still only large firms invest in AI (McElheran et al., 2024). Depending on which firms drive the productivity J-curve, we can infer whether or not we are experiencing a J-curve for AI.

In studying the impacts of firms' intangible investment activity on productivity mismeasurement, our paper makes three contributions to the literature. First, we measure intangible investment at the firm-level across all private non-financial sectors. We develop a novel measure of intangible investment using a microdataset of business-to-business (B2B) firm-level transactions. This approach is inspired by Dhyne et al. (2021) who developed a measure of ICT investments in a similar way. The measure of intangible investment includes all domestic purchases from intangibles suppliers. This is a major improvement on earlier research that is based on Compustat or survey data covering only large firms (Crouzet and Eberly, 2019; Brynjolfsson et al., 2021; Kaus et al., 2024). Furthermore, most of the existing literature fails to capture the full extent of intangible investment at the firm level. For instance, Bresnahan et al. (2002) and Bloom et al. (2019) capture the productivity effect of management and organizational practices whereas Dhyne et al. (2021) focus on software. This paper captures intangible investment in all its aspects since our approach allows to construct separate measures for investments in software & databases, R&D, artistic originals, new products, design, market research, employer-provided training, and organizational structures.

Second, we implement an empirical approach based on evidence that firms' intangibles expenditures occur in discrete episodes of lumpy investment (Kaus et al., 2024).[3] In particular, we leverage spikes in intangibles cost shares to define intangible investment events. We exploit the timing of these events in a difference-in-differences event-study methodology for identifying causal effects on firms' productivity mismeasurement. This approach is made possible by the relatively high frequency of intangible investment events in our data. The advantage of this approach is that it allows for more credible identification of firm-level effects: this is important because the literature

[3] Aghion et al. (2020) and Bessen et al. (2025) use similar approaches for automation.

has shown that intangibles are concentrated within large firms (Autor et al., 2020), a finding we replicate in our data.

Third, by linking our annual firm data to comprehensive data on ICT investment (we use the measure introduced by Dhyne et al. (2021)), we can examine whether the Solow Paradox (Solow, 1987) can be explained by the complementarity between ICT investment and intangibles (Bresnahan et al., 2002; Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2003; Bloom et al., 2014; Dhyne et al., 2021). We leverage the timing of ICT investment spikes similarly as we did for intangibles spikes in our main analysis. To our knowledge, our paper provides the first causal evidence of the impact of firm-level ICT investment on productivity mismeasurement. Our paper complements the finding by Brynjolfsson and Hitt (1996), Brynjolfsson and Hitt (2003) and Brynjolfsson et al. (2021) on explaining the Solow Paradox of ICT investments.

We find that intangibles lead to a 7-year cumulative TFP underestimation of 3 percent. Compared to other intangibles, intangibles related to innovative property intangibles (R&D, entertainment, and design) mainly drive this J-curve due to the relatively low marginal product (1.3712 for innovative property, 2.1078 for economic competencies, and 4.0283 for computerized information). Turning to effect heterogeneity, we find that this impact of intangibles on productivity mismeasurement are larger for smaller firms, low-skilled firms, labor-intensive firms, and young firms. The reasoning behind this is that these firms have little experience with intangibles, and hence require a longer adjustment period. We prove this by showing that training hours, the ICT investment ratio, and the entrance of new skilled employee only increase for small, young, and low capital-intensive firms. Finally, we argue that the Solow Paradox could be explained by the complementarity between ICT and intangibles (Brynjolfsson and Hitt, 2003): We find that ICT investment spikes, combined with large increases in intangibles, lead to an underestimation of true productivity growth at the firm and aggregate level.

This paper is structured as follows. Section 2 presents the data sources and the descriptive evidence on the relationship between firm size and intangible capital. Section 3 explains the econometric model and the approach that we use to estimate productivity. Section 4 explains how the lumpiness of firms' intangible expenditures is used to identify intangible investment events, and documents these events in our data. Section 5 reports our main results on the effects of intangible investment on firm-level productivity mismeasurement using our difference-in-differences

event-study design. In Section 6 we provide tangible evidence on how the complementary between ICT and intangibles could explain the Solow Paradox, while Section 7 speculates whether we are experiencing a productivity J-curve due to AI investment. The final section concludes.

2 Data

2.1 Data sources and measurement

We combine different confidential micro data sets that were provided by the National Bank of Belgium (NBB) and ECOOM Leuven. All the administrative data described hereafter is confidential and could only be stored and accessed in person in a fully-secured location at the National Bank of Belgium (NBB).

The first one is the B2B transactions data. The Belgian B2B Transactions data set is constructed from yearly customer listing in the value-added tax (VAT) declarations of firms. All sales invoices above the amount of 250 Euro for all customers have to be reported. For a more in dept explanation, we refer to the work of Duprez et al. (2023). We use the customer listing of all firms that are active in intangible selling industries to calculate a yearly measure of intangible investment for the period 2002-2019. Our measure of intangible investments is based on the work of Corrado et al. (2005, 2009, 2012). The authors identified three types of intangible asset categories: (i) computerized information, (ii) innovative property, and, (iii) economic competencies. These intangible categories are populated with several asset types. Asset types are, for instance, software, databases, scientific R&D, and employer-provided training. In order to obtain a firm-level measure of intangible investment, we use the business-to-business (B2B) purchases related to the industries (NACE Rev. 2 code) that produce or sell intangible services. Table 1 shows the list of NACE Rev. 2 codes that are considered as intangible in this paper. This approach is similar to the one used in Dhyne et al. (2021) where they use customer listings to develop a measure for ICT-investment. The benefit of our data set is that it covers all domestic intangibles suppliers. We complement this dataset with the in-house R&D expenditures data set from ECOOM Leuven which measures the total expenditures to in-house R&D projects (this, for example, includes labor expenses on researchers). Figure A.3 in appendix A provides more information on the importance of each data source in our measure of intangible investment.

The second data set consists of the annual company accounts administered by the Central Balance Sheet Office at the NBB. All incorporated companies with limited legal liability are required to file their annual accounts at the NBB for tax compliance purposes. This gives additional financial and operational characteristics of each firm, comprising information on value added, labor costs, employment, intermediate inputs of goods and services, and capital stocks and expenditures, which enables us to estimate Total Factor Productivity (TFP) for each firm. Fiscal years have been annualized to calendar years to match the unit of observation in the NBB B2B data. We combine this with the Belgian Value-added Tax Declarations data set, consisting of the sales, total investments, and intermediate input expenditures of the firm. We provide additional details on these data sources in Appendix A and show the effects of our cleaning procedures on sample size.

2.2 Intangible capital investments

An important advantage of our data is the availability of a direct measure of intangible investment at the firm level. In particular, intangible investment costs are defined as expenditures on third-party intangible services. While the disadvantage of this measure is that we do not know the exact intangible technology being used by the firm, it does capture all intangible technologies rather than focusing on a single one. Further, we measure it at the level of the firm rather than the industry, and across all private non-financial sectors.

Table 2 shows summary statistics on annual intangible costs for firms, both in levels, per worker, and as a percentage of total capital stock. This highlights several things. First, almost one-fifth of firm-year observations has zero intangibles expenditures. Second, the average intangible cost share is 6.38%, corresponding to an outlay of around 143,192 euros annually, or 10,741 euros per worker. Third, this distribution is highly right-skewed as the median is only 2.00% – this skewness persists even when removing observations with zero intangible investment costs.

The top panel of Table 3 further shows how these intangible investment costs and cost shares differ by broad (one-digit) sector. Our comprehensive measure of intangibles indicates that all sectors have intangible expenditures, though there is substantial variation at the firm level both between and within each of these sectors. Average expenditures at the sectoral level range from 4,225 to 46,998 euros per worker. The highest mean intangible investment expenditures per worker are observed in Information & communication, followed by Utilities, Finance & insurance, and

Real estate. Conversely, Accommodation & food serving has the lowest expenditure per worker, followed by Construction, Non-high tech manufacturing, and Transportation & storage. However, there is much variation between firms in the same sector, as shown by the standard deviations of the intangibles share in total capital. While we do not use either this sectoral or between-firm variation in our empirical identification strategy, we will consider effect heterogeneity across sectors since the nature of intangible technologies may be sector-specific.

Table 3 also reports the same statistics but separately by firm size class, grouped into 6 classes: the smallest firms have up to 19 employees whereas the largest have more than 500. Unsurprisingly, intangible investment levels rise with firm size: firms with fewer than 20 employees spend around 29,000 euros annually on intangible services, whereas the largest firms spend close to 20 million euros. Less obviously, this table also reveals that intangible investment shares increase with firm size, particularly at the very bottom: the smallest firms have average intangible investment shares of around 5.94%, whereas firms with between 100 to 200 employees have a cost share of 11.49%. This increases to 12% for firms between 200 and 500 workers, and 12.17% for firms with more than 500 workers. This is consistent with the literature's findings that more productive and therefore larger firms are more likely to invest in intangibles (Autor et al., 2020; Lashkari and Boussard, 2024).[4] However, there is substantial variation within size classes, also.[5].

2.3 Comparison with balance sheet intangibles

Balance sheet intangibles are at best an imperfect measure of intangible capital. A first potential issue with balance sheet intangibles is the recording of these assets in the annual accounts. For intangible assets to appear on the firm's balance sheet, several conditions first need to be met. First, the asset must be clearly identifiable, meaning it can be separated from other assets. Second, the asset must create future economic benefits by contributing to the firm's income. Third, the costs to acquire, develop, or improve the asset must be clearly measurable. Usually, costs for developing or purchasing intangible assets are recorded as expenses unless they meet the rules for being capitalized (Enache and Srivastava, 2018). For example, software development costs can be

[4] We will explore the relationship between firm size and intangibles demand more thoroughly in Subsection 2.4 as similar to Lashkari and Boussard (2024).

[5] Figure A.8 further illustrates how the distribution of intangible cost expenditures per worker and intangible cost over sales change over time. It shows that both the means and variances of intangible costs per worker and intangible shares have increased over time. This is in contrast to tangible investment, shown in Figure A.9

capitalized if they meet the criteria, but research costs must always be recorded as expenses. Once capitalized, intangible assets are gradually written off over their useful life. However, some assets, like goodwill, do not have a set lifespan and are treated differently.

The size of the firm affects how intangible assets are handled. Small firms follow simpler accounting rules and do not have to provide as much detail about intangible assets in their financial statements. They can often choose to report these assets in a more straightforward way, for example as a cost. Medium and large firms, on the other hand, have stricter rules. They must provide detailed information, such as how the asset's value is being written off, how long it is expected to last, and what type of asset it is. Larger firms also need to regularly check the value of certain assets, like goodwill, to see if their value has dropped and adjust it if necessary.

Second, because they reflect the overall value of acquired intangibles, they conflate different types of intangible capital: software, intellectual property, brand, and business processes. The total book value of acquired intangibles may itself be a biased measure of their fundamental value, because of potential over- or undervaluation at the time of acquisitions (Crouzet and Eberly, 2019). In most cases, intangible assets on a firm's balance sheet are created when the company acquires another business. The only exceptions where intangible assets may appear on a company's balance sheet through internal efforts are: (i) development of software intended for sale or lease and (ii) exploratory costs in the oil and gas industry. In these scenarios, the costs meet specific criteria that allow them to be capitalized rather than expensed.

Table D.2 shows summary statistics on annual intangible investment per worker for firms, where we compare the B2B-based measure with the balance sheet variable – which we constructed using the perpetual inventory method (PIM). Several results emerge. First, the balance sheet variable is less comprehensive than the B2B-based measure in the sense that more observations report a zero value (18.6% for the B2B-based measure and 82.7% for the balance sheet variable). Second, intangible investment per worker is larger for our measure compared to the balance sheet investment variable: we report an average intangible investment per worker of 13,900 euros while the balance sheet variable has an average of 4,700 per worker. Third, when removing observations with zero intangible investment costs, the average balance sheet intangible investment per worker becomes larger than the average B2B intangible investment per worker, indicating that only very big firms report intangibles on their balance sheet.

Table D.3 further shows how these intangible investment measures differ by broad (one-digit) sector. Our comprehensive measure of intangibles produces for virtually all sectors a larger value per worker than the balance sheet variable – with the Utilities sector the only exception. The largest differences are reported in Construction: we report an average intangible investment per worker of 7,083 euros, while the balance sheet variable report an average investment of 876 per worker. Similar statements can be made when considering firm size, reported in Table D.4. Our measure report for all size groups a larger value (ranging from 1.05 to 4.44 times the balance sheet variable). This difference is mainly driven by the smaller firms that report a lot of zero or low values on their balance sheet.

2.4 The demand for intangibles and firm size

It is important to note that large firms are more likely to provide intangible services in-house instead of buying them externally. Because in-house intangibles developments are not accounted for in our intangible investment data, we could possibly underestimate the intangible input share in large firms, leading to an upward bias in the marginal product estimate. There are two reasons why this phenomenon is unlikely to affect our results. First, the in-house creation of intangibles is mainly the case for computerized information (software and databases), which is only a part of the intangibles we consider. Second, as we will show below, the share of intangible services increases instead of decreases with firm size.

We investigate the within-industry relationship between intangibles per employee and the scale of production across firms by estimating the equation

$$Intangiblesperemployee_{it} = FE_{Size_{it}} + FE_{ind_{it}t} + FE_{age_{it}} + \zeta_{it}, \tag{1}$$

where $Intangiblesperemployee_{it}$ denotes a measure of demand for intangibles (investments or stocks of intangibles) relative to the number of employees, $FE_{Size_{it}}$ denotes a size-class dummy corresponding to firm i's number of employees at time t, and $FE_{ind_{it}t}$ stands for a flexible set of industry-time fixed effects (at the four-digit level). In addition, we further add age $FE_{age_{it}}$ dummies to flexibly control for the effect of age.

Figure 1 shows the estimated coefficients for different size classes. The estimates are reported

relative to the estimated dummy for the size class corresponding to zero to five employees. We find a strong relationship between firm size and intangibles per employee, both in terms of investment and stock. For instance, a typical firm with more than 250 employees invests close to €5000 per employee more in intangibles than firms with 0-5 employees. The intangibles premium of larger firms is fairly sizeable considering that the unweighted mean intangibles per employee across all firms is around €8000 (€88,000/11, see Table A.3). As the figure indicates, the results are robust with respect to using stocks rather than investments.

Next, we measure firm scale in terms of output (added value and sales) and intermediate inputs (excl. intangibles), and estimate the intangibles demand equation

$$log(Intangiblesperemployee_{it}) = \eta log(Size_{it}) + FE_{ind_{it}t} + FE_{age_{it}} + \zeta_{it}, \tag{2}$$

where $Size_{it}$ denotes firm added value, sales, or intermediate inputs. The coefficient of interest is η, which measures the relationship between size and demand for intangibles. The results are presented in Table 4, columns 1-3. The coefficients are in the 0.3-0.36 (0.39-0.45) range, suggesting that raising the scale of the firm by a factor of 2 raises its intangible investment (stock) by about 30-36 (39-45) percent.

As a next step, we also include firm fixed effect FE_i in Equation 2 to examine the within-firm relationship between firm scale and intangibles. Columns 4-6 of Table 4 present the coefficients of firm size in the same regression as before that now additionally include firm fixed effects. We find positive and significant - although extensively lower - coefficients, ranging between 0.12 and 0.30 (0.03 and 0.07) when considering intangible investment per employee (intangible assets per employee) as outcome.

The results presented so far suggest the potential presence of scale dependence in intangibles demand. Similar results are found by Lashkari and Boussard (2024), documenting similar patterns between size and IT demand. This is consistent with the literature's findings that more productive and therefore larger firms are more likely to invest in intangibles. Since intangibles lack a physical presence, they require a way to store them (Crouzet et al., 2022). The storage medium can be several objects (for instance a computer, a patent, or a person). This has economic implications. The fact that intangibles can be used simultaneously in production in different locations and process

leads to some degree of *non-rivalry in use*, allowing for economies of scale and scope (Crouzet and Eberly, 2019). The results shown in are indicative of these properties. Another explanation can be the relationship between size and management practices. For instance, Bloom et al. (2012) find that multinational firms have larger values of its IT capital stock per employee, which are driven by better management practices.

3 Production function estimation

We assume firms produce final output with a Cobb–Douglas technology

$$Y_{it} = M_{it}^{\beta_M} L_{it}^{\beta_L} K_{it}^{\beta_K} U_{it}^{\beta_U} A_{it}, \tag{3}$$

where Y_{it} is the gross output of firm i at time t, M_{it} are expenditures on intermediates, L_{it} is labor, K_{it} is the tangible capital stock, and U_{it} is the intangible capital stock. A_{it} is a productivity shifter. Taking logs of Equation 3 yields the following empirical production function

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_u u_{it} + \omega_{it} + \varepsilon_{it}, \tag{4}$$

where $logA_{it} = \beta_0 + \omega_{it} + \varepsilon_{it}$, with ω_{it} denoting firm TFP and ε_{it} a residual that is assumed to be conditional mean independent of current and past inputs.

However, econometricians do not observe TFP at the firm-level. This leads to possible simultaneity bias because firms typically adjust capital and labor inputs in function of their productivity (Marschak and Andrews, 1944). The result of this endogeneity is biased output elasticities. In our example, if more productive firms invest more in intangible capital, we will likely overestimate the output elasticity of intangible capital in an ordinary least squares (OLS) estimation of Equation 3. Besides this well-known simultaneity bias, measurement error in the measured capital stock (both tangible as intangible) can introduce bias in the estimated output elasticities. The presence of measurement error in constructing the capital stock is well-known and poses an enormous challenge for any empirical analysis of productivity. It may lead to under-estimating the role of capital, and therefore capital deepening in explaining output differences across firms, industry dynamics and ultimately economic growth (Collard-Wexler and De Loecker, 2020).

We correct for these issues by applying the estimation strategy proposed by Collard-Wexler and De Loecker (2020), which jointly deals with measurement error in capital and the standard simultaneity bias. Capital stock mismeasurement is introduced by assuming errors-in-variable structure, where the observed log of the capital stock (k and u) is the sum of the log true capital stock (k^* and u^*) and the measurement error (ϵ^k and ϵ^u). ϵ^k and ϵ^u are orthogonal to the true capital stock but are allowed to be serially correlated over time. In a first, we isolate the productivity shocks using the control function approach by Ackerberg et al. (2015). In a second step, the capital variables can be instrumented by assuming log-linearity of the production function. As proposed by Collard-Wexler and De Loecker (2020), we will exploit lagged investment as instruments.

First, we estimate gross output production functions for the 'average' firm by pooling firms from all manufacturing industries and years (see Table 5). For the 'traditional' production factors, we find output elasticities that are much in line with the literature: 0.69-0.74 for intermediates, 0.15-0.20 for labor, and 0.03-0.07 for tangible capital. For total intangible capital, the estimated output elasticity is 0.01-0.06.

As in Brynjolfsson and Hitt (1996), we calculate the marginal product of each input as the product of its output elasticity and the ratio of gross output to the input value:

$$MP_u = \frac{\delta Y}{\delta U} = \frac{\delta Y}{\delta U}\frac{U}{Y}\frac{Y}{U} = \beta_u \frac{Y}{U} = \frac{\beta_u}{U/Y} \tag{5}$$

Next, we calculate the intangible capital input share for each observation and take the mean of the resulting distribution after winsorizing at the 1% level to avoid biases from outliers. Based on the estimated output elasticities of intangible capital, the marginal product of intangible capital is 0.98, or $MP_u = \frac{\beta_u}{U/Y} = \frac{0.0616}{0.0631} = 0.9762$. Thus, investing an additional euro in intangible capital increases gross output on average by 98 cents. For tangible capital, intermediates, and labor, the input shares are 0.41, 0.66, and 0.19, respectively, so the marginal product of tangible capital is EUR 0.16, the marginal product of intermediates is EUR 0.82, and the marginal product of labor is EUR 0.23.

We rerun Equation 4 using the estimation procedure by Collard-Wexler and De Loecker (2020) but changing the intangible capital stock by intangibles related to computerized information, innovative property, and economic competencies. The largest output elasticity is related to economic

competencies (0.0432), followed by innovative property (0.0417), and computerized information (0.0396). We also estimate the marginal product using Equation 5 for these three different asset types. The largest marginal product is related to computerized information ($\frac{0.0396}{0.0098} = 4.0283$), meaning that one additional euro in computerized intangibles leads to a larger increase in gross output compared to the other types ($\frac{0.0432}{0.0205} = 2.1078$ for economic competencies and $\frac{0.0417}{0.0304} = 1.3712$ for innovative property).

Finally, we estimate the output elasticity of intangibles using different measures: (i) the balance sheet intangible capital stock, (ii) the B2B-based intangible capital stock excluding possible intangibles fees[6], and (iii) the B2B-based intangible capital stock including intangible imports. In Appendix D.4, we show the way we constructed these intangible capital stocks, along with some descriptive statistics. We find that the output elasticity for the balance sheet intangible capital stock (0.0274) is roughly two times lower than our baseline results. The reason is that this variable is badly reported: 83% of the data contains zero values, leading to low variation in this variable. The coefficients for intangible capital stocks without fees (0.0745) and with imports (0.0642) are very similar to our baseline.

4 Intangible investment events

4.1 Defining intangible spike events

We identify events using what we call intangible investment spikes. This is similar to the one by Bessen et al. (2025) for automation. We define an intangible investment spike as follows. Firm j has an intangible cost spike in year τ if its real intangible investment I_{jt} relative to real total capital averaged across all years t, $\bar{TK}_j$, are at least thrice the average firm-level share excluding year τ:

$$spike_{j\tau} = \mathbb{1}\left\{\frac{I_{j\tau}}{\bar{TK}_j} \geq 3 \times \frac{1}{T-1}\sum_{t\neq\tau}^{T}\left(\frac{I_{jt}}{\bar{TK}_j}\right)\right\} \tag{6}$$

where $\mathbb{1}$ denotes the indicator function. As such, a firm that has intangible investment costs around one percent of all already existing tangible and intangible capital stock for year $t \neq \tau$ will be classified as having an intangible investment spike in $t = \tau$ if its intangible costs in τ exceed

[6]We thank David Baqaee for pointing this out.

three percent of average total capital over years t. Finally, we define an intangible investment event as the year when the firm has its first increase in intangible investment share that qualifies as a spike.[7][8] As a robustness, we experiment with different definitions of intangible investment spikes: we use sales, number of workers, or intermediates (excluding intangibles) instead of tangible capital as a denominator in Equation 6.

4.2 Summary statistics of intangible investment events

Out of the total number of 199,484 firms with at least 3 years of intangibles data, there are 97,496 firms that have at least one spike in their intangible share between 2002 and 2019.[9] That is, 48,9% of the firms in our sample spike at least once over the 18 years of observation.[10] Out of the firms that have at least one intangibles spike, the large majority spikes only once over 2002–2019, although some spike twice and up to six times at most.

Figure 2 shows the evolution of intangibles shares around intangible investment events. This is constructed by redefining time τ as event time: the difference between the actual calendar year and the calendar year of the spike, such that all intangible spike events line up in $\tau = 0$. Figure 2 uses the sample of 97,496 firms, showing a clear one-period increase in the intangibles share when a firm has its intangible spike event. Figure C.1 in Appenix C.3 shows that this increase is driven by intangible investments rising, not total capital decreasing.

We also assess the 'lumpiness' of intangibles expenditures. We find that while only 6.7% of firm-year observations are intangible investment spikes, these make up 8.4% of total investment in intangibles across all firms that we observe at least three times in our data. Further, among firms that have an intangible investment spike, on average 54% of all observed intangible expenditures occurs during such spikes (with a median of 57%): if intangible expenditures were evenly distributed within firms over time, any one year would only correspond to 7.3% of the total outlay. This

[7] Firms without an intangible investment event do not necessarily have zero intangibles costs, but their intangibles expenditures do not vary much relative to total capital, implying they do not undergo intangible investment events as we define them. Firms without such events do have lower intangible investment costs also on average, however.

[8] Note that intangible investment costs capture the use of third-party intangibles services: this raises the question whether these events capture outsourcing at the firm-level. However, for outsourcing, we would expect to see a sustained increase of costs for the firm (reflecting a flow of wages to these outsourced workers) rather than a temporary spike.

[9] Shown in Appendix Table C.1

[10] We also find that this percentage varies relatively little across sectors (ranging from 35% in Real Estate to 53% in Construction). For firm size, we see a clear declining trend between firm size and spike frequency. The smallest firms are most likely to have intangible investment events. See Appendix Table C.2 for details.

suggests that while firms also have outlays on intangibles that do not fall within our strict intangible investment event definition, intangible investments are lumpy.

5 Do intangible investments cause a productivity J-curve?

Following the recent literature examining changes in firm-level outcomes from firm-level investment spikes that was summarized in the introduction (Aghion et al., 2020; Bessen et al., 2025), this section briefly discusses how our intangible investment events correlate with firm-level outcomes, in particular firm-level employment and the firm's intangible-to-tangible capital ratio, and added value. Subsection 5.1 compares firms with an intangible investment event to firms without an intangible investment event, showing that these firms are on substantially different trajectories. Subsection 5.2 therefore presents an analysis of the impact of intangible investment only using the sample of firms with an intangible investment event.

5.1 Comparing treated to non-treated firms

We first ask how firms with an intangible investment event differ from those without an intangible investment event: as outcomes, we consider growth in firm-level employment, in intangible-to-tangible capital ratio, and in the firm's added value. We estimate variants of the following model:

$$\Delta lnY_{it} = \beta \times A_i + D_t + D_j + \gamma X_i + \epsilon_{it}, \tag{7}$$

where the dependent variables are annual log changes in employment, in the intangible-to-tangible capital ratio, and in the added value for firm i in calendar year t. A_i is a dummy for the firm having an intangibles event over the 2002–2019 period, D_t and D_j are calendar year and four-digit sector fixed effects, and X_i additional controls consisting of baseline firm-level characteristics.[11] The term ε_{it} is an error term and standard errors are clustered at the firm-level. The coefficient of interest, β, tells us whether firms investing in intangibles experience different employment, intangible-to-tangible capital ratio, and added value trajectories.

[11] Table D.1 in Appendix D estimates a linear probability model where the dependent variable is a dummy for the firm having an intangible investment event over 2002–2019, showing that smaller firms and firms paying higher wages are more likely to invest in intangibles.

Table 6 shows that investing firms have 1.4 to 1.7% higher employment growth. Similar statements can be made for added value (1.0 to 1.4%), and intangible-to-tangible capital ratio (1.1 to 3.6%). In sum, these results suggest that investing firms grow faster in size, intangible capital share[12], and added value than non-investing firms which in part motivate our empirical design, outlined in the next section.

5.2 Difference-in-differences only using treated firms

We set up our data in a stacked difference-in-differences design as in e.g. Cengiz et al. (2019) and Bessen et al. (2025). More specifically, we create separate datasets for each cohort of firms that have their first intangible investment event in year c, with c ranging from 2005 to 2012. The variable τ represents event time and is calculated as the calendar year t minus the year c when the subsidy event occurred ($\tau = t - c$). Within each dataset, we included observations where τ ranges from -3 to 6, defining our event window. Then for each dataset, we add observations for the same calendar years on all firms that have an intangible investment event in year c + 7 or later as controls. For example, our first cohort of treated firms are firms that have their first intangible investment event in 2005. The event window surrounding this event contains the calendar years from 2002 to 2011. All control firms for the 2005-cohort are those firms that we observe over the same event window (2002 to 2011), and that have their first intangible investment event later than 2011.[13] These firms are "clean controls" in the sense that they do not have an intangible investment event during the event window. We repeat this procedure for each cohort of firms. Finally, we stack the cohort-specific datasets so that they line up in terms of event time (τ ranging from -3 to 6).

The by now well-documented problems related to two-way fixed effects in an event-study design arise from staggered treatment timing (de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). By creating a balanced panel in event time, we have effectively eliminated the staggered timing in the data, and hence do not suffer from the issues that staggered timing may create. Most notably, we do not use "already-treated" units as control units. Baker et al. (2022) show that a stacked difference-in-differences

[12] Appendix D.2 shows similar results when using a balanced panel of firms.

[13] Appendix D.3 shows results using non-investing firms as control group: we find diverging pre-trends in TFP mismeasurement in this comparison. This is consistent with the evidence presented in Subsection 5.1 and suggests that non-investing firms are not a good control group for investing firms in our case.

setup recovers the true treatment effects in the case of staggered timing, just as the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) approaches do. Using this stacked dataset, we estimate the following Difference-in-Differences specification:

$$y_{it} = \alpha + \sum_{\tau=-3}^{-2} \delta_\tau \times I_\tau \times Treat_i + \sum_{\tau=0}^{6} \delta_\tau \times I_\tau \times Treat_i + \lambda_{st} + \eta_i + \epsilon_{it}, \tag{8}$$

where i indexes firms by cohort (since individual firms can appear multiple times in the dataset). I_t are the leads and lags in event time, with $\tau = -1$ as the reference category. $Treat_i$ is the dummy variable indicating treatment, which equals to one for firms that experience an intangible investment spike in the event window. λ_{st} is a set of four-digit sector $\times$ calendar year fixed effects and η_i are a set of cohort by firm fixed effects. y_{it} is the (log) outcome variable of interest.

5.3 Results

We begin by estimating the impact of firm-level intangible investment on the firm's total factor productivity mismeasurement.[14] These estimates of parameters δ_t in Equation 8 are shown in panel (a) in Figure 3, to capture changes in annual TFP mismeasurement relative to their $\tau = -1$ level. The estimates highlight that the firm's TFP is underestimated as a result of the intangible investment event. Indeed, the average firm's TFP is underestimated by about 0.80% in $\tau = 0$; 0.89% in $\tau = 1$; 0.58% in $\tau = 2$; 0.32% in $\tau = 3$; 0.19% in $\tau = 4$; 0.16% in $\tau = 5$; and 0.05% in $\tau = 6$. Overall, TFP underestimation increases by 2.99% (=0.80 + 0.89 + 0.58 + 0.32 + 0.19 + 0.16 + 0.05) cumulatively of the firm's TFP mismeasurement in $\tau = -1$ after 7 years. Given that measured TFP grows by 1% annually on average, this reflects a non-negligible mismeasurement to TFP trajectories. More information can be found in Table D.12, column 1.

The dynamics of productivity mismeasurement follows a J-curve, which has been introduced by Brynjolfsson et al. (2021) as the *Productivity J-curve* at the aggregate level. According to Brynjolfsson et al. (2021), every general purpose technology (GPT) (for example, the computer in the 1980s and now artificial intelligence) leads to a Solow-like paradox, where "a technological revolution, a drastic change in our productive lives" is generally accompanied by "a slowing-down of productivity growth, not by a step up" (Solow, 1987). The reasoning for this that these GPT's require large

[14] Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level.

complementary intangible investments, but these are badly measured. The J-curve patterns is the result from two opposite forces. When firms adopt a new General Purpose Technology (GPT), total factor productivity growth is initially underestimated. This is because capital and labor are being used to accumulate intangible capital stocks that are not directly measured. Later on, measured productivity growth overstates actual productivity growth, as the capital service flows from these intangible stocks begin to produce measurable output. Thus, the error in measured total factor productivity growth follows a J-curve: it initially declines as the investment in unmeasured capital exceeds investment in other types of capital, and then increases as growing intangible stocks start contributing to measured production.

Our study finds that this *Productivity J-curve* also exists at the firm-level. Intangible assets are rarely allowed to be placed on the balance sheet. Instead, these intangibles are typically commingled with operating expenses in the selling, general, and administrative (SG&A) category of expenses (Enache and Srivastava, 2018). Hence, SG&A is the largest cost item for many knowledge-intensive firms (e.g., Google, Intel, Merck, International Business Machines, Microsoft) but carries scant details on its constituent items other than R&D and advertising. At the moment that firms experience an intangible investment spike, the difference between actual and true intermediate services start to diverge (captured by M in the production function). This creates this initial dip at $\tau = 0$. After a while, the intangible capital stock starts to build up (U in the production function) and becomes more important in production.[15] As this term start to increase, the difference between measured and actual productivity start to decrease. This is nicely demonstrated in Figure C.1, where we observe a significant increase in intangible expenditures (investment) at $\tau = 0$, while the total capital stock gradually increases over time.

We have found that intangible investments lead to productivity mismeasurement: this raises the question whether this effect is caused by specific intangible investment types or occurs with every intangible investment type. We analyze the effects of intangible investment types (computerized information, innovative property, and economic competencies) in a similar way to that of total intangible investment events, and directly contrast it to each other. Since these three intangible investment types are correlated at the firm level, we remove firms which have other intangible

[15] Kaus et al. (2024) find that a positive relationship between the output elasticity of intangible capital and intangible capital intensity.

investment spikes within our estimation window to rule out that our event is partially capturing investment in other intangibles.

In Appendix E, we show some descriptive statistics for these three different intangible asset types. Investments in economic competencies are higher than the other two types across the distribution, both in total and per worker. We provide further details of these investments by sector and firm size in Appendix E. In order to compare intangible investment type events, we construct investment spikes in the same way we have for total intangible investment but using investment per worker. We use the same threshold, assigning firms an investment spike if their investment per worker exceeds three times their usual level. Comparing the different intangibles spikes, computerized information investment spikes are most frequent. However, all have a clear one-period increase in investments per worker when a firm has its intangible investment type event.

We construct three different datasets. We only retain those computerized information investment events where there is no other intangible investment (innovative property and economic competencies) event occurring in the estimation window for either treated or control group firms. These different investment events are correlated across firms over time: firms that have recently had one type of event are more likely to also experience the other sometime soon, even in the same year. This implies any estimated impact of computerized information investment may be contaminated by the other investment types, and vice versa. We do the same for the other two intangible investment types (innovative property and economic competencies). For each of the three samples, we then estimate Equation 8 and report results in Figure 3, panel (b). More information can be found in Table D.12, columns 2-4.

This comparison leads to several findings. First and foremost, investments in computerized information (software & databases) and economic competencies (organizational capital, training etc.) do not lead to an underestimation of true productivity. In fact, these investment types rather cause an overestimation rather than an underestimation of true productivity. This is in contrast to innovative property (R&D, artistic originals, new designs etc.), which does lead to a clear underestimation of true productivity. This means that investments in innovative property are more likely to lead to a period of productivity underestimation than computerized and economic competencies investments. These finding can be explained by our results from Section 3: the largest marginal product is related to computerized information ($\frac{0.0396}{0.0098} = 4.0283$), meaning that

one additional euro in computerized intangibles leads to a larger increase in gross output compared to the other types ($\frac{0.0432}{0.0205} = 2.1078$ for economic competencies and $\frac{0.0417}{0.0304} = 1.3712$ for innovative property). This means that computerized information capital is more productive and can be easily implemented in production to produce output. Innovative property requires a longer adjustment period to implement and has less guarantees of tangible results.

5.4 Effect heterogeneity

Is the J-curve a general phenomenon or is this result driven by specific type of firms? To evaluate this, we rerun Equation 8 for different subset of firms. First, we consider firm size heterogeneity in columns (1) and (2) of Table 7. The size thresholds are determined by an EU directive. A firm is classified as "large" if at least two of the following three criteria are exceeded: (i) 50 full-time equivalent employees, (ii) sales of €9 million, (iii) total balance sheet of €4.5 million. Otherwise, the firm is classified as "small". We find that small firms experience a productivity J-curve, while bigger firms do not. Why is this the case? Bigger firms are more able to adopt to new innovations and investment thanks to their better management practices and skilled labor (or, in other words, their intangible capital stock). As a results, their adaptation period is shorter than smaller firms, which determines the existence of a J-curve. For example,Criscuolo and Martin (2009) and Bloom et al. (2012) find that multinational firms are better in introducing information and communication (ICT) technologies thanks to their better management capital, leading to direct productivity effects.

Second, we mainly find that the J-curve is present in low-capital intensive firms. Low capital-intensive firms are firms with a capital-labor ratio in the bottom three quartiles of the total capital-labor distribution. These firms are typically characterized as having small intangible capital shares. Hence, introducing intangible capital in the firm require large adjustments: they must retrain workers, introduce new management practices and so on (Brynjolfsson et al., 2021). Capital-intensive firms already have large intangible capital stock prior to intangible investment shocks. Hence, they have already experience with this kind of capital. For example, Autor et al. (2020) point out that productive superstar firms have a lower labor share due to a larger amount of intangible capital. This is an indication that there is a clear relationship between firm performance and intangible capital.

Third, we find that low-skilled firms experience the J-curve, while skilled firms do not. We

define the fraction of skilled workers as the number of employees with college education or higher as a share of the total reported employees (full-time equivalent). These data are only available from 2008 onward, so we average these over 2008 to 2019. Firms are "high-skilled" if the firm is in the top quartile of the skill share distribution, defined as the share of full-time-equivalent workers with a college degree. The fact that only low-skilled firms experience a J-curve is because they experience an adjustment period after the investment. Since their personnel is low-skilled, their skills need to be update through training. Productive and skilled firms do not suffer from this issue since skilled employees tend to select into these firms (Song et al., 2019).

Finally, our results indicate that mainly younger (age below 15) firms experience the productivity J-curve. Coad et al. (2013) show that older firms have higher productivity, higher profits, larger size, lower debt ratios, and higher equity ratios. Hence, new innovations require less complementary investments compared to younger firms. These investments are riskier for smaller firms (Coad et al., 2016), which is related to their lack of experience in doing intangible investments (Criscuolo et al., 2012). Hence, when younger firms start to innovate, they require large amounts of complementary intangible assets to make use of them.

We found that mainly small, low capital-insensitive, and young firms experience the intangibles-related productivity J-curve. The main argument for these results is that these firms require a longer adjustment period to make use of new innovation by doing complementary intangible investments. Is this the case? We explore this adjustment process by examining different outcome variables related to this: the entrance of skilled employees within the firm, the number of training hours, the log ratio of ICT over tangible investment, and log tangible investment. In Appendix D.6 we show that these adjustment processes are mainly concentrated within small, low capital-insensitive, and young firms, indicating clear evidence that these firms experience an adjustment process, while other (bigger, capital-intensive, and old firms) do not.

5.5 Robustness tests

As a first robustness check, we alter the definition of intangible investment spikes. Rather than using intangible investment as a share over the total capital stock, we can construct intangible investment events from sharp increases in intangible outlays normalized by different variables. We consider three different definitions: (i) intangible investment over "other" intermediates, (ii)

intangible investment per worker, and (iii) intangible investment over gross output. All variations produce similar results to our baseline estimates, as seen in panel (a) of Figure F.1.

Further, we show that results are robust to varying the spike threshold from 2 to 5 times the average intangible investment share (our baseline is thrice the average intangibles share). Panel (b) in Figure F.1 reveals that estimated effect sizes are somewhat larger the higher the threshold, as expected, but these differences are not statistically significant. This highlights that our results are not driven by the specific spike size cut-off we employ in our baseline estimates.

Next we show that the existence of the productivity J-curve is not driven by outlier. In panel (a) of Figure F.3, we show that winsorizing TFP mismeasurement at the 0.5% or dropping the bottom and top 1% of the TFP mismeasurement distribution has no significant impact on our results. As a further robustness check, we construct events for firm-level investments which we expect to be neutral in terms of productivity mismeasurement: spikes in "material fixed assets". This investment comprising items like furniture, shelving, silos, containers, and pellets, buildings, land, means of transportation, machines, communication equipment, and computers; it excludes immaterial assets such as software and licenses. We construct spikes in material fixed assets analogously to intangible investment – these expenditures are also lumpy, allowing for the construction of spikes. We estimate the difference-in-differences models for the overlapping sample of firms where we observe both intangible investment events and at least three years of data on fixed material assets.[16] In contrast to intangible investment events, events based on fixed material assets do not have any impact on firms' productivity mismeasurement. This shows that the impacts we find for intangible investment events are not a mechanical outcome of constructing firm-level events the way we do. Results are shown in Figure F.3, panel (b).

We also examine the impact of intangibles on productivity mismeasurement using alternative definitions of intangibles spikes: (i) Balance sheet intangibles, (ii), B2B + imports, and, (iii) B2B - "fees". We find very similar results using intangibles adjusted for imports or fees, but not for balance sheet intangibles (see Figure F.4). The reason is that this variable exhibit very few spikes (76% of firms exhibit no balance sheet intangible spikes) and has a low output elasticity. This indicates that our B2B-based measure is better equipped for this type of analysis, while balance

[16] We also examine the impact of tangible investment spikes while removing firms with an intangible investment spike in our sample. We do this since these two different spikes are correlated, as shown in Table C.3.

sheet intangibles fail to do so.

Finally, we also apply the nearest neighbor matching procedure. Our estimates can be considered causal effects if the identifying assumptions hold: parallel trends in the absence of intangible investment events and no anticipation of the subsidy event. A straightforward way to test for parallel trends is to check if $\delta_\tau = 0$ for $\delta_\tau < 0$, which appears to be the case in Figure 3. In our baseline approach, the control group includes firms who have not yet received an intangible investment. As another robustness check we use an alternative control group of non-yet treated firms, by applying a matching approach. In particular, we use nearest neighbor matching procedure, which selects the closest possible control firm to be paired with each treated firm (Imbens and Wooldridge, 2009). We use the multi-variate Mahalanobis distance to find close matches on the basis of the pre-treated average values of employment (FTE) and/or age. We use exact matching, that is each treated firm is matched to exactly one control firm. Since the treatment period varies per treated firm, we implement this procedure separately for each treatment period and firm. We also require that matches take place between firms operating within the same 2-digit NACE sector. Figure F.5 shows the results.

6 A tangible example: ICT and the Solow Paradox

We have found that intangible investment spikes lead to productivity mismeasurement: this raises the question whether ICT investments - an example of a GPT - also leads to productivity mismeasurment as argumented in Brynjolfsson et al. (2021). Early work in the literature on the productivity effects of GPT's was spurred by the famous quote of (Solow, 1987, p.36): "You can see the computer age everywhere but in the productivity statistics." This quote received a lot of attention because productivity growth indeed started to decline right at the moment computer investments took off. It is possible that the adoption of ICT coincided with an increase in intangible capital, resulting in productivity mismeasurement. In fact, several papers highlighted the correlation between intangible capital (for instance, management practices) and ICT intensity (Bresnahan et al., 2002; Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2003; Bloom et al., 2014; Dhyne et al., 2021).[17]

[17]For example, Brynjolfsson et al. (2002) find that ICT investment is correlated with training, hiring skilled employees, and changes in management styles. This is a clear indication that ICT investments require significant

We explore this hypothesis by examining the impact of ICT investment spikes (as similarly defined as intangibles spikes in Equation 6) on productivity mismeasurement. The definition of ICT investment is the same as in (Dhyne et al., 2021).[18] Firm j has an ICT cost spike in year τ if its real ICT investment I_{jt}^{ICT} relative to real total capital averaged across all years t, $\bar{TK}_j$, are at least thrice the average firm-level share excluding year τ:

$$spike_{j\tau} = \mathbb{1}\left\{\frac{I_{j\tau}^{ICT}}{\bar{TK}_j} \geq 3 \times \frac{1}{T-1}\sum_{t\neq\tau}^{T}\left(\frac{I_{jt}^{ICT}}{\bar{TK}_j}\right)\right\} \tag{9}$$

where $\mathbb{1}$ denotes the indicator function. As such, a firm that has ICT investment costs around one percent of all already existing tangible and intangible capital stock for year $t \neq \tau$ will be classified as having an ICT investment spike in $t = \tau$ if its ICT costs in τ exceed three percent of average total capital over years t. The evolution of ICT investment per worker around ICT investment events is shown in panel (a) of Figure 4, indicating a clear one-period increase in ICT investments per worker.

We estimate the impact of firm-level ICT investment on the firm's total factor productivity mismeasurement, where productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP. The estimates of parameters δ_t in Equation 8 are shown in panel (b) in Figure 4, denoted by the gray triangles. Although the difference between measured and adjusted log TFP declines (the difference declines with 1% after 2 years), these differences are not statistically significant from zero. A reason is that not all ICT events coincide with intangibles leading to large standard errors for our estimates. Earlier investments in ICT are probably more correlated with intangibles than ICT investments nowadays: ICT is a technology that most firms use and know, which was less the case in the 1980s and 1990s. Moreover, we see that mismeasurement happens with a lag, which is something similar to the finding by Brynjolfsson and Hitt (2003).

To fully capture the impact of intangibles on the mismeasurement of productivity when firms start to invest in ICT, we alter the definition in the following way: we require the same condition

adjustment processes.

[18] Appendix A.8 provides more information on the construction of the ICT investment variable.

of Equation 9, but we additionally require that

$$\frac{I_{j\tau}}{TK_{j\tau}} \geq 2 \times \frac{I_{j\tau-1}}{TKj\tau - 1} \tag{10}$$

implying intangible capital deepening goes up with a significant amount at the moment of an ICT spike. We re-estimate Equation 8 with this new definition of ICT investment moments and plot the results in panel (b) of Figure 4 shown by the black circles. Our results show that ICT investment combined with large increases in intangibles lead to significant productivity growth underestimation: the difference between measured log TFP and intangibles-adjusted log TFP goes down by 0.5% indicating that intangibles-adjusted TFP grows faster than measured TFP. Our results complement the finding by Brynjolfsson and Hitt (1996), Brynjolfsson and Hitt (2003) and Brynjolfsson et al. (2021) on explaining the Solow Paradox of ICT investments: when computer investments are combined with intangible investment we will underestimate true productivity growth. For example, Brynjolfsson et al. (2021) argue that TFP levels are approximately 16% higher when it is adjusted for intangibles related to computer hardware and software.

7 Are we experiencing a J-curve due to hidden AI investments?

The literature presents two perspectives on how AI can contribute to firm-level productivity (Czarnitzki et al., 2023). One view treats AI as an intangible asset, which firms can invest in and leverage to generate output through a production function (Brynjolfsson et al., 2019, 2021). The other view highlights how AI-driven techniques can enhance a firm's innovative capabilities, thereby boosting productivity through their impact on R&D, innovation, and the creation of new ideas (Aghion et al., 2017). If we adopt the first perspective, considering AI as a form of intangible capital, it is plausible that we are currently witnessing a J-curve effect due to underlying AI investments, as proposed by Brynjolfsson et al. (2019).

Studies have been emerging that try to measure the impact of AI on sales, employment, and productivity, finding a positive relationship. Czarnitzki et al. (2023) find that AI use is associated with higher productivity: AI users annually sell, on average, 13.9% more than non-users. Yang (2022) find that the presence of AI patents has a significantly positive influence on productivity.

Firms with AI patents are associated with a 13.07% higher productivity than other firms. Babina et al. (2024) document a strong and consistent pattern of higher growth among firms that start investing in AI: a one-standard-deviation increase in AI investments over the 8-year period corresponds to a 19.5% increase in sales and a 18.1% increase in employment. Causal effects of AI on productivity are captured by Brynjolfsson et al. (2023) which estimates the impact of the adoption of a generative AI tool that provides conversational guidance for customer support agents. Access to the tool increases productivity by 14% on average.

However, AI adoption remains concentrated within bigger firms and the studies above only consider relatively big firms. McElheran et al. (2024) added a new question to the annual business survey in the US to document the early adoption and diffusion of artificial intelligence-related technologies. They find that fewer than 6% of firms used AI-related technologies though most very large firms reported at least some AI use.[19] It is certainly possible we are experiencing a J-curve due to hidden AI investments. The question, of course, is to what extent. Larger companies have more skilled employees, and as we demonstrate, these firms do not really experience the J-curve: They adapt more quickly to these new investments and can introduce them more easily because their higher share of skilled labor and better management practices. As soon as smaller and low skilled firms start to invest in AI, we will really experience a J-curve for AI.

8 Conclusion

We develop a novel measure of intangible investment using a microdataset of business-to-business (B2B) firm-level transactions. The measure of intangible investment includes all domestic purchases from intangibles suppliers. This is a major improvement on earlier research that is based on Compustat or survey data covering only large firms. Furthermore, most of the existing literature fails to capture the full extent of intangible investment at the firm level. This paper captures intangible investment in all its aspects since our approach allows to construct separate measures for investments in software & databases, R&D, artistic originals, new products, design, market research, employer-provided training, and organizational structures.

We estimate the impacts of firms' intangible investment activities on firm-level productivity, us-

[19] In a recent survey by Andries et al. (2021) similar results are found: very small firms rarely use AI (2.1-7.7%) while 12.4-37.1% bigger firms use AI within their firms. See Appendix A.7 for more information.

ing our firm-level data measure on intangible investments across all non-financial private sectors in Belgium over 2002–2019. Leveraging a difference-in-differences event-study design exploiting spikes in intangible investment, we show that intangible investment at the firm significantly increases productivity underestimation. The impacts of intangibles on total factor productivity underestimation are larger for smaller firms, for low capital-intensive firms firms, and non-services firms. The reasoning behind this is that these firms have little experience with intangibles, and hence require a longer adjustment period. We show this by examining the impact of intangible investment spikes on training hours, the ratio of ICT investment over total tangible investment, and the entrance of new skilled employees within the firm. We only see positive and significant effects for small, young, and low capital-intensive firms indicating that indeed they mainly experience this adjustment period.

We provide also new evidence on the Solow Paradox. ICT and intangibles are complementary assets. Hence, increases in ICT investment can lead to productivity mismeasurement. We indeed find that ICT investment spikes, combined with large increases in intangibles, lead to an underestimation of true productivity growth at the firm and aggregate level. More speculatively, we argue that we are at the forefront of an AI productivity paradox. At the moment, high-skilled and large firms mainly invest in AI. As soon as smaller, low skilled, and young firms start to invest in AI, we will really experience a J-curve for AI.

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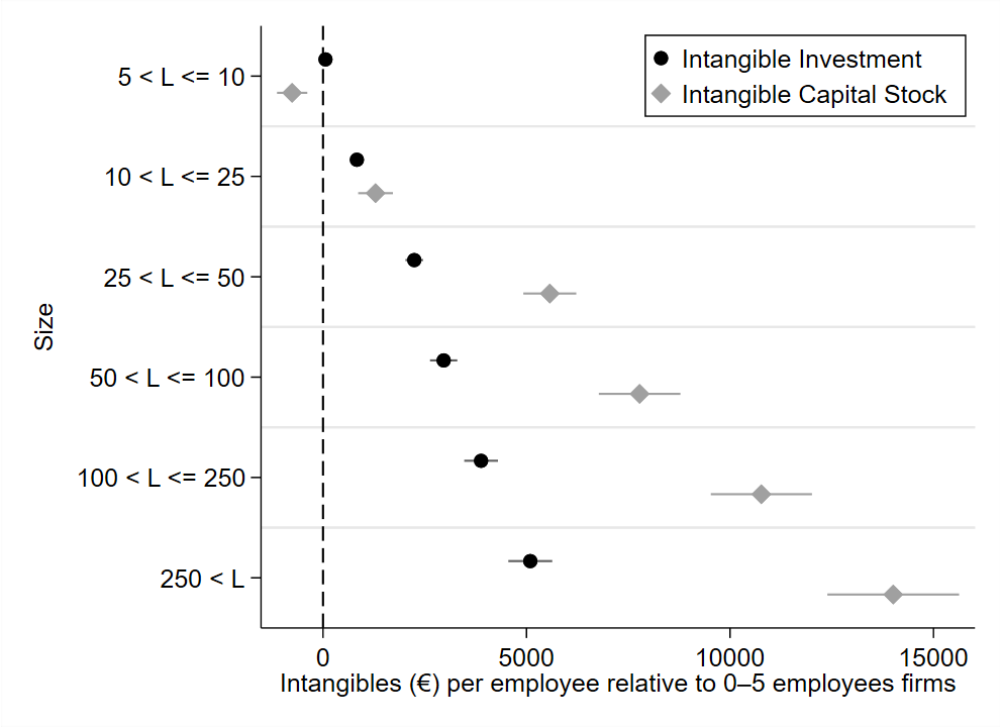
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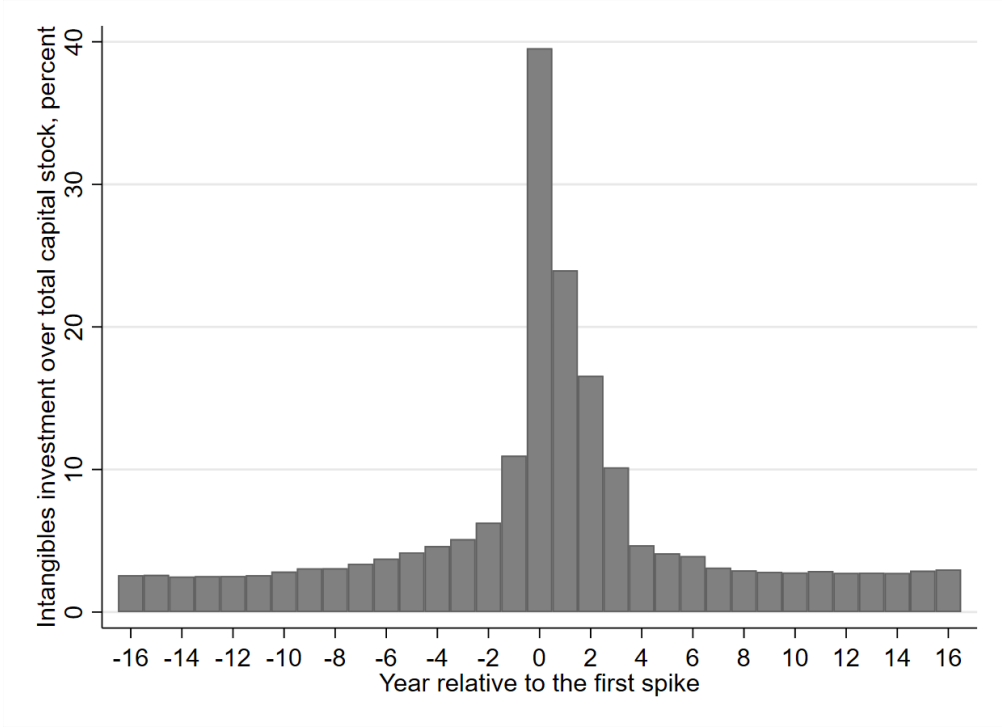
Figures

Figure 1: Cross-sectional relationship between intangibles per employee and firm size



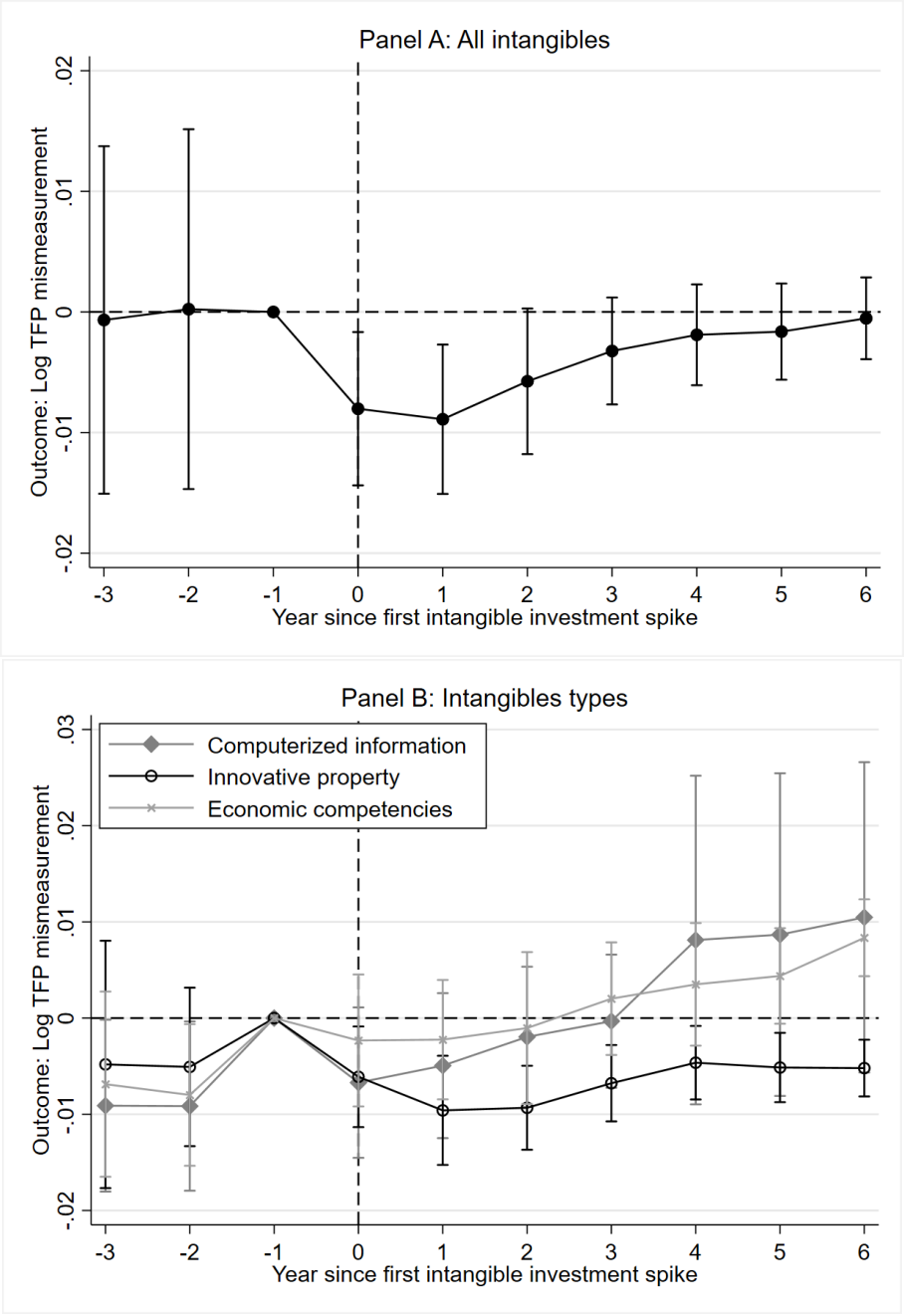
Notes: Figure 1 reports average intangible investment and stock per employee by firm size class, estimated by Equation 1. Averages are conditional on a set of flexible fixed effects constructed from the interaction of four-digit industry codes and time dummies, and age fixed effects. The bands around the estimates show the 95 percent confidence intervals.

Figure 2: Intangible investment shares around events



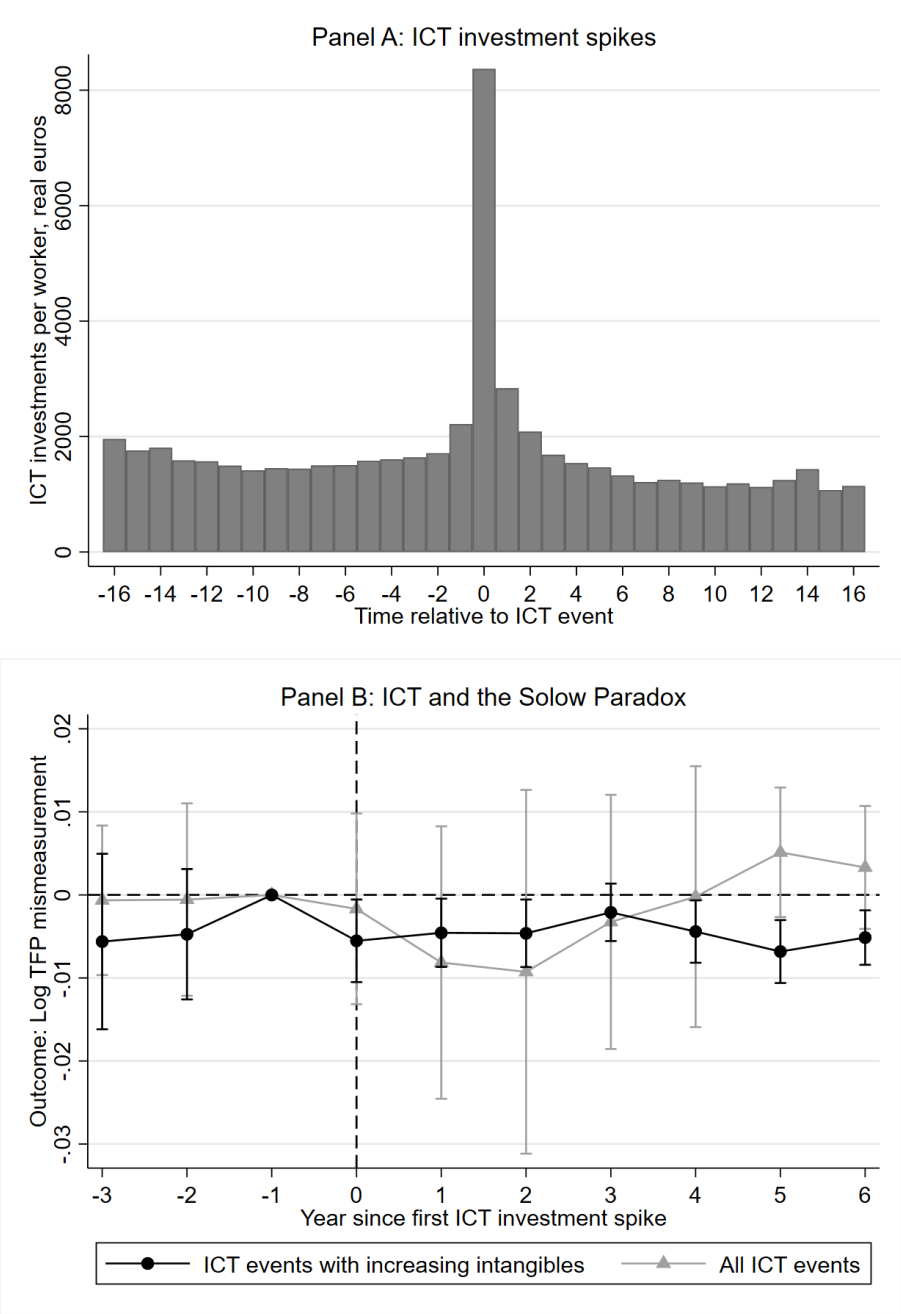
Notes: Figure 2 shows the intangible investment shares (as a share of total capital) around intangible investment events.

Figure 3: Effect of intangible investment spike on productivity mismeasurement



Notes: N = 61,348 for all intangibles (panel a), N = 36,280 for computerized information events, N = 13,405 for innovative property events, and N = 18,438 for economic competencies events (panel b). Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level. All models are weighted by firm-level employment size in $\tau = -1$. Whiskers reflect 95% confidence intervals.

Figure 4: A tangible example: ICT and the Solow Paradox



Notes: Panel (a) shows ICT investment per worker around ICT investment events. Panel (b) shows the impact of ICT investment events on productivity mismeasurement. N = 19,868 for ICT events with increasing intangibles and N = 51,118 for all ICT events. ICT investments are defined as in Dhyne et al. (2021). Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level. All models are weighted by firm-level employment size in $\tau = -1$. Whiskers reflect 95% confidence intervals.

Tables

Table 1: Intangibles selling industries

Intangible Asset Type	NACE Rev. 2 Code
	A. Computerized Information
(i) Software	6201, 6209, 6312
(ii) Database	6202, 6203, 6311
	B. Innovative Property
(i) R&D (Scientific)	7211, 7219, 7220
(ii) Entertainment & Artistic Originals	7410, 7420, 7430, 7911, 7912, 7990, 8810, 8891, 8899, 9001, 9002, 9003, 9004, 9311, 9312, 9313, 9319, 9321, 9329, 9604
(iii) Design & other new Product/Systems	7111, 7112, 7120
	C. Economic Competencies
(i) Advertising/Market Research	7311, 7312, 7320
(ii) Employer-provided Training/Organizational Structures	7021, 7022, 7490, 7810, 7830, 8510, 8520, 8531, 8532, 8541, 8542, 8551, 8552, 8559, 8560

Notes: Table 1 shows the NACE Rev. 2 that produce or sell intangible services. Intangible asset categories and types are based on Corrado et al. (2005, 2009, 2012). Table A.1 shows the description of each NACE Rev. 2 Code considered as intangible providers.

Table 2: Intangible investments

	All Observations			**Intangible investment > 0**		
	Investment level	Investment per worker	Investment share (%)	Investment level	Investment per worker	Investment share (%)
p5	0	0	0	407	150	0.21
p10	0	0	0	652	267	0.39
p25	524	249	0.25	1,836	717	1.09
p50	3,695	1,432	2.00	6,588	2,256	3.47
p75	20,522	5,539	7.8	31,886	7,349	10.44
p90	117,307	18,416	19.57	158,554	22,719	22.45
p95	296,870	37,749	27.95	380,034	45,114	30.33
Mean	*143,192*	*10,741*	*6.38*	*176,194*	*13,000*	*7.98*
Observations		2,026,780			1,647,155	
Pct with 0 costs		18%			0%	

Notes: Intangible investment level and per worker are reported in 2015 euros, intangibles share is calculated as a percentage of total capital. The number of observations is the number of firms times the number of years.

Table 3: Intangibles by sector and firm size class

	Total value	Value per Worker		Value Share (%)		No. of Observations	
	Mean	*Mean*	*SD*	*Mean*	*SD*	*Firms*	*Firms× Years*
A. Sector							
Manufacturing - High Tech	1,477,955	13,593	86,325	9.41	10.9	3,018	36,866
Manufacturing - Other	189,537	6,960	56,637	5.24	8.72	21,699	248,095
Utilities	1,468,334	25,386	157,610	5.51	9.19	1,032	11,480
Construction	42,763	6,831	73,095	4.8	8.56	37,863	383,032
Wholesale & Retail	110,622	11,942	86,354	7.61	10.98	69,485	734,766
Transport and Storage	155,526	10,582	410,797	4.59	9.57	10,174	108,734
Accommodation & Food Serv.	15,388	4,225	26,755	3.87	7.47	25,175	223,372
Information & Communication	1,066,337	46,998	174,328	14.78	14.74	2,474	22,352
Finance & Insurance	240,250	24,905	177,184	7.15	14.14	766	7,332
Real Estate	58,161	22,729	88,896	9.59	13.56	6,130	53,407
Prof., Scientific & Tech. Serv.	146,462	16,696	75,418	9.06	13.03	11,345	101,305
Admin. & Support Act.	107,295	16,746	175,693	6.85	11.64	10,323	96,039
B. Firm size class							
$L \leq 19$	29,197	10,793	131,822	5.94	10.12	184,754	1,825,157
$20 < L \leq 49$	269,815	9,613	71,270	9.72	11.12	9,628	129,268
$50 < L \leq 99$	650,670	10,544	54,150	11.3	11.22	2,584	35,684
$100 < L \leq 199$	1,454,252	11,808	49,769	11.49	11.02	1,352	19,641
$200 < L \leq 499$	3,384,157	13,380	123,099	12	10.81	747	11,003
$500 < L$	19,661,221	13,119	30,773	12.17	10.31	358	5,749

Notes: Table 3 shows intangible investment in 2015 euros, intangible investment shares as a percentage of total capital. Total N firms is 199,423; Total N firms × years is 202,6502.

Table 4: Regressions of log intangibles per employee on log firm size

	Within-industry			Within-firm		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Intangible Investment per Employee						
Size (Proxied by Added value)	0.3328***			0.2956***		
	(0.0009)			(0.0035)		
Size (Proxied by Sales)		0.3577***			0.2458***	
		(0.0009)			(0.0041)	
Size (Proxied by Inputs)			0.2977***			0.1157***
			(0.0008)			(0.0037)
Observations	1,425,022	1,425,022	1,424,876	1,425,022	1,425,022	1,424,876
A. Intangible Assets per Employee						
Size (Proxied by Added value)	0.4067***			0.0537***		
	(0.0009)			(0.0027)		
Size (Proxied by Sales)		0.4542***			0.0671***	
		(0.0009)			(0.0034)	
Size (Proxied by Inputs)			0.3880***			0.0325***
			(0.0008)			(0.0029)
Observations	1,638,584	1,638,584	1,638,346	1,638,584	1,638,584	1,638,346

Notes: Table 4 shows the regression results of Equation 2. The dependent variable is the logarithm of intangibles per employee (Panel A considers intangible investments, while panel B takes intangible assets as outcome variable). The independent variable is the logarithm of firm size proxied by added value, sales, and inputs. The time period is 2002-2019. All columns include a full set of four-digit industry classification fixed effects interacted with year fixed effects, and within-industry results also include a full set of age fixed effects. An elasticity of 0.3 means that raising intermediates by a factor of 2 raises intangible investment per employee by 30 percent. Within-firm standard errors are clustered at the level of the firm. $*p<0.10$, $**p<0.05$, $***p<0.01$.

Table 5: Production function estimation

	OLS		CWDL (2020)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment	0.2115***	0 2073***	0.1629***	0.1547***	0.1562***	0.2134***	0.1336***
	(0.0016)	(0.0016)	(0.0014)	(0.0019)	(0.0261)	(0.0326)	(0.0239)
Tangible capital	0.0304***	0.0295***	0.0750***	0.0654***	0.0595***	0.0315**	0.0813***
	(0.0006)	(0.0006)	(0.0013)	(0.0012)	(0.0156)	(0.0152)	(0.0151)
Intermediates	0.7424***	0.7367***	0.7369***	0.6915***	0.7304***	0.7054***	0.7156***
	(0.0015)	(0.0016)	(0.0010)	(0.0018)	(0.0029)	(0.0158)	(0.0034)
Intangible capital		0.0089***		0.0616***			
		(0.0005)		(0.0008)			
Computerized Information					0.0396***		
					(0.0053)		
Innovative Property						0.0417***	
						(0.0037)	
Economic Competencies							0.0432***
							(0.0046)
No. of firms	150,008	150,008	138,647	132,195	98,226	111,864	113,326
No of observations	1,158,952	1,158,952	933,165	839,188	539,111	636,913	609,833

Notes: Table 5 shows the production function estimation results using ordinary least squares (OLS) and the estimation technique by Collard-Wexler and De Loecker (2020) (CWDL). $*p<0.10$, $**p<0.05$, $***p<0.01$.

Table 6: Firm-level outcomes for intangibles investing vs non-intangible investing firms

	Δ log FTE		Δ log Added Value		Δ log Intangible-Tangible Capital	
	(1)	(2)	(3)	(4)	(5)	(6)
Investing	0.0168***	0.0138***	0.0142***	0.0101***	0.0355***	0.0112***
	(0.0032)	(0.0034)	(0.0032)	(0.0033)	(0.0029)	(0.0028)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
4-Digit Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Initial Values	No	Yes	No	Yes	No	Yes

Notes: Table 6 estimates Equation 7 for different outcome variables. N = 1,065,244 firm-year observations, where 97,496 out of 99,484 unique firms invest in intangibles. All models control for year and four-digit sector fixed effects. Columns 2, 4, and 6 control for initial intangible over total capital ratio. Standard errors are clustered at the firm-level. All Values are reported in 2015 euros. ∗p<0.10, ∗∗p<0.05, ∗ ∗ ∗p<0.01.

Table 7: Effect heterogeneity

	Small firms	Big firms	Low capital-intensive firms	High capital-intensive firms	Low-Skilled firms	High-Skilled firms	Young firms	Old firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2 or more years before event	-0.0035	0.0057	0.0002	-0.0016	-0.0025	0.0009	0.0078	-0.0065
	(0.0058)	(0.0132)	(0.0087)	(0.0070)	(0.0041)	(0.0196)	(0.0110)	(0.0083)
Year of event	-0.0058	-0.0043	-0.0057	-0.0080**	-0.0067***	0.0157	-0.0081	-0.0032
	(0.0045)	(0.0068)	(0.0040)	(0.0033)	(0.0025)	(0.0112)	(0.0060)	(0.0038)
1 year after event	-0.0067**	-0.0066	-0.0086**	-0.0018	-0.0068***	0.0061	-0.0108**	-0.0030
	(0.0028)	(0.0065)	(0.0040)	(0.0030)	(0.0019)	(0.0106)	(0.0046)	(0.0033)
2 or more years after event	-0.0061***	0.0013	-0.0024	-0.0003	-0.0037*	0.0086	-0.0087***	0.0016
	(0.0012)	(0.0035)	(0.0018)	(0.0035)	(0.0019)	(0.0058)	(0.0023)	(0.0023)
No. of firms	54,298	13,633	45,623	15,697	59,184	2,148	29,816	31,502

Notes: Table 7 shows the regression results of Equation 8. (1) Small firms, (2) Big firms, (3) Services firms, (4) Non-services firms, (5) Low-skilled firms, (6) High-skilled firms, (7) Young firms, and (8) Old firms. A firm is classified as "large" if at least two of the following three criteria are exceeded: (i) 50 full-time equivalent employees, (ii) sales of €9 million, (iii) total balance sheet of €4.5 million. High capital-intensive firms are firms with a capital-labor ratio in the top quartile of the total capital-labor distribution. High-skilled firms are firms in the top quartile of the skill share distribution. Old firms are firms with an age (defined by the difference between calender year and incorporation year) larger than 15. All models are weighted by firm-level employment size in $\tau = -1$. $*p<0.10$, $**p<0.05$, $***p<0.01$.

Online Appendix for "Unveiling the J-curve: How Intangibles Drive Productivity Mismeasurement"

Gert Bijnens — National Bank of Belgium

Jozef Konings — Nazarbayev University GSB, KU Leuven and CEPR

Aaron Putseys — KU Leuven

March 17, 2025

Appendix A. Data construction and statistics

A.1 Administrative and survey data

We combine different confidential micro data sets that were provided by the National Bank of Belgium (NBB) and ECOOM Leuven. All the administrative data described hereafter is confidential and could only be stored and accessed in person in a fully-secured location at the National Bank of Belgium (NBB).

A.1.1 Company accounts data from the NBB Central Balance Sheet Office

The company accounts from the NBB Central Balance Sheet Office encompass all registered companies in Belgium, providing comprehensive information such as annual data crucial for estimating production functions. This data includes metrics like value added, sales, labor, intermediate inputs, and capital. Small enterprises are mandated to submit a condensed version of their annual accounts, whereas larger enterprises must furnish a more exhaustive, detailed version. The criteria for determining size thresholds are established by an EU directive.[20] A company is designated as "large" if it exceeds at least two of the following three criteria: (i) 50 full-time equivalent employees, (ii) sales totaling 9 million EUR, (iii) a total balance sheet of 4.5 million EUR. Conversely, a company is categorized as "small," relieving them from reporting sales and intermediate inputs

[20] EU directive 2013/34/EU, we refer to the website of the NBB Central Balance sheet Office for more information.

data, but necessitating the reporting of value added, capital, and employment. Approximately 90% of the entities within the company accounts data fall within this small category.

A.1.2 VAT declarations

Every VAT-liable company is obligated to regularly report to the federal public service of finance the value of investment goods it has acquired. This serves as a direct gauge of the overall tangible investments made by the company. Additionally, companies are required to disclose their total sales and purchases of inputs. The NBB compiles this comprehensive data on sales, investments, and intermediate inputs for both large and small enterprises. The information is extracted from quarterly VAT declarations, then annualized and aligned with the reporting period of the annual accounts by the NBB. The sales data from quarterly VAT declarations encompasses transactions with final consumers and exports, mirroring the accounts data. Similarly, the intermediate inputs encompass material goods, raw materials, service inputs, and imported inputs. Figure A.1 gives an example of the form that firms have to fill in on a quarterly frequency. Code 81 and 82 capture respectively intermediate goods and services, while code 83 denotes the total amount of investment goods purchases that quarter.

Figure A.1: Example of a VAT declaration form


KADER III : INKOMENDE HANDELINGEN

A. Bedrag van de inkomende handelingen rekening houdend met de ontvangen creditnota's en andere verbeteringen :
- handelsgoederen, grond- en hulpstoffen , 81
- diensten en diverse goederen , 82
- bedrijfsmiddelen , 83

B. Bedrag van de ontvangen creditnota's en de negatieve verbeteringen :
- met betrekking tot de handelingen ingeschreven in de roosters 86 en 88 , 84
- met betrekking tot de andere handelingen van kader III , 85

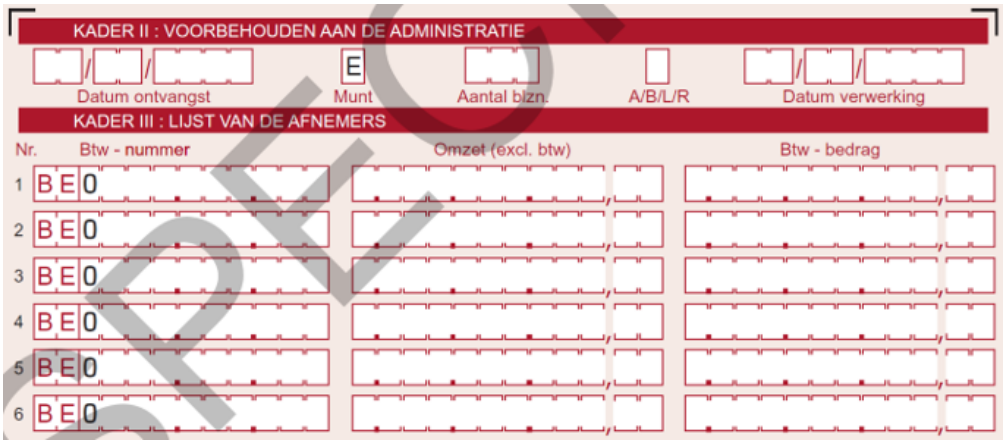
C. Intracommunautaire verwervingen verricht in België en ABC-verkopen , 86

D. Andere inkomende handelingen waarvoor de btw verschuldigd is door de aangever , 87

E. Intracommunautaire diensten met verlegging van heffing , 88

Notes: This figure provides an example of a form that firms have to fill in on a quarterly frequency. Codes 81, 82, and 83 respectively capture intermediate goods, intermediate services, and investment goods.

Figure A.2: Example of a customer listings form



Notes: This figure gives an example of the customers listings of a firm that each firm has to annually declare to the federal public service of finance.

A.1.3 Business-to-business (B2B) data

The B2B data reports information from the customer listings of firms, which VAT liable firms have to declare yearly to the federal public service of finance (see Figure A.2 for an example). In this listing, firms have to report the VAT number and associated revenues it obtained from each of its customers. Indirectly, this also learns how much each customers buys. We exploit this information to obtain intangible purchases for each customer. More specifically, we use the customer listings of firms that are active in NACE codes of intangible services industries as detailed in Table A.1. From their customer listings, we deduce how much intangible goods and intangible services each of its customers bought. For each customer, we sum its intangible purchases across all intangible producing firms. This is our firm level measure for Belgian intangible investments.

A.1.4 Research and development expenditure (R&D) from ECOOM Leuven

Expenditures on in-house Research and Development (R&D) originate from ECOOM (KU Leuven)[21] and are acquired through a bi-annual survey encompassing all companies known to engage in R&D projects. Identification of these companies involves various methods, such as those reporting R&D costs in their annual company accounts, applying for patents, receiving tax credits for R&D

[21] More information can be found on the website of ECOOM Leuven.

expenditures, obtaining R&D subsidies, and inclusion in a roster of R&D-active firms provided by technology employer federations. Additionally, a search in the general media is conducted. Furthermore, the study incorporates a stratified random sample of the overall business population to identify potential R&D-active firms that may not be initially recognized. We add these in-house R&D expenditures to our measure of R&D expenditures recovered from the customer listings. Figure A.3 shows the yearly distribution for the intangible investment types by data source. It shows that the addition of the ECOOM survey data has a significant contribution to the measure of R&D investment. This is not surprising since the majority if R&D is developed in-house.

Table A.1: Intangibles selling industries

Intangible Asset Type	NACE Rev. 2 code	Description
A. Computerized Information:		
(i) Software	6201	Computer Programming Activities
	6209	Other Information Technology and Computer Service Activities
	6312	Web Portals
(ii) Database	6202	Computer Consultancy Activities
	6203	Computer Facilities management Activities
	6311	Data Processing, Hosting and Related Activities
B. Innovative Property:		
(i) R&D (Scientific)	7211	Research and Experimental Development on Natural Sciences and Engineering
	7219	Other Research and Experimental Development on Natural Sciences
	7220	Research and experimental development on social sciences and humanities
(ii) Entertainment & Artistic Originals	7410	Specialized design activities
	7420	Photographic activities
	7430	Translation and interpretation activities
	7911	Travel agency activities
	7912	Tour operator activities
	7990	Other reservation service and related activities
	8810	Social work activities without accommodation for the elderly and disabled
	8891	Child day-care activities

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Intangible Asset Type	NACE Rev. 2 code	Description
	8899	Other social work activities without accommodation n.e.c.
	9001	Performing arts
	9002	Support activities to performing arts
	9003	Artistic creation
	9004	Operation of arts facilities
	9311	Operation of sports facilities
	9312	Activities of sport clubs
	9313	Fitness facilities
	9319	Other sports activities
	9321	Activities of amusement parks and theme parks
	9329	Other amusement and recreation activities
	9604	Physical well-being activities
(iii) Design and other new	7111	Architectural Activities
Product/Systems	7112	Engineering Activities and Related Technical Consultancy
	7120	Technical Testing and Analysis
C. Economic Competencies:		
(i) Advertising/Market	7311	Advertising agencies
Research	7312	Media representation
	7320	Market research and public opinion polling
(ii) Employer-provided	7021	Public relations and communication activities
Training/	7022	Business and other management consultancy activities
Organizational	7490	Other professional, scientific and technical activities n.e.c.
Structures	7810	Activities of employment placement agencies
	7830	Other human resources provision

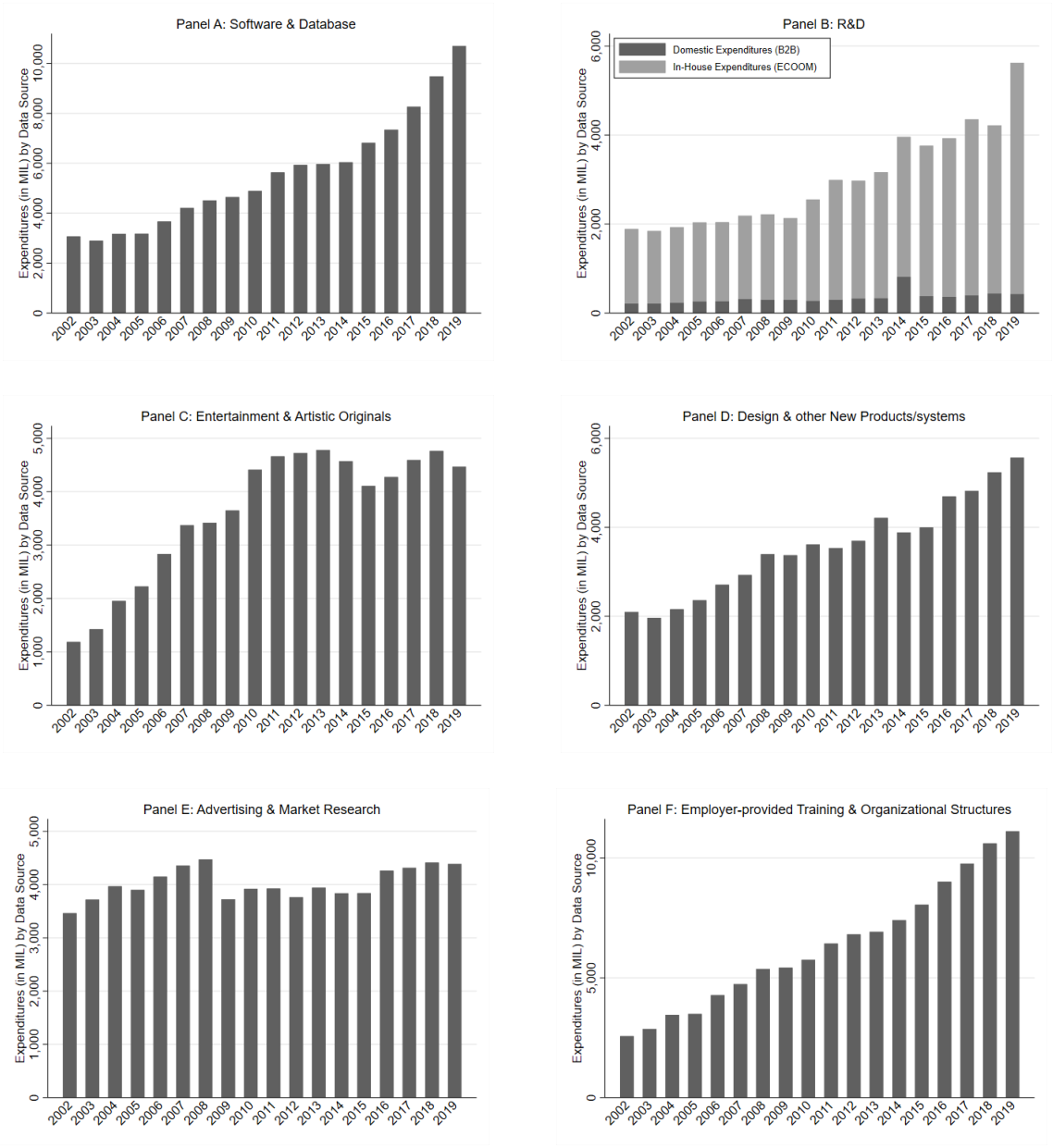
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Intangible Asset Type	NACE Rev. 2 code	Description
	8510	Pre-primary education
	8520	Primary education
	8531	General secondary education
	8532	Technical and vocational secondary education
	8541	Post-secondary non-tertiary education
	8542	Tertiary education
	8551	Sports and recreation education
	8552	Cultural education
	8559	Other education n.e.c.
	8560	Educational support activities

Notes: Table A.1 shows the NACE Rev. 2 that produce or sell intangible services. Intangible asset categories and types are based on Corrado et al. (2005, 2009, 2012).

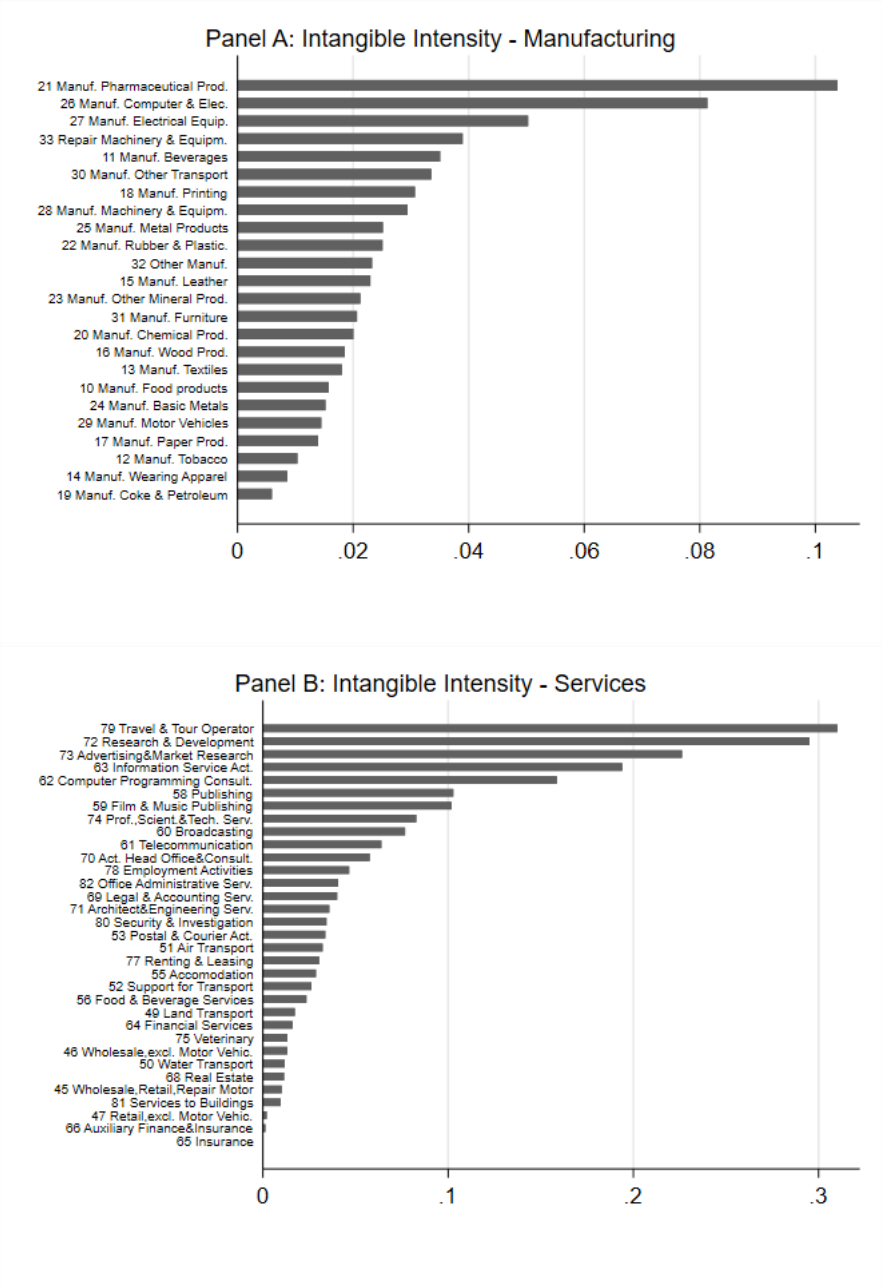
Figure A.3: The evolution of intangible investment type by data source



Notes: Figure A.3 shows the distribution of intangible investment type by data source for the period 2002-2019: the black bars correspond to the B2B dataset and the gray bars to the ECOOM dataset. For every intangible asset type, we see an increase in investment over time.

A.2 Intangible intensity

Figure A.4: Intangible intensity in manufacturing and services industries



Notes: Figure A.4 shows the intangible intensity (intangible investment as a ratio over sales) in manufacturing and services industries (NACE 2-digit).

A.3 Sample construction for estimating the production function

This appendix provides additional information on how the final data set is constructed. We start from the annual company accounts data of Belgian firms, to which we merge the other data sets based on the firm's unique VAT-number. Our panel covers the years 2002-2019 and initially counts 676,908 firms. We focus on the private sector and drop the intangibles producing industries in Table A.1. For firms active in intangibles producing industries, intangibles purchases are mostly intermediate inputs instead of investments. Therefore, we cannot use information on intangible purchases by these firms to measure intangible investment and intangible capital. This reduces the sample to 489,509 firms. Furthermore, we only retain firms for which we have information in their annual accounts on their industry code, value added, sales, employment and capital, since these are needed for the estimation of production functions. This reduces the sample to 250,011 firms.

To construct capital stocks, we need information from the VAT declarations and strictly positive investments in intangible capital in at least one year. For 97 firms we observe no VAT declarations, which is due to some activities being exempted from filing taxes.[22] From the remaining 249,914 firms, there are 15,565 firms that never invest in intangibles and for which it is not possible to derive strictly positive capital stocks, which we require for theoretical consistency in a Cobb Douglas production function. This reduces the sample to 234,349 firms. In the estimation, we cannot use firms for which we do not observe all inputs in at least one year and since we estimate a log-linear Cobb Douglas production function, we also cannot include negative values. This reduces the sample to 226,600 firms. Finally, we exclude firms for which material and/or labor expenditures are larger than total turnover. Table A.2 characterizes the steps taken in constructing the final sample of firms. This results in a final sample of 214,316 firms that represent about 1,55 million employees, 134,98 billion in added value and 667,22 billion in turnover, which is a significant part of the Belgian private sector. Figure A.5 shows the distribution of employment, added value, sales and intangible investment in our final sample. Figure A.6 shows the distribution of the intangible investment types.

[22] Article 44 of the VAT tax code describes in detail which activities are exempted. This are mainly activities in the socio-cultural sector, the financial and real estate sector.

Table A.2: Summary statistics for the steps of the construction of the final sample of firms

Year	No. of Firms	No. of Firms	No. of Firms	No. of Firms	No. of Firms	No. of Firms	No. of Firms
Sample	I	II	III	IV	V	VI	VII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2002	277,428	216,125	130,773	130,708	123,195	93,626	79,045
2003	295,060	227,380	138,658	138,591	130,917	97,147	81,893
2004	305,857	234,878	144,036	143,970	136,421	100,064	83,863
2005	314,683	239,884	144,036	147,444	140,091	101,312	86,378
2006	328,467	248,214	147,508	152,324	145,015	103,510	89,650
2007	341,925	255,966	156,539	156,475	149,271	105,241	91,581
2008	355,204	262,966	159,731	159,665	152,498	105,314	92,330
2009	367,159	269,547	162,888	162,821	155,708	105,730	93,503
2010	372,624	270,623	162,346	162,285	155,405	104,631	93,127
2011	383,605	276,177	163,669	163,606	156,795	105,838	94,334
2012	395,689	283,571	166,880	166,814	159,896	107,299	95,841
2013	397,279	283,267	165,599	165,537	158,947	105,568	94,875
2014	403,450	287,469	166,843	166,782	160,300	106,763	96,559
2015	409,259	290,390	166,434	166,374	159,929	106,086	96,379
2016	419,714	296,558	166,880	166,821	160,300	102,829	93,727
2017	430,868	303,114	166,955	166,896	160,215	102,071	93,165
2018	441,445	308,492	165,585	165,527	158,682	101,685	93,167
2019	435,948	302,853	158,065	158,012	151,095	96,915	89,308

Notes: Table A.2 presents the number of unique firms in 6 samples. Sample I - the sample in Columns (1) firms in the economy of Belgium each year. Sample II - the sample in Column (2) - excludes from Sample I those firms that are in the public sector and in intangible-providing sectors (see Table A.1 for the list of sectors). Sample III - the sample in Column (3) - keeps only those firms from Sample II that have the information necessary to compute productivity. Sample IV - the sample in Column (4) - starts from sample III and drops the firms with no VAT Declarations. Sample V - the sample in Column (5) - drops firms that never invest in intangibles. Sample VI - the sample in Column (6) - drops firms for which we do not observe all inputs in at least one year and since we estimate a log-linear Cobb Douglas production function, we also cannot include negative values. Finally, in Sample VII drops firms with extreme labor and intermediates expenditures. Sample VII is the final sample used in the analysis.

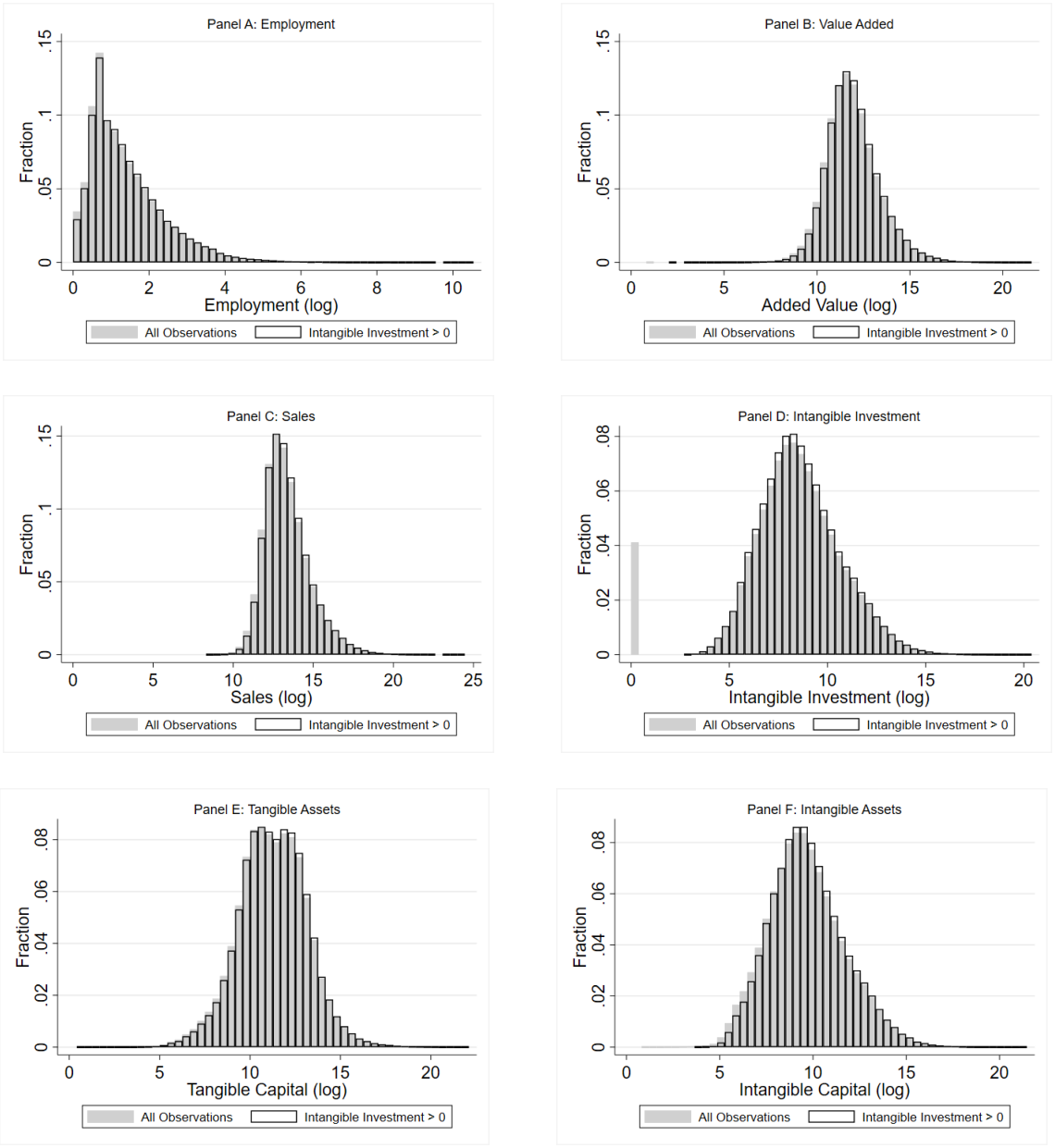
Table A.3 provides descriptive statistics of the main variables used in our analysis. We also report the corrected added value and intermediate inputs, where intangible investments are subtracted from intermediates (Enache and Srivastava, 2018). The average firm employs 11 full-time equivalents in our sample. The median firm employs 2 full-time workers. Average value added equals to EUR 964,000. This implies that labor productivity for an average firm is equal to EUR 87,600. The average tangible and intangible capital is around EUR 935,000 and EUR 202,000, respectively. Since the standard deviations are relatively high, there exist large differences at the firm level intangible capital stock. This means that the aggregate picture hides a lot of the firm-level heterogeneity. Moreover, there exists extensive heterogeneity in the investment variables due to the fact that the underlying distributions are highly right-skewed.

Table A.3: Descriptive statistics

	Mean	Median	SD
Measured Value Added (X1,000 €)	877	137	12,077
Corrected Value Added (X1,000 €)	964	147	13,030
Tangible Capital (X1,000 €)	935	129	16,039
Intangible Capital (X1,000 €)	268	14	3,988
Employment	10,55	2	159
Tangible Investment (X1,000 €)	146	18	2,717
Intangible Investment (X1,000 €)	88	4	1,331
Sales (X1,000 €)	4,889	538	153,059
Wage Bill (X1,000 €)	530	72	7,222
Measured Intermediate Inputs (X1,000 €)	3,557	341	74,598
Corrected Intermediate Inputs (X1,000 €)	3,467	328	74,048

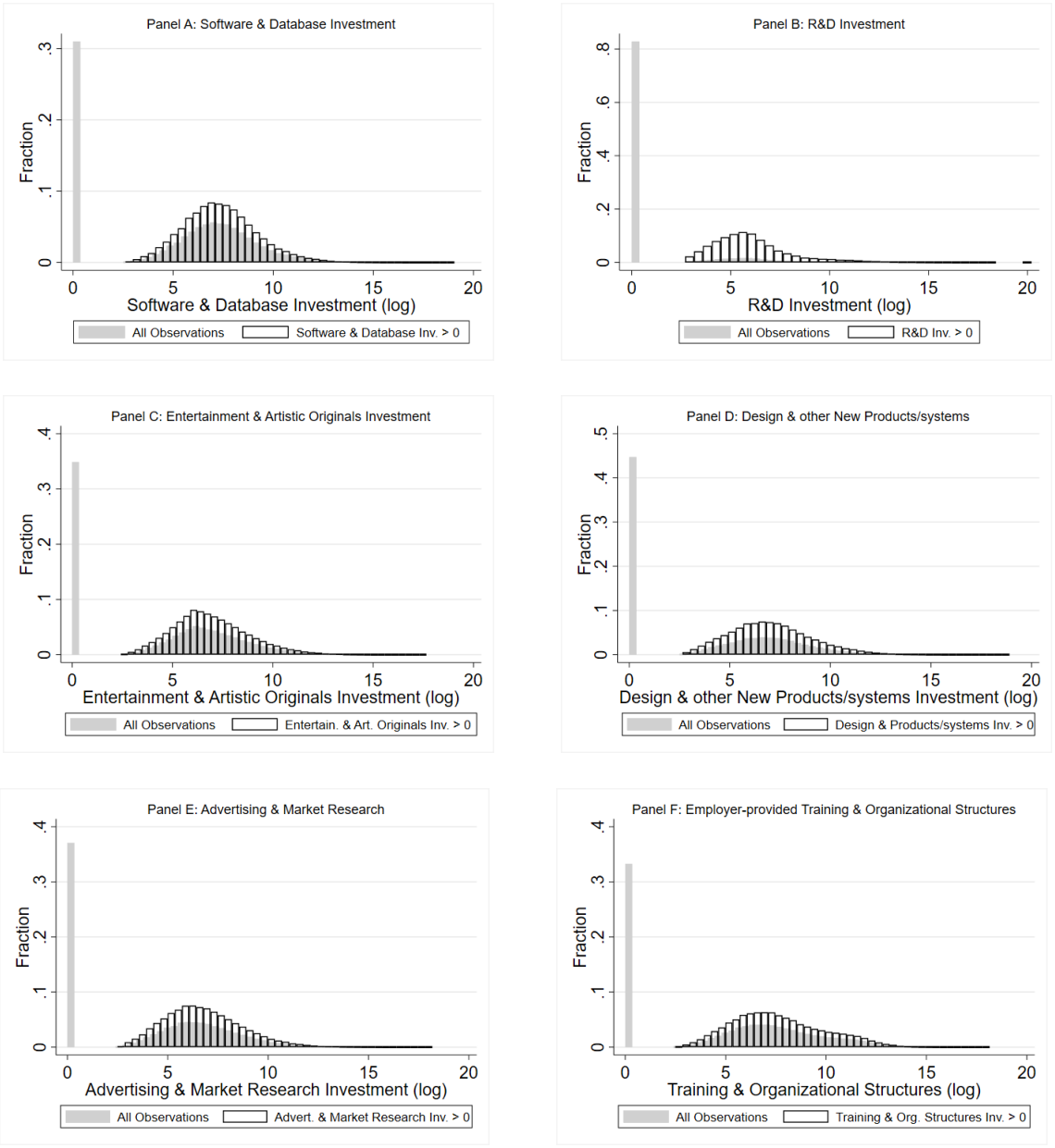
Notes: Table A.3 shows the descriptive statistics of the main variables in the analysis. These descriptive statistics are based on our main analysis sample of firms with non-missing values for value added, labor, tangible capital, and intangible capital. Moreover, we do not allow for observations for which expenditures on labor and/or materials are larger than sales (214,304). The average number of observations is 1,638,584. Value added and intermediate inputs are corrected for intangible investments. Descriptive statistics are at the firm level, after taking averages over time per firm. All variables are denoted in 2015 Euros.

Figure A.5: The distribution of the main variables



Notes: Figure A.5 shows the distribution of employment, added value, sales, intangible investment, tangible assets, and intangible assets in our baseline sample.

Figure A.6: The distribution of the intangible investment types



Notes: Figure A.6 shows the distribution of software & Database, R&D, Entertainment & Artistic Originals, Design & New Products/systems, Advertising & Market Research, and Employer-provided Training & Organizational Structures Investment in our baseline sample.

A.4 Construction of intangible capital stocks

We construct real intangible capital using the Perpetual Inventory Method (PIM). This method allows us to optimally exploit our unique data on intangible purchases. The formula of the PIM is the following:

$$K_{it}^{U} = K_{it-1}^{U} \times (1 - \delta_U) + I_{it}^{U} \tag{A.1}$$

In which K_{it}^{U} refers to the real intangible capital stock of firm i in year t, δ_U refers to the depreciation rate for intangible capital and I_{it}^{U} refers to real intangible investments. We rely on data of the EU KLEMS initiative to turn the nominal values from our data set into real values.[23] The EU KLEMS data provides gross fixed capital formation deflators at the 2 two-digit level for the entire period of our sample. For tangible investments, we use the average of the gross fixed capital formation deflator from The Netherlands, France, Germany and Luxembourg. For intangible investments, we compute the intangible capital deflator based on the average of this deflator from The Netherlands, France, Germany and Luxembourg. We retrieve depreciation rates from Corrado et al. (2012) on intangible capital.

The first step in applying the PIM is calculating the initial intangible capital stock. This is necessary because intangible capital is not reported in annual accounts in a sufficient way. The literature does not provide a straightforward solution to obtain initial capital stocks. In this appendix, we describe the approach used to obtain the results from the main body of the paper. To obtain the initial stocks, we predicted the firm's intangible capital intensity and use this to obtain its share in initial nominal total assets. We use our unique data on intangible purchases to predict this intangible capital intensity. First, we obtain nominal intangible investments from:

$$I_{it}^{U} = \textit{Intangible Purchases}_{it} \tag{A.2}$$

We use intangible deflator to turn these nominal investments into real values. Next, we take the average of the real investment flows from the first 3 years the firm is in the sample. We do this because firms do not invest in intangibles every year and to avoid errors in the initial capital stocks

[23] More specifically, we rely on the capital input files from The Netherlands, France and Luxembourg of the 2023 release. There is no capital input file for Belgium so we assume that the average of prices for Intangibles in The Netherlands, France, Germany and Luxembourg are close to those of Belgium.

from outlier investments. We limit ourselves to the first 3 years because (i) longer periods could be less informative about the initial intangible capital stock (ii) firms can change their business model over time, i.e. becoming more or less intangible focused (iii) this is consistent with the finding that it takes some years before intangible stocks reach steady state in most industries (Knott et al., 2003). Hall and Mairesse (1995) construct an initial capital stock by simply dividing a firm's investment in t=0 by the depreciation rate plus a fixed annual growth rate. We modify this formula by using the average investment during the firm's first three years in the data (to account for the fact that many firms have zero investments in a single year). This gives an initial capital stock for period t=0:

$$K_{i0}^{U} = \frac{1}{3} \times \sum_{t=1}^{3} \frac{I_{it}^{U}}{g_{it}^{U} + \delta^{U}} \tag{A.3}$$

With I_{it}^{U} the real intangible investment of the firm , g_{it}^{U} the constant average past growth rate of real intangible investments and δ^{U} the intangible capital depreciation rate. This is in line with how Kaus et al. (2024) and Dhyne et al. (2021) implemented the PIM in their analysis.

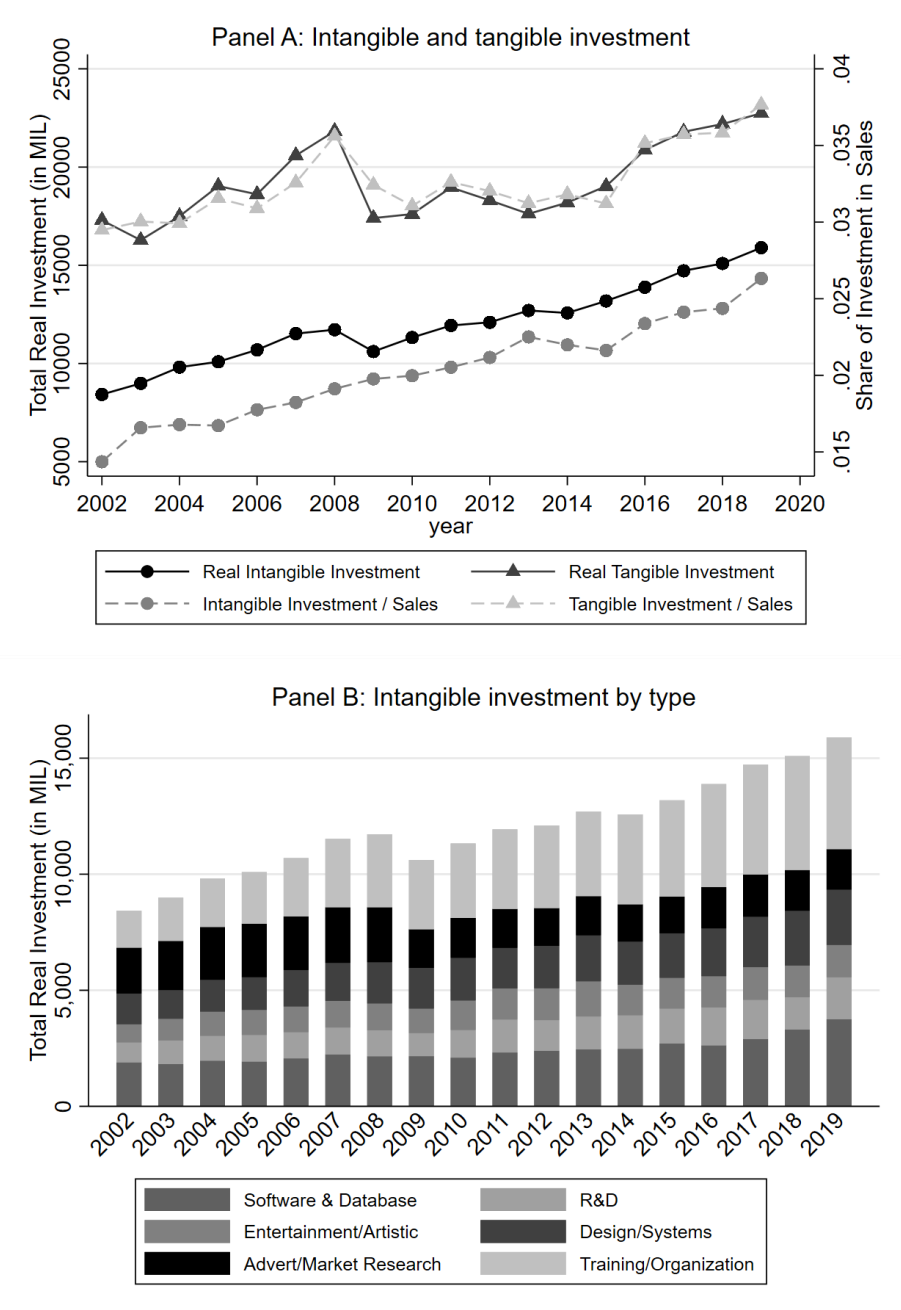
A.5 Intangible capital deepening over time

Appendix A provides additional details. In Panel A of Figure A.7, we consider the aggregate real intangible investments over the period 2002-2019. Values are converted to real terms (in 2015 Euros). This highlights several things. First, the amount of intangible investments has increased steadily over the past two decades. Investment in intangible capital rose from 8 billion EUR in 2002 to almost 17.5 billion EUR in 2019. Further, the share of intangible investment in the total turnover has also increased over time. In 2002, the share of intangible investment in total sales was around 1.5 percent. In 2019, the share of intangibles increased to 2.5 percent. Lastly, the share of tangible investment in sales have remained constant around 3 percent. In contrast, the share of intangibles have increases steadily. This finding relates to the large body of research which connects the weakness of physical investment rates since the early 2000s with the rise of intangible investment (Hall, 2015; Gutiérrez and Philippon, 2017; Alexander and Eberly, 2018; Crouzet and Eberly, 2018, 2019).

Our measure of intangible investments allows us to analyze the evolution of the different components of intangibles. Panel B of Figure A.7 further show the evolution of the intangible components in real terms. Most of the components experienced a positive trend over time. Most striking is the increasing importance of investments in employer-provided training and organizational structures. Over the course of 18 years, its value increased from less than 2 billion to more than 5 billion euros.

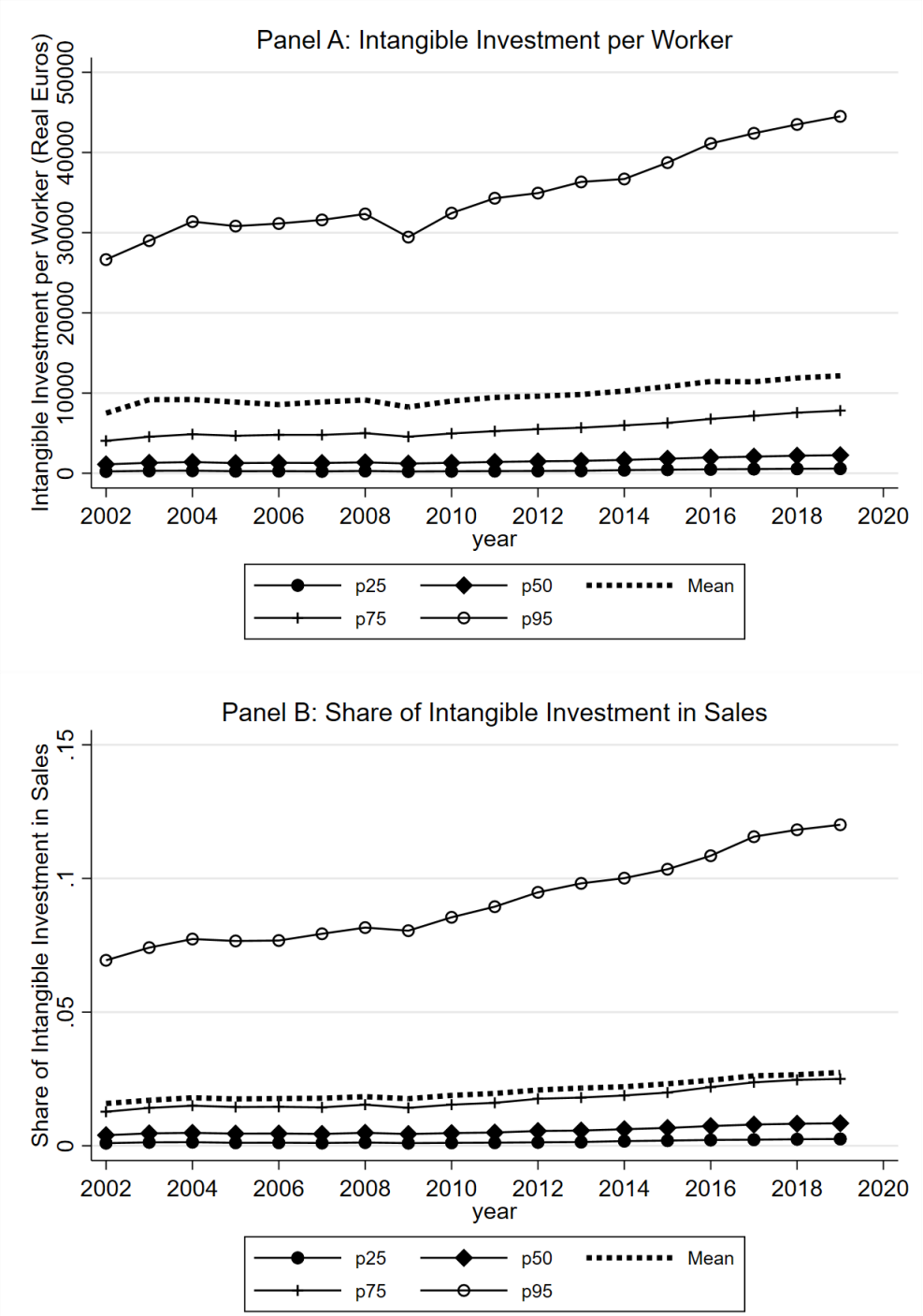
Figure A.8 shows how the distribution of intangible investment per worker (top panel) and intangible investment over sales (bottom panel) have changed over time. Mean intangible investment per worker and the mean intangible investment over sales are rising over 2002–2019. Furthermore, besides increases in means, there is a fanning out of the distributions with intangible investment rising faster for higher percentiles. This is in contrast to tangible investment, shown in Figure A.9, which have been relatively flat throughout the sample period.

Figure A.7: The importance of tangible and intangible investment over time



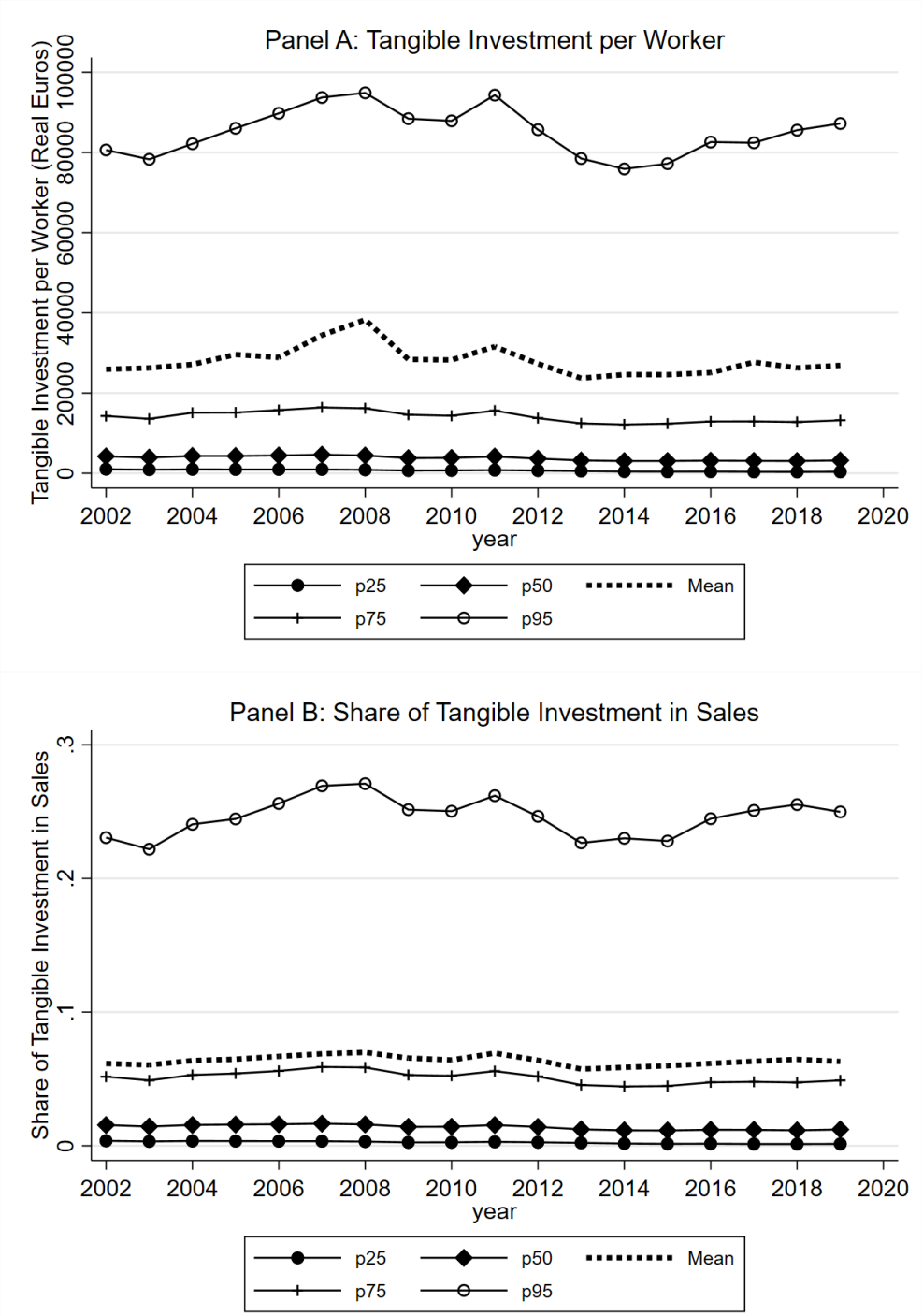
Notes: Panel A plots the aggregate real intangible investment, the aggregate real tangible investment, the share of real intangible investment in total sales, and the share of real tangible investment in total sales from 2002 to 2019. Panel B shows the sum of real intangible investment type the period 2002-2019. Investment series are deflated to 2015 Euros.

Figure A.8: Intangible capital deepening



Notes: Figure A.8 shows how the distribution of intangible investments per worker (Panel A) and intangible investment shares (Panel B) have changed over time.

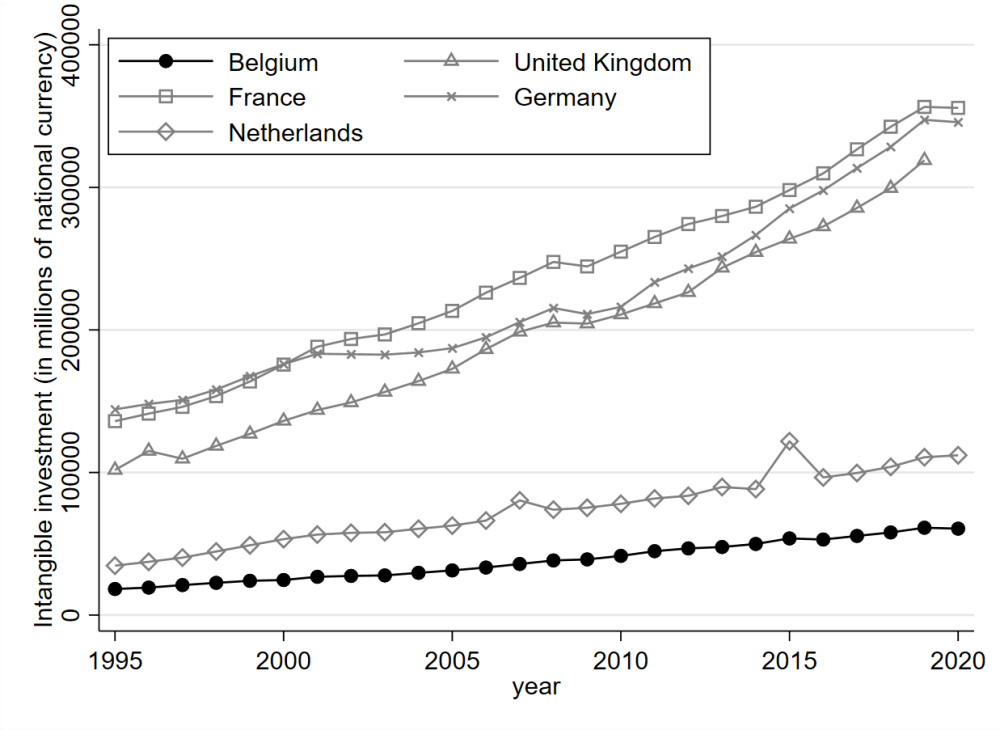
Figure A.9: Tangible capital deepening



Notes: Figure A.8 shows how the distribution of tangible investments per worker (Panel A) and tangible investment shares (Panel B) have changed over time.

A.6 Comparison with sectoral intangibles data from EUKlems

Figure A.10: Comparison with sectoral intangibles data from EUKlems



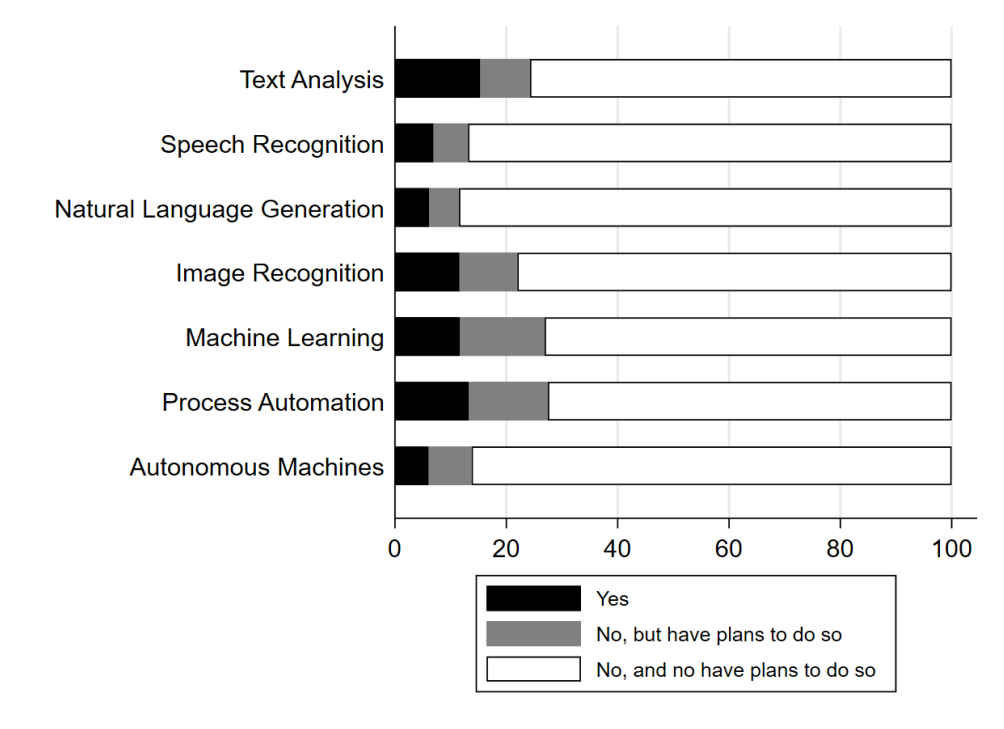
Notes: Figure A.10 shows the evolution of aggregate intangible investment for multiple countries.

A.7 AI-CS Survey by ECOOM and IMEC

On behalf of the Department of Economy, Science and Innovation (EWI) of the Flemish government, ECOOM and IMEC map the adoption, use, and expertise in Artificial Intelligence (AI) among Flemish companies. The aim is to provide an initial baseline measurement to enable current monitoring of the maturity, barriers, and needs regarding AI, thereby contributing to the evaluation of the impact of the relevant Flemish action plan. Future measurement moments will offer the opportunity to obtain a longitudinal overview of the evolution of AI among Flemish companies and consider it as an international benchmark.

This AI Barometer provides a scientifically substantiated picture of the extent to which Flemish companies integrate data-driven applications into their operations and offerings. It is based on two crucial methodological principles. First, a large-scale, random sample (sample size of 14,274 companies, with 1,717 usable responses in total) that is representative of the population of Flemish companies by company size and sector of activity. Second, a validated measurement instrument aligned with similar European questionnaires that can serve as benchmarks.

Figure A.11: AI usage within firms



Notes: Source: Andries et al. (2021).

Table A.4: Usage of various AI technologies across companies of different sizes.

	Text Analysis	**Speech Recognition**	**Natural Language Generation**	**Image Recognition**	**Machine Learning**	**Process Automation**	**Autonomous Machines**
5-9 employees	7.7%	4.7%	4.5%	5.8%	3.1%	6.1%	2.1%
10-49 employees	8.3%	4.9%	4.2%	5.7%	6.9%	7.0%	3.6%
50-249 employees	20.8%	5.7%	6.1%	11.3%	13.7%	11.7%	6.6%
More than 249 employees	34.9%	15.9%	12.4%	29.7%	34.4%	37.1%	15.8%

Notes: N = 1,717. Source: Andries et al. (2021).

A.8 Information and Communication Technology expenditure (ICT)

Firm level ICT spending is from Dhyne et al. (2021). They construct ICT spending from the B2B VAT transactions data as follows. First, all firms that produce or sell ICT-related products or services are identified using their main 4-digit NACE sector code, as listed in Table A.5. Second, using the B2B data, all of a firm i's customers j are identified. The total ICT spending by each firm j is computed by taking the sum of all of firm j's purchases from all firm i's that are active in any of the ICT sectors.

Table A.5: ICT selling industries

ICT type	NACE Rev 2 code	Description
IT goods	2620	Manufacture of computers and peripheral equipment
	4651	Wholesale of computers, computer peripheral equipment and software
	4741	Retail sale of computers, peripheral units and software in specialized stores
	5829	Other software publishing
IT services	6200	Computer programming, consultancy and related activities
	6201	Computer programming activities
	6202	Computer consultancy activities
	6203	Computer facilities management activities
	6209	Other information technology and computer service activities
	6311	Data processing, hosting and related activities
	6312	Web portals
Communication goods	2630	Manufacture of communication equipment
	4652	Wholesale of electronic and telecommunications equipment and parts
	4742	Retail sale of telecommunications equipment in specialized stores
Communication services	6110	Wired telecommunications activities
	6120	Wireless telecommunications activities
	6130	Satellite telecommunications activities
	6190	Other telecommunications activities

Notes: Table A.5 shows the NACE Rev. 2 that produce or sell ICT, developed by Dhyne et al. (2021).

Appendix B. Production function estimation

This appendix provides more details on the GMM control function estimators that we use to overcome the simultaneity bias in production function estimation. Semiparametric estimation of production functions was introduced by Olley and Pakes (1996, henceforth OP). The idea is to control in the estimation of production functions for the unobserved productivity residual with other variables through which firms signal their productivity. The OP model relies on the firm's investment demand to control for the unobserved productivity. Levinsohn and Petrin (2003, henceforth LP) rely on the demand for material inputs instead of investment demand to proxy for unobserved productivity because investments are lumpy and often equal to zero. Ackerberg et al. (2015, henceforth ACF) extended the LP estimator to guarantee unbiased identification of the production function coefficients. Collard-Wexler and De Loecker (2020, henceforth CWDL) propose a similar estimation approach that relies on the firm's materials demand to proxy for unobserved productivity that is also robust to measurement error in capital. Capital stock mismeasurement is introduced by assuming errors-in-variable structure, where the observed log of the capital stock (k and u) is the sum of the log true capital stock (k^* and u^*) and the measurement error (ϵ^k and ϵ^u):

$$x = x^* + \epsilon^x, \tag{B.1}$$

where $x \in \{k, u\}$. This linear form of measurement error allows us to use IV to rid the model of bias from error-in-variables. ϵ^k and ϵ^u are orthogonal to the true capital stock but are allowed to be serially correlated over time.

We detail the CWDL estimator for our augmented production function. To preserve the linear structure of the estimation equation, they suggest to write productivity as an AR(1) process. We start from the augmented Cobb Douglas production function:

$$y_{it} \;=\; \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_u u_{it} + \omega_{it} + \varepsilon_{it}. \tag{B.2}$$

The first step in our approach is to extract the productivity shock, thereby eliminating the persistent part of the productivity process. In doing this, we follow the control function approach of Ackerberg et al. (2015). Productivity is replaced by the inverted input demand equation, and after

a first stage projection, the productivity shock $\tilde{\xi}_{it}$ is obtained (for a given value of the parameters) using:

$$\tilde{\xi}_{it}(\beta) = \omega_{it}(\beta) - \rho\omega_{it-1}(\beta), \tag{B.3}$$

where $\omega_{it}(\beta) = q_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_u u_{it}$, and in the presence of measurement error:

$$\tilde{\xi}_{it} = \xi_{it} - \beta_k \epsilon^k_{it} - \beta_u \epsilon^u_{it} + \rho\beta_k \epsilon^k_{it-1} + \rho\beta_u \epsilon^u_{it-1}. \tag{B.4}$$

We invert the material demand equation (under profit maximization) and obtain a log linear expression for productivity given by:

$$\omega_{it} = -ln\beta_m + (1 - \beta_m)m_{it} + p^m_t - p_t - \beta_l l_{it} - \beta_k k_{it} - \beta_u u_{it} - \beta_0, \tag{B.5}$$

where all lower cases denote logs, and p^m and p are the material input and output price, respectively. The identification and estimation of the material coefficient follows immediately from the assumption of perfect competitive output markets. Taking the first-order condition of profits with respect to materials immediately generates $\beta_m = \frac{P^m M}{PQ}$, as an estimate. Due to the potential measurement error in output, taking the average of the material-revenue share would yield a biased estimate. Instead, we take the median material revenue share across the sample to obtain a consistent estimate of β_m.

We denote output by y_{it}, where it is understood that under the gross output specification it is given by $y_{it} = q_{it} - \hat{\beta}_m m_{it}$. Replacing the unobserved productivity term by the control function (under both models considered above) gives:

$$y_{it} = \delta_t + \delta_l l_{it} + \delta_k k_{it} + \delta_u u_{it} + \delta_m m_{it} + \tilde{\epsilon}_{it} \equiv \Phi_{it} + \tilde{\epsilon}_{it}, \tag{B.6}$$

where δ_t captures the constant term and the time-varying prices (under the gross output specification), $\tilde{\epsilon}_{it} = \epsilon_{it} - \delta_k \epsilon^k_{it} - \delta_u \epsilon^u_{it}$, and we use δ_h ($h \in \{l, m, k, u\}$) to denote the reduced-form parameters, on each input, capturing both the production function coefficients and the parameters governing the control for unobserved productivity. The first stage consists of running a simple linear IV-regression where capital is instrumented with z_{it}. The moment conditions to obtain predicted

output are given by:

$$E\left[\tilde{\epsilon}_{it}\begin{pmatrix} l_{it} \\ z_{it} \\ m_{it} \end{pmatrix}\right] = 0. \tag{B.7}$$

CWDL suggest to instrument the capital stock variables with lagged investments. The idea is that the investment variables contain less measurement error than the stock variables. As explained in Appendix A3, we have detailed information on tangible and intangible investment flows.

Appendix C. Intangible investment events

C.1 Intangible investment spike frequency

Table C.1: Intangible spike frequency

Spike frequency	N firms	pct of N firms
0	101,988	51.1
1	67,477	33.8
2	23,186	11.6
3	5,728	2.9
4	938	0.5
5 or 6	167	0.1
Total	199,484	100

Notes: Spike frequency is defined as the total number of spikes occurring over 2002-2019. The total number of firms is 199,484 and the total number of firms with at least one intangible investment spike is 97,496.

C.2 Intangible investment events across sectors and firm size classes

Table C.2: Share of firms ever having an intangible investment spike

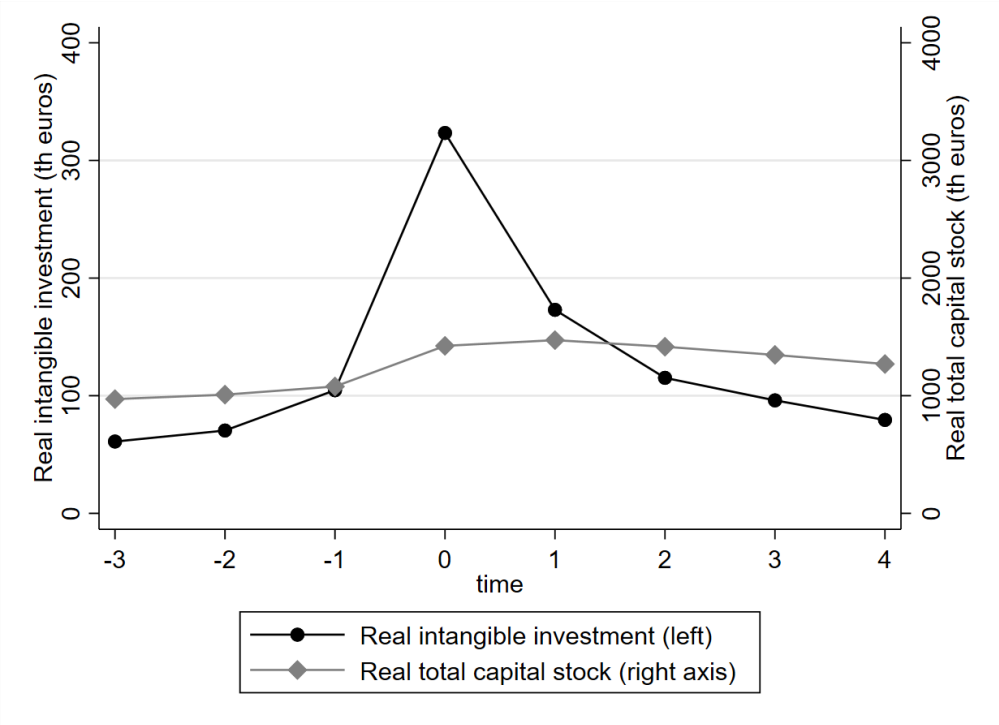
A. Sector	
Manufacturing - High Tech	0.46
Manufacturing - Other	0.49
Utilities	0.45
Construction	0.53
Wholesale & Retail	0.51
Transport and Storage	0.47
Accommodation & Food Serv.	0.48
Information & Communication	0.42
Finance & Insurance	0.49
Real Estate	0.35
Prof., Scientific & Tech. Serv.	0.40
Admin. & Support Act.	0.48
B. Firm size class	
$L \leq 19$	0.50
$20 < L \leq 49$	0.40
$50 < L \leq 99$	0.32
$100 < L \leq 199$	0.27
$200 < L \leq 499$	0.25
$500 < L$	0.19

Notes: N = 199,484.

C.3 Intangible investment and total capital around intangible investment events

Figure C.1 shows the two components making up our intangible investment spike measure, intangible investment (defined as expenditures) and total capital stock, for a balanced sample of firms around intangible investment events. This highlights that intangible investment spikes are driven by increases in intangible expenditures, not decreases in total capital stock.

Figure C.1: Intangibles expenditures and total capital around intangible investment spikes



Notes: Balanced sample of firms

C.4 Correlation between tangible and intangible investment spikes

Table C.3 estimates a firm-level linear probability model where the dependent variable is a dummy for the firm having at least one intangible investment spike over 2002–2019, while the independent variable is a dummy for the firm having at least one tangible investment spike over 2002–2019. Results are robust to including average employment size and/or average age as control variables.

Table C.3: Correlates of a firm ever having an intangible investment spike

	Outcome: ever having an intangible investment spike			
	(1)	(2)	(3)	(4)
Ever tangible spike	0.0392***	0.0390***	0.0400***	0.0399***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Mean FTE		-0.0001***		-0.0001***
		(0.0000)		(0.0000)
Mean Age			0.0020***	0.0020***
			(0.0001)	(0.0001)
Constant	0.4683***	0.4691***	0.4410***	0.4411***
	(0.0016)	(0.0016)	(0.0021)	(0.0021)
Observations	199,484	199,423	199,484	199,423

Notes: Each observation is a unique firm. The dependent variable is having an intangible investment spike at any point in the sample. $*p<0.10$, $**p<0.05$, $***p<0.01$.

Appendix D. Firm-level analyses

D.1 Predicting intangible investment events

Table D.1 estimates a firm-level linear probability model where the dependent variable is a dummy for the firm having at least one intangible investment spike over 2002–2019. This table highlights that firms that have intangible investment events are different from those that do not. In particular, the probability of having an intangible investment event is higher for firms that pay higher wages, have lower labor productivity, and have a lower intangible capital per employee. Moreover, smaller firms are more likely to experience such events, as well as firms active in manufacturing, construction, and wholesale & retail.

Table D.1: Correlates of a firm ever having an intangible investment spike

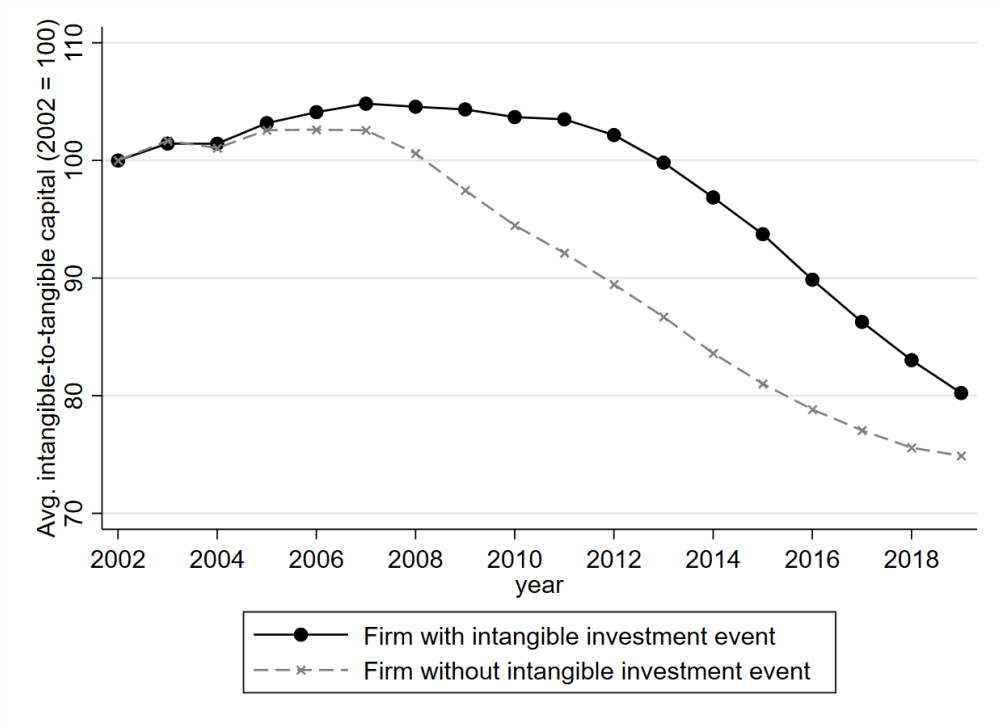
Mean wage	0.0257***	DE Utilities	-0.0079
	(0.0027)		(0.0184)
Mean labor productivity	-0.0091***	F Construction	0.0440***
	(0.0013)		(0.0098)
Mean intangible capital/employee	-0.0018***	G Wholesale & Retail	0.0270***
	(0.0005)		(0.0096)
L $\leq$ 20	*reference*	H Transport	-0.0062
			(0.0107)
20 $<$ L $\leq$ 50	-0.0674***	I Accommodation & Food Serv.	-0.0094
	(0.0051)		(0.0100)
50 $<$ L $\leq$ 100	-0.1255***	J Information & Communication	-0.0708***
	(0.0096)		(0.0141)
100 $<$ L $\leq$ 200	-0.1989***	K Finance & Insurance	0.0047
	(0.0133)		(0.0208)
200 $<$ L $\leq$ 500	-0.1994***	L Real Estate	-0.1343***
	(0.0179)		(0.0116)
500 $<$ L	-0.2491***	M Prof. Scientific & Tech. Serv.	-0.0969***
	(0.0251)		(0.0106)
C Manufacturing - High Tech	*reference*	N Admin. & Support Act.	-0.0028
			(0.0107)
C Manufacturing - Other	0.0176*	Constant	0.3535***
	(0.0100)		(0.0316)

Notes: 182,214 observations, each observation is a unique firm. The dependent variable is having an intangible investment spike at any point in the sample. $*p<0.10$, $**p<0.05$, $***p<0.01$.

D.2 Intangible-to-tangible capital growth for investing and non-investing firms: balanced panel

Figure D.1 uses the balanced panel of firms existing over the entire 18-year period and plots a time series of firm-level intangible-to-tangible capital ratio averaged across firms with and without an intangible investment event with both series normalized to 100 in 2002.

Figure D.1: Average intangible-to-tangible capital for firms with and without intangible investment events



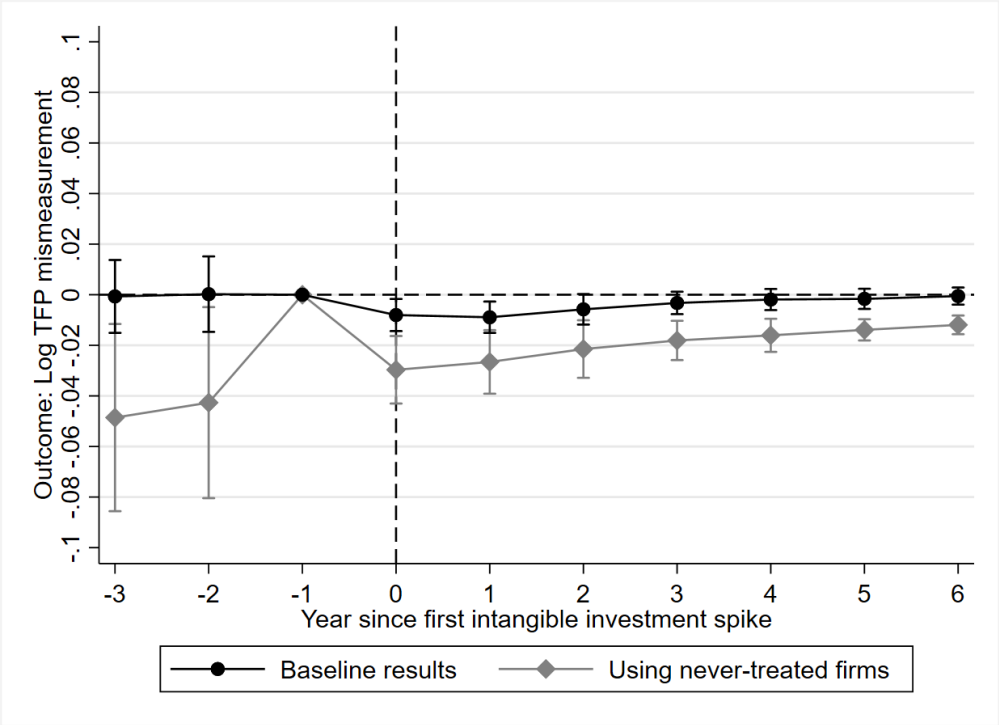
Notes: All firms existing over the entire 18-year period 2002–2019. N = 18,246 for firms with an intangible investment event and N = 12,861 for firms without an intangible investment event.

D.3 Difference-in-differences with non-investing firms

Here, we construct a different control group for our main analysis. Instead of using firms that invest in intangibles later, we use firms that do not invest in intangibles over the period we observe them. We follow the same steps in constructing the sample as a stacked difference-in-differences as discussed in the main text and estimate the same models.

Figure D.2 reports the findings for TFP mismeasurement. All estimates are weighted by firm size. The figure reveal that for TFP mismeasurement there are clear divergent pretrends between investing and non-investing firms, which do not seem to exist when comparing investing with later-investing firms.

Figure D.2: Using later-investing vs non-investing firms as control group



Notes: N = 61,348 for later-investing firms and N= 136,421 for non-investing firms as control group. Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level. All models are weighted by firm-level employment size in $\tau = -1$. Whiskers reflect 95% confidence intervals.

D.4 Comparison with different intangibles measures

D.4.1 Comparison with balance sheet-based intangibles measure

As explained in Subsection 2.3, intangible capital is not always allowed to be reported on the balance sheet of firms. How does our measure compares to the balance sheet variable? We construct an intangible investment variable from the balance sheet variable using the perpetual income method, where $I_{u,i,t} = U_{i,t} - U_{i,t-1} \times (1 - \delta_u)$, where δ_u denotes the depreciation rate of intangible capital.

Table D.2: Intangible investments from the balance sheets

	Baseline		**Balance sheet**	
	Investment level	Investment per worker	Investment level	Investment per worker
p5	0	0	0	0
p10	0	0	0	0
p25	529	251	0	0
p50	3,724	1,442	0	0
p75	20,813	5,598	0	0
p90	119,438	18,783	4,151	1,001
p95	302,310	38,785	23,354	5,729
Mean	146,815	11,527	72,924	4,726
Mean excl. zeros	180,539	13,943	420,671	26,466
Obs.	2,033,043		2,033,043	
Obs. with 0 costs	379,761		1,680,610	

Notes: Intangible investment level and per worker are reported in 2015 euros for each type. The number of observations is the number of firms times the number of years.

Table D.3: B2B-based intangible investments and balance sheet intangibles by sector

	B2B exp.	**Balance sheet inv.**	**Ratio B2B to**	**Nr. of obs.**	
	per worker	**per worker**	**balance sheet**	*Firms*	*Firms* × *yrs*
Manufacturing - High Tech	15,261	4,893	3.12	2,914	35,731
Manufacturing - Other	7,206	1,658	4.35	20,591	236,073
Utilities	57,635	142,688	0.40	987	11,147
Construction	7,083	876	8.09	34,712	352,750
Wholesale & Retail	12,211	3,706	3.29	64,936	691,636
Transport and Storage	10,994	4,841	2.27	9,502	102,827
Accommodation & Food Serv.	4,499	2,915	1,54	23,066	203,358
Information & Communication	51,656	25,060	2.06	2,254	20,686
Finance & Insurance	27,232	16,616	1,64	727	7,014
Real Estate	24,579	3,886	6.33	5,657	49,217
Prof., Scientific & Tech. Serv.	19,593	15,594	1.26	10,662	95,023
Admin. & Support Act.	18,300	5,902	3.10	9,472	88,881

Notes: Overlapping sample of firms. N = 199,930.

Table D.4: B2B-based intangible investments and balance sheet intangibles by firm size class

	B2B exp. per worker	**Balance sheet inv. per worker**	**Ratio B2B to balance sheet**	**Nr. of obs.** *Firms*	*Firms* × *yrs*
L ≤ 19	11,581	4,621	2.51	170,852	1,693,569
20 < L ≤ 49	10,554	5,830	1.81	9,595	128,819
50 < L ≤ 99	10,959	3,603	3.04	2,580	35,598
100 < L ≤ 199	12,645	2,850	4.44	1,351	19,625
200 < L ≤ 499	13,512	12,893	1.05	745	10,991
500 < L	13,366	8,504	1.57	357	5,741

Notes: Overlapping sample of firms. N = 199,930.

D.4.2 Comparison with intangibles measure without "fees"

It could be that our measure also pick up intangible service fees rather than investment. For example, firms paying an annual service fee to use Microsoft packages, Teams, and so on.[24] To avoid this, we alter our measure of intangible investment by replacing the 25th bottom our baseline intangible investment measure (where we look at the distribution of values larger than zero) to zero.

Table D.5: Intangible investments without fees

	Baseline		**B2B - fees**	
	Investment level	Investment per worker	Investment level	Investment per worker
p5	0	0	0	0
p10	0	0	0	0
p25	529	251	0	0
p50	3,724	1,442	3,724	1,248
p75	20,813	5,598	20,813	5,474
p90	119,438	18,783	119,438	18,783
p95	302,310	38,785	302,310	38,785
Mean	146,815	11,527	146,683	11,385
Mean excl. zeros	180,539	13,943	229,795	17,336
Obs.	2,033,043		2,033,043	
Obs. with 0 costs	379,761		735,312	

Notes: Intangible investment level and per worker are reported in 2015 euros for each type. The number of observations is the number of firms times the number of years.

[24] We thank David Baqaee for suggesting this possibility.

Table D.6: B2B-based intangible investments and B2B without fees by sector

	B2B exp. per worker	**B2B without fees per worker**	**Ratio B2B to B2B without fees**	**Nr. of obs.** *Firms*	*Firms* × *yrs*
Manufacturing - High Tech	15,261	15,206	1.00	2,914	35,731
Manufacturing - Other	7,206	7,110	1.01	20,591	236,073
Utilities	57,635	57,589	1.00	987	11,147
Construction	7,083	6,930	1.02	34,712	352,750
Wholesale & Retail	12,211	12,080	1.01	64,936	691,636
Transport and Storage	10,994	10,911	1.01	9,502	102,827
Accommodation & Food Serv.	4,499	4,221	1.07	23,066	203,358
Information & Communication	51,656	51,573	1.00	2,254	20,686
Finance & Insurance	27,232	27,181	1.00	727	7,014
Real Estate	24,579	24,458	1.00	5,657	49,217
Prof., Scientific & Tech. Serv.	19,593	19,442	1.01	10,662	95,023
Admin. & Support Act.	18,300	18,170	1.01	9,472	88,881

Notes: Overlapping sample of firms. N = 199,930.

Table D.7: B2B-based intangible investments and B2B without fees by firm size class

	B2B exp. per worker	**B2B without fees per worker**	**Ratio B2B to B2B without fees**	**Nr. of obs.** *Firms*	*Firms* × *yrs*
L ≤ 19	11,581	11,423	1.01	170,852	1,693,569
20 < L ≤ 49	10,554	10,552	1.00	9,595	128,819
50 < L ≤ 99	10,959	10,957	1.00	2,580	35,598
100 < L ≤ 199	12,645	12,644	1.00	1,351	19,625
200 < L ≤ 499	13,512	13,512	1.00	745	10,991
500 < L	13,366	13,366	1.00	357	5,741

Notes: Overlapping sample of firms. N = 199,930.

D.4.3 Comparison with intangibles measure with imports

The inter-firm transaction data set provides information on domestic intangible investments for all Belgian firms. However, for a small open economy such as Belgium, it could be that firms also import intangibles. Therefore, we supplement the B2B data with firm-level import data from the Belgian Balance of Payments Survey to capture intangible purchases from abroad. This data set is a survey collected by the National Bank of Belgium to construct the Balance of Payments of Belgium.

Table D.8: Intangible investments with imports

	Baseline		**B2B + imports**	
	Investment level	Investment per worker	Investment level	Investment per worker
p5	0	0	0	0
p10	0	0	0	0
p25	529	251	534	254
p50	3,724	1,442	3,748	1,458
p75	20,813	5,598	21,136	5,722
p90	119,438	18,783	123,838	19,530
p95	302,310	38,785	321,663	40,857
Mean	146,815	11,527	238,182	12,686
Mean excl. zeros	180,539	13,943	292,648	15,333
Obs.	2,033,043		2,033,043	
Obs. with 0 costs	379,761		378,383	

Notes: Intangible investment level and per worker are reported in 2015 euros for each type. The number of observations is the number of firms times the number of years.

Table D.9: B2B-based intangible investments and B2B with imports by sector

	B2B exp. per worker	**B2B with imports per worker**	**Ratio B2B to B2B with imports**	**Nr. of obs.** *Firms*	*Firms* × *yrs*
Manufacturing - High Tech	15,261	17,222	0.89	2,914	35,731
Manufacturing - Other	7,206	7,497	0.96	20,591	236,073
Utilities	57,635	61,780	0.93	987	11,147
Construction	7,083	7,158	0.99	34,712	352,750
Wholesale & Retail	12,211	13,018	0.94	64,936	691,636
Transport and Storage	10,994	11,769	0.93	9,502	102,827
Accommodation & Food Serv.	4,499	4,604	0.98	23,066	203,358
Information & Communication	51,656	79,334	0.65	2,254	20,686
Finance & Insurance	27,232	40,499	0.67	727	7,014
Real Estate	24,579	25,094	0.98	5,657	49,217
Prof., Scientific & Tech. Serv.	19,593	24,779	0.79	10,662	95,023
Admin. & Support Act.	18,300	19,886	0.92	9,472	88,881

Notes: Overlapping sample of firms. N = 199,930.

Table D.10: B2B-based intangible investments and B2B with imports by firm size class

	B2B exp. per worker	**B2B with imports per worker**	**Ratio B2B to B2B with imports**	**Nr. of obs.** *Firms*	*Firms* × *yrs*
L ≤ 19	11,581	12,381	0.94	170,852	1,693,569
20 < L ≤ 49	10,554	13,319	0.79	9,595	128,819
50 < L ≤ 99	10,959	14,415	0.76	2,580	35,598
100 < L ≤ 199	12,645	16,741	0.76	1,351	19,625
200 < L ≤ 499	13,512	34,775	0.39	745	10,991
500 < L	13,366	21,661	0.62	357	5,741

Notes: Overlapping sample of firms. N = 199,930.

D.4.4 Production function estimation

Table D.11: Production function estimation

	Gross-output production function estimator by CWDL (2020)			
	Baseline	*Balance sheet*	*B2B - fee*	*B2B + imports*
	(1)	(2)	(3)	(4)
Employment	0.1547***	0.2120***	0.1266***	0.1535***
	(0.0019)	(0.0293)	(0.0198)	(0.0016)
Tangible capital	0.0654***	0.0486**	0.0761***	0.0663***
	(0.0012)	(0.0213)	(0.0112)	(0.0012)
Intermediates	0.6915***	0.7114***	0.6970***	0.6889***
	(0.0018)	(0.0180)	(0.0036)	(0.0017)
Intangible capital	0.0616***	0.0274***	0.0745***	0.0642***
	(0.0008)	(0.0070)	(0.0023)	(0.0009)
No. of firms	132,195	48,985	115,901	132,185
No of observations	839,188	169,821	690,488	839,161

Notes: Table D.11 shows the production function estimation results using the estimation technique by Collard-Wexler and De Loecker (2020) (CWDL) for different defintions of intangible capital. ∗p<0.10, ∗∗p<0.05, ∗ ∗ ∗p<0.01.

D.5 Baseline results

Table D.12: Effect of intangible investment spike on productivity mismeasurement

	All intangibles (1)	Computerized information (2)	Innovative property (3)	Economic competencies (4)
3 years before event	-0.0007	-0.0091**	-0.0048	-0.0069
	(0.0074)	(0.0046)	(0.0066)	(0.0049)
2 years before event	0.0002	-0.0091**	-0.0051	-0.0080**
	(0.0076)	(0.0045)	(0.0042)	(0.0038)
Year of event	-0.0080**	-0.0067*	-0.0061**	-0.0023
	(0 .0032)	(0.0040)	(0.0027)	(0.0035)
1 year after event	-0.0089***	-0.0049	-0.0096***	-0.0022
	(0.0032)	(0.0038)	(0.0029)	(0.0032)
2 years after event	-0.0058*	-0.0020	-0.0093***	-0.0010
	(0.0031)	(0.0037)	(0.0022)	(0.0040)
3 years after event	-0.0032	-0.0003	-0.0068***	0.0020
	(0.0023)	(0.0035)	(0.0020)	(0.0030)
4 years after event	-0.0019	0.0081	-0.0046**	0.0035
	(0.0021)	(0.0087)	(0.0020)	(0.0033)
5 years after event	-0.0016	0.0087	-0.0051***	0.0044*
	(0.0020)	(0.0086)	(0.0018)	(0.0025)
6 years after event	-0.0005	0.0105	-0.0052***	0.0084***
	(0.0017)	(0.0082)	(0.0015)	(0.0020)
No. of firms	61,348	36,280	13,405	18,438

Notes: Table D.12 shows the regression results of Equation 8. Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level. All models are weighted by firm-level employment size in $\tau = -1$. $*p<0.10$, $**p<0.05$, $***p<0.01$.

D.6 Explaining heterogeneity

In previous section, we found that mainly small, low capital-insensitive, and young firms experience the intangibles-related productivity J-curve. The main argument for these results is that these firms require a longer adjustment period to make use of new innovation by doing complementary intangible investments. Is this the case? We explore this adjustment process by examining different outcome variables related to this: the entrance of skilled employees within the firm, the number of training hours, the log ratio of ICT over tangible investment, and log tangible investment. We consider effect heterogeneity by firm characteristics: firm size, firm age, and capital-labor ratio. For each of the groups considered here, we contrast the effect against the same group at the control firm by using an interaction term. In particular, we estimate the following model:

$$y_{it} = \alpha + \delta_0 \times Treat_i \times Post_{i\tau} + \sum_k \delta_k \times Treat_i \times Post_\tau \times z_{ki} + \lambda_{st} + Post_i \times z_{ki} + \eta_i + \epsilon_{it}, \quad \text{(D.1)}$$

where, as before, i indexes firms by cohort. We estimate the average annual treatment effect of the entire post-treatment period rather than estimating the year-by-year coefficients. The average annual effect is captured by $Post_{i\tau}$, which is a dummy variable indicating the post treatment period. z_{ki} are discrete variables indicating the firm characteristics described above. $Treat_i$ is the dummy variable indicating treatment, which equals to one for firms that experiences an intangible investment spike in the event window. λ_{st} is a set of four-digit sector $\times$ calendar year fixed effects and η_i are a set of cohort by firm fixed effects. y_{it} is the (log) outcome variable of interest. Results are shown in Table D.13.

We first consider firm size heterogeneity, presented in panel (a) of Table D.13. Several results emerge. First, following an intangible investment event, we find that firms hire new skilled employees in the first six years after the intangible investment event. This increase in the number of skilled workers hired are generally larger for smaller firms: in firms with up to 20 employees, the number of new skilled employees go up by 107.5% annually over the six years following the intangible investment event, whereas larger firms increase the hiring of skilled employees by 8.3 to 53.0% annually. Smaller firms are less-skilled as skilled workers typically select into productive firms (Song et al., 2019). Hence, these smaller firms require new skilled employees to make this

new investments work within the firm (Brynjolfsson et al., 2021).

Besides hiring new skilled employees, firms also update the skills of existing employees by increasing training initiatives (measured by training hours). We find that training initiatives indeed go up, but is again concentrated within smaller firms: smaller firms increase training hours by a factor of 8, while bigger firms see less of an increase. Finally, smaller firms increase the ICT share of tangible investments - which are generally very skill intensive, while we see a muted increase in the ICT share for larger firms. A concrete example is the introduction of the computer. When managers introduce the computer in the firm, they need to update the skills of existing employees (training), they need to hire more skilled employees that are able to work with the computer or maintain it (ICT personnel), and improve the ICT infrastructure to make it work (ICT investment share). We do not see such effects for larger firms, indicating that they were already more skilled and more prepared to begin with. We can make similar statement for firm age (panel b) and capital-intensity (panel c).

Table D.13: Other firm-level outcomes

	Entry of skilled labor	No. of training hours	Log ICT investment share	Log tangible investment
		A. Firm Size		
FTE $\leq$ 20	1.0748***	8.0232**	0.0484*	0.2310***
	(0.0769)	(3.8914)	(0.0267)	(0.0179)
Derivations from reference group for:				
20-50 FTE	-0.5667***	-2.6296	-0.0346	0.0765*
	(0.0862)	(3.4799)	(0.0624)	(0.0451)
50-100 FTE	-0.9923***	-5.8990*	-0.2565**	0.3340***
	(0.1073)	(3.4117)	(0.1089)	(0.0939)
100-200 FTE	-0.6158*	-6.6724*	0.1059	0.1759
	(0.3245)	(3.9688)	(0.2006)	(0.1186)
200-500 FTE	-0.8299***	-9.2194**	0.3153	0.2488
	(0.1819)	(4.0675)	(0.2016)	(0.2083)
FTE $\geq$ 500	-0.5449***	-4.8149	-0.5438	0.6148
	(0.1406)	(4.2052)	(0.5956)	(0.6365)
N	16,956	202,897	815,162	949,320
		B. Firm Age		
Age $\leq$ 15	0.5104***	5.9769***	0.0134	0.3126***
	(0.0942)	(1.4992)	(0.0663)	(0.0512)
Derivations from reference group for:				
15-25 Age	-0.3986***	-8.0548***	0.0603	-0.0260
	(0.0859)	(1.8887)	(0.0988)	(0.0676)
Age $>$ 25	-0.3292***	-5.4578***	-1.0929	1.5180*
	(0.1016)	(1.6238)	(0.8480)	(0.7889)
N	16,956	202,897	815,162	949,320
		C. Firm Capital-Labor Ratio		
Capital/FTE $\leq$ p25	0.6711***	5.4249***	0.2369**	0.2650***
	(0.0407)	(1.7981)	(0.1072)	(0.0867)
Derivations from reference group for:				
p25-p50 Capital/FTE	-0.4028***	-2.1716	-0.1312	0.1483
	(0.1500)	(2.6462)	(0.1271)	(0.1012)
Capital/FTE $>$ p50	-0.5669***	-4.3802**	-0.5442**	0.2529
	(0.1847)	(1.7921)	(0.2140)	(0.2211)
N	16,956	202,897	815,162	949,320

Notes: All coefficients are average annual effects over the post-treatment period ($\tau = 0$ through $\tau = 6$). All models are weighted by firm-level employment size in $\tau = -1$. $*$p<0.10, $**$p<0.05, $***$p<0.01.

Appendix E. Descriptives for spikes by type

Table E.1 shows the distribution of intangible investment types across firms and years, highlighting investments in economic competencies are on average the largest, followed by innovative investments and investments in software and databases. Table E.2 shows the distribution of intangible investment type spikes: while more firms have computerized investment spikes than innovative and economic competencies spikes, Figure E.1-Figure E.3 show that each investment spikes are characterized by a large one-time increase in investment. Table E.3 compares intangible investments types per worker across firms by sector and firm size. As expected, Information and communication has the highest computer investment per worker, followed by Finance & Insurance. The same is true for investments in economic competencies. For innovative investments, we find that the largest investment per worker in concentrated within Utilities, followed by Information and communication. We generally see higher investment per worker for larger than smaller firms.

Table E.1: Intangible investments

	Computerized info.		**Innovative property**		**Econ. competencies**	
	Investment level	Investment per worker	Investment level	Investment per worker	Investment level	Investment per worker
p5	0	0	0	0	0	0
p10	0	0	0	0	0	0
p25	0	0	0	0	0	0
p50	0	17	497	150	520	168
p75	2,672	748	4,244	1,051	6,004	1,627
p90	12,998	2,756	25,293	4,354	54,835	8402
p95	36,634	5,532	77,209	10,155	160,728	20,174
Mean	30,449	1,933	55,807	3,729	60,559	5,866
Mean excl. zeros	62,165	3,829	96,169	6,256	107,612	10,124
Obs.	2,033,043		2,033,043		2,033,043	
Obs. with 0 costs	1,037,236		853,250		888,947	

Notes: Intangible investment level and per worker are reported in 2015 euros for each type. The number of observations is the number of firms times the number of years.

Table E.2: Intangible spike frequency by type

	Percentage of firms with event type		
Nr of spikes	Computerized info.	Innovative property	Econ. competencies
0	66.2	79.3	83.1
1	21.4	12.7	11.4
2	9.4	6.1	3.8
3	2.5	1.5	1.3
4	0.4	0.2	0.4
5 or 6	0.1	0.2	0

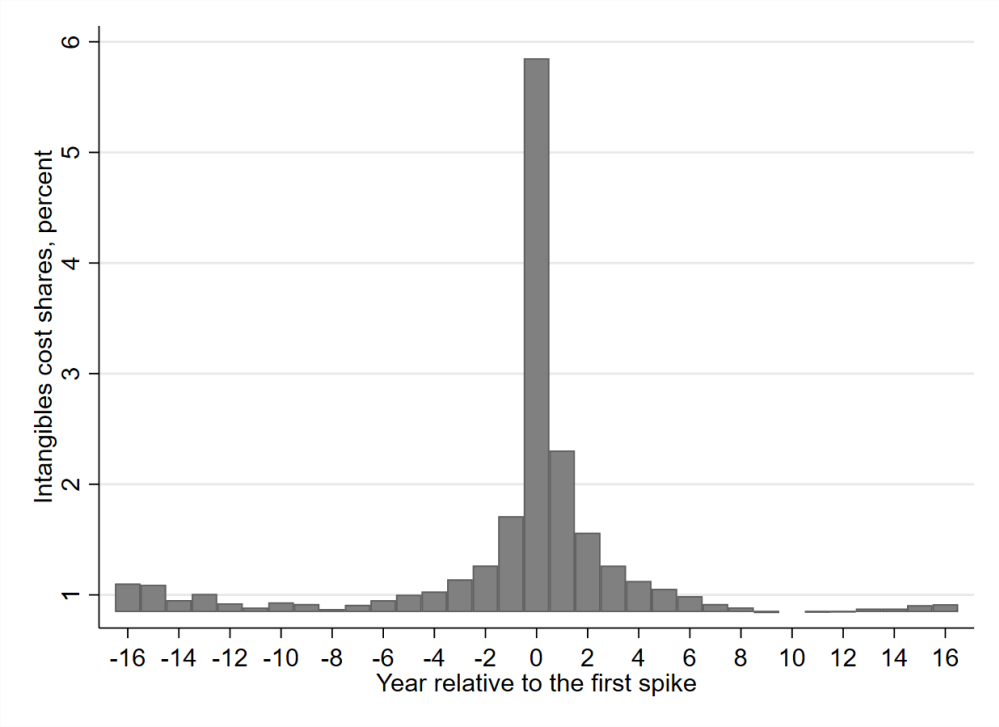
Notes: Overlapping sample of firms. N = 199,930.

Table E.3: Intangibles by sector and firm size class

	Computerized info. per worker	**Innovative prop. per worker**	**Econ. competencies per worker**
A. Sector			
Manufacturing - High Tech	1,915	7,951	5,395
Manufacturing - Other	848	2,739	3,619
Utilities	4,909	41,993	10,733
Construction	814	3,288	2,981
Wholesale & Retail	2,345	2,999	6,867
Transport and Storage	1,977	3,204	5,813
Accommodation & Food Serv.	571	1,984	1,944
Information & Communication	9,553	18,103	23,999
Finance & Insurance	7,429	6,066	13,737
Real Estate	2,680	9,328	12,571
Prof., Scientific & Tech. Serv.	4,352	2,885	12,356
Admin. & Support Act.	3,534	6,161	8,605
B. Firm size class			
$L \leq 19$	1,925	3,727	5,929
$20 < L \leq 49$	1,826	3,526	5,202
$50 < L \leq 99$	2,099	3,361	5,499
$100 < L \leq 199$	2,308	4,803	5,534
$200 < L \leq 499$	2,720	4,274	6,518
$500 < L$	2,748	6,293	4,325

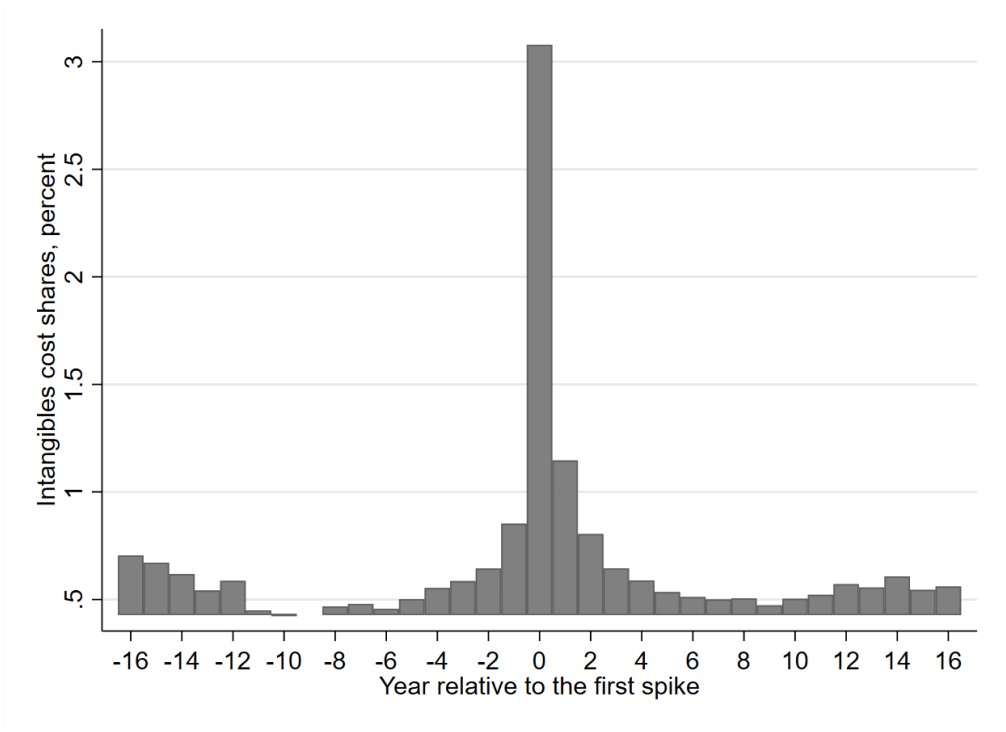
Notes: Overlapping sample of firms. N = 199,930.

Figure E.1: Computerized intangible investment shares around events



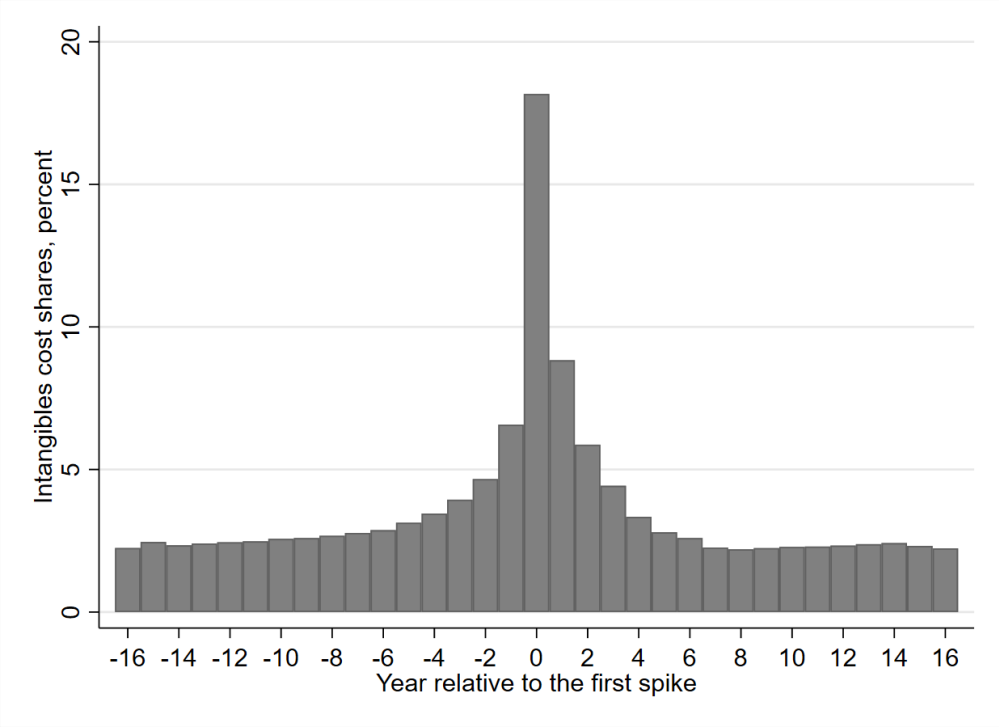
Notes: Figure E.1 shows the computerized intangible investment shares (as a share of total capital) around computerized intangible investment events.

Figure E.2: Innovative intangible investment shares around events



Notes: Figure E.2 shows the innovative intangible investment shares (as a share of total capital) around innovative intangible investment events.

Figure E.3: Economic competencies intangible investment shares around events



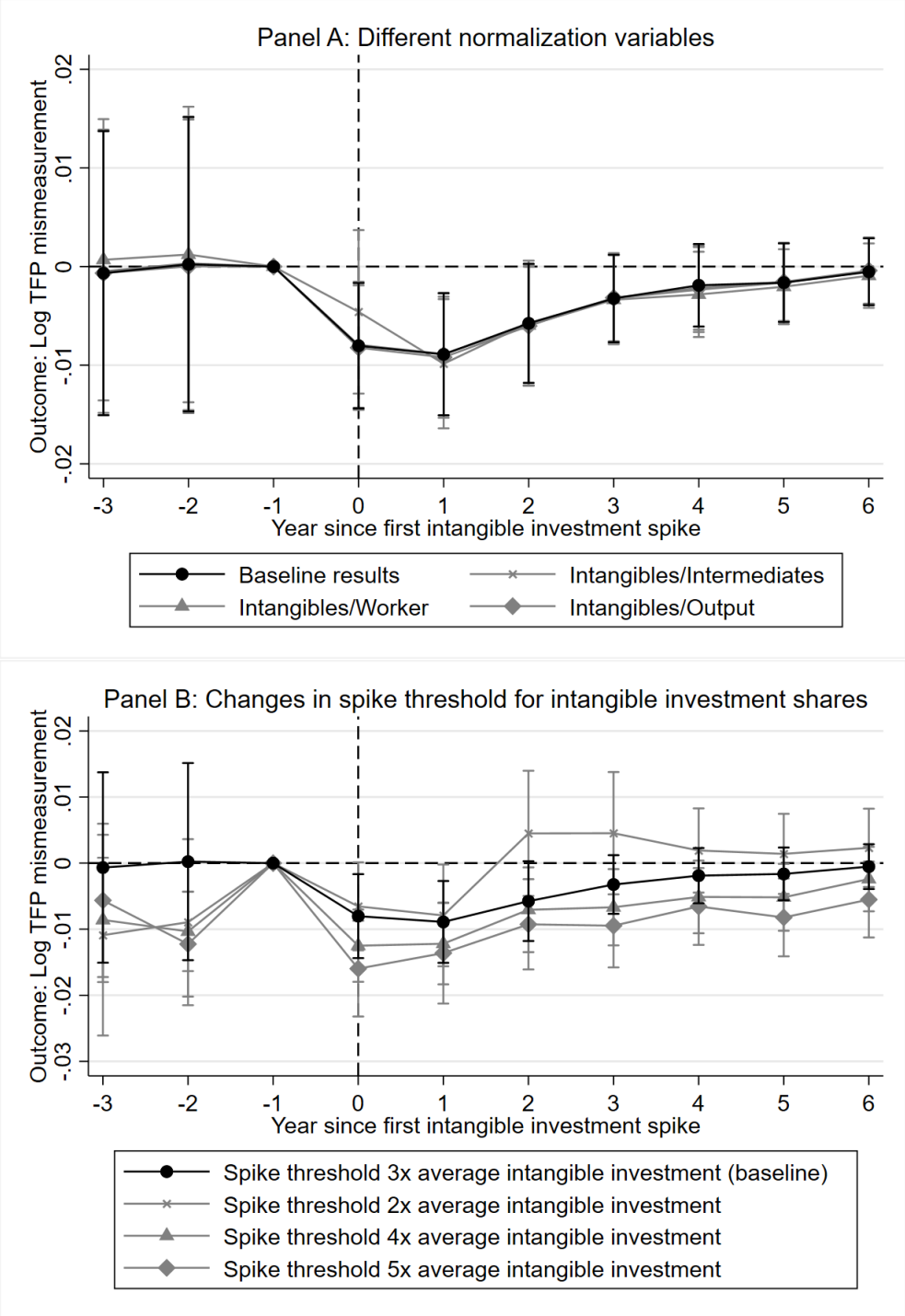
Notes: Figure E.3 shows the economic competencies intangible investment shares (as a share of total capital) around economic competencies intangible investment events.

Appendix F. Robustness tests

F.1 Alternative definitions of intangible investment events

Rather than using intangible investment over total capital (i.e. intangible investment over tangible and intangible), we can construct intangible investment events from sharp increases in intangibles outlays per worker. We then also use sales and intermediates as a denominator. All variations produce similar results to our baseline estimates, as seen in panel (a) of Figure F.1. Further, we show that results are robust to varying the spike threshold from two to five times the average intangibles share (our baseline is thrice the average intangibles costs). Panel (b) in Figure F.1 reveals that estimated effect sizes are somewhat larger the higher the threshold, as expected, but these differences are not statistically significant. This highlights that our results are not driven by the specific spike size cut-off we employ in our baseline estimates.

Figure F.1: Robustness to different definitions of intangible investment events



F.2 Constructing placebo events

In this subsection we report descriptive statistics for our placebo analysis using spikes in material fixed assets. The results of this analysis are reported in section F.3. Table F.1 shows the distributions of investments in material assets in the overlapping sample of firms, both in real euros, as a share over total capital, and in real euros per worker. Table F.2 shows the frequency of tangible spikes in this sample, where we consider spikes in material fixed assets placebo spikes. Lastly, Figure F.2 shows the evolution of investments in material fixed assets around placebo spikes.

Table F.1: Tangible investments

	All Observations			**Tangible investment > 0**		
	Investment level	Investment per worker	Investment share (%)	Investment level	Investment per worker	Investment share (%)
p5	0	0	0	740	270	0.5
p10	0	0	0	1,364	531	1
p25	1,063	473	0.62	4,519	1,622	2.98
p50	10,503	3,369	5.37	19,772	5,494	8.65
p75	48,660	13,599	15.93	66,080	18,020	19.39
p90	168,536	4,2825	29.77	216,952	52,607	32.97
p95	372,332	87,056	39.66	463,237	105,015	42.98
mean	*219,292*	*33,127*	*10.93*	*270,129*	*40,227*	*13.67*
Observations		2,026,780			1,645,351	
Pct with 0 costs		19%			0%	

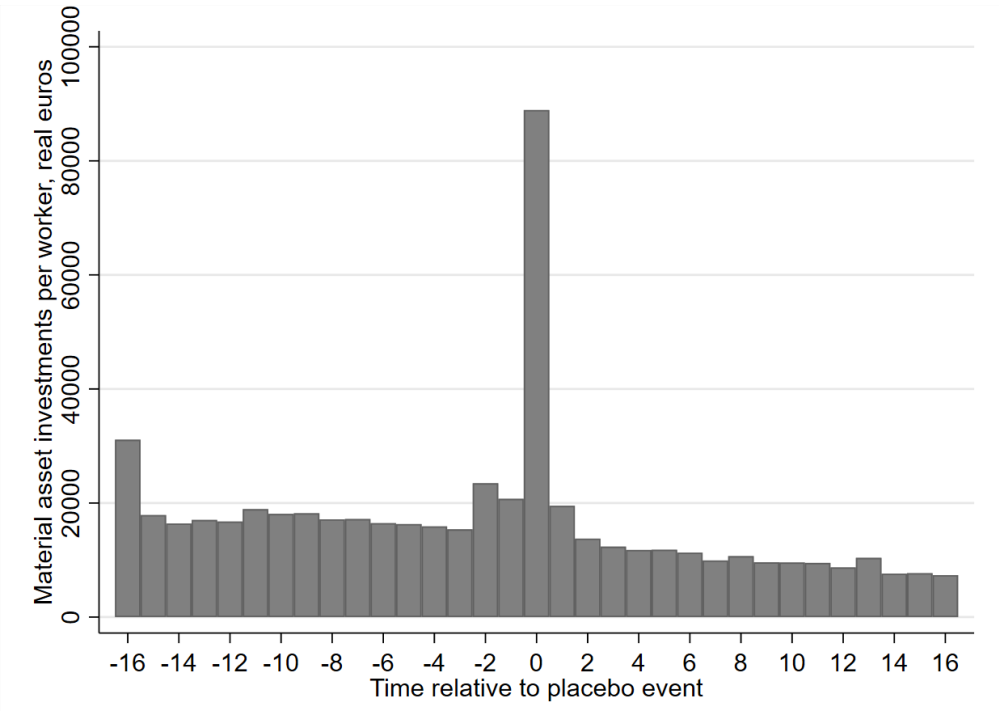
Notes: Tangible investment level and per worker are reported in 2015 euros, tangibles share is calculated as a percentage of total capital. The number of observations is the number of firms times the number of years.

Table F.2: Tangible spike frequency

Spike frequency	N firms	pct of N firms
0	95115	47.68
1	76066	38.13
2	23159	11.61
3	4646	2.33
4	477	0.24
5	21	0.01
Total	199,484	100

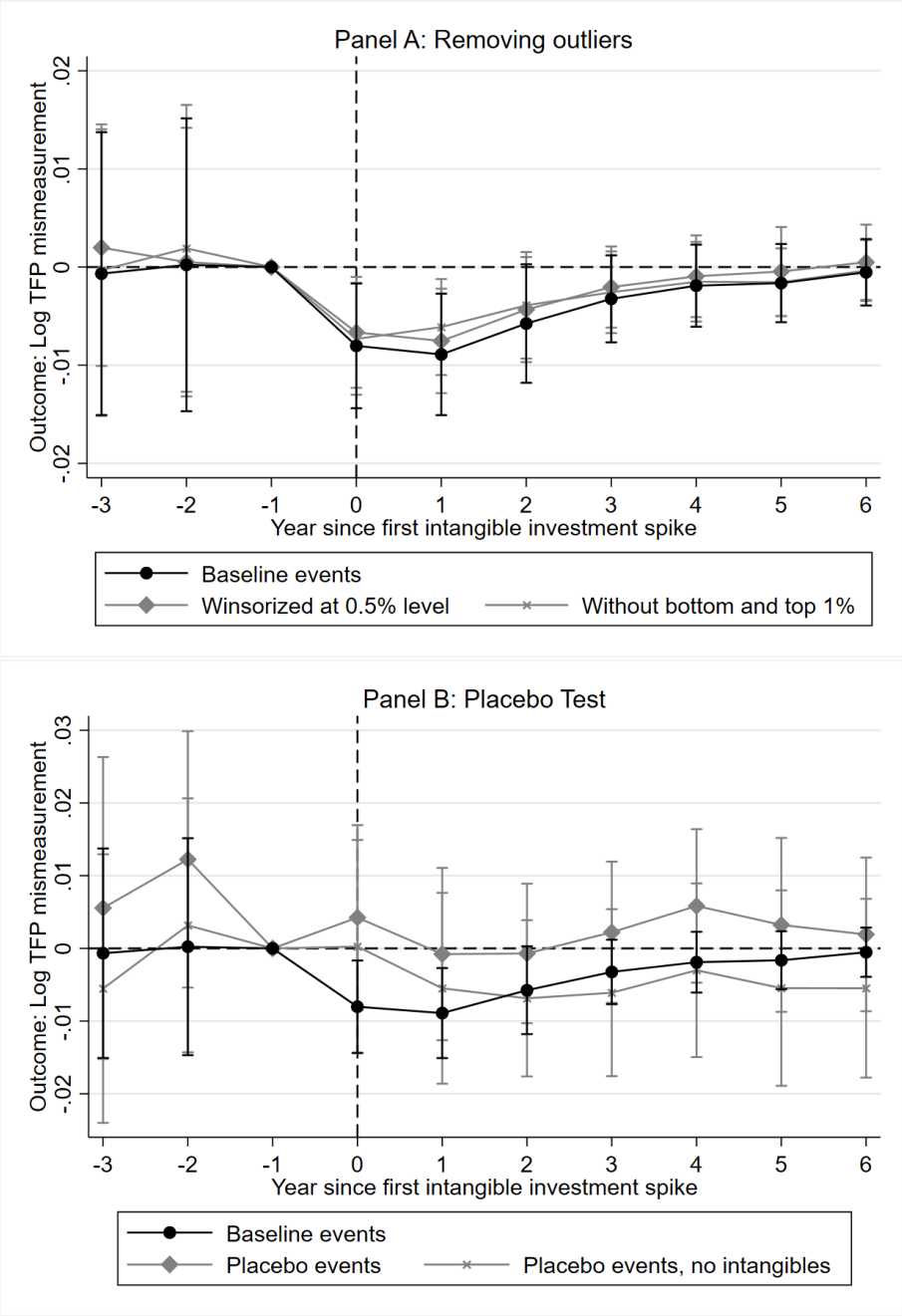
Notes: Spike frequency is defined as the total number of spikes occurring over 2002-2019. The total number of firms is 199,484 and the total number of firms with at least one tangible investment spike is 104,369.

Figure F.2: Placebo events: Spikes in material fixed assets



F.3 Robustness to outliers and placebo events

Figure F.3: Robustness tests



F.4 Comparison with different intangibles measures

We use employment as denominator instead of total capital since otherwise the spikes will not be comparable for these different asset types as it changes the definition of a spike. We define an intangible investment spike as follows. Firm j has an intangible investment spike in year τ if its real intangible investment I_{jt} relative to total employment L averaged across all years t, $\bar{L}_j$, are at least thrice the average firm-level cost share excluding year τ:

$$spike_{j\tau} = \mathbb{1}\left\{\frac{I_{j\tau}}{\bar{L}_j} \geq 3 \times \frac{1}{T-1}\sum_{t\neq\tau}^{T}\left(\frac{I_{jt}}{\bar{L}_j}\right)\right\}, \tag{F.1}$$

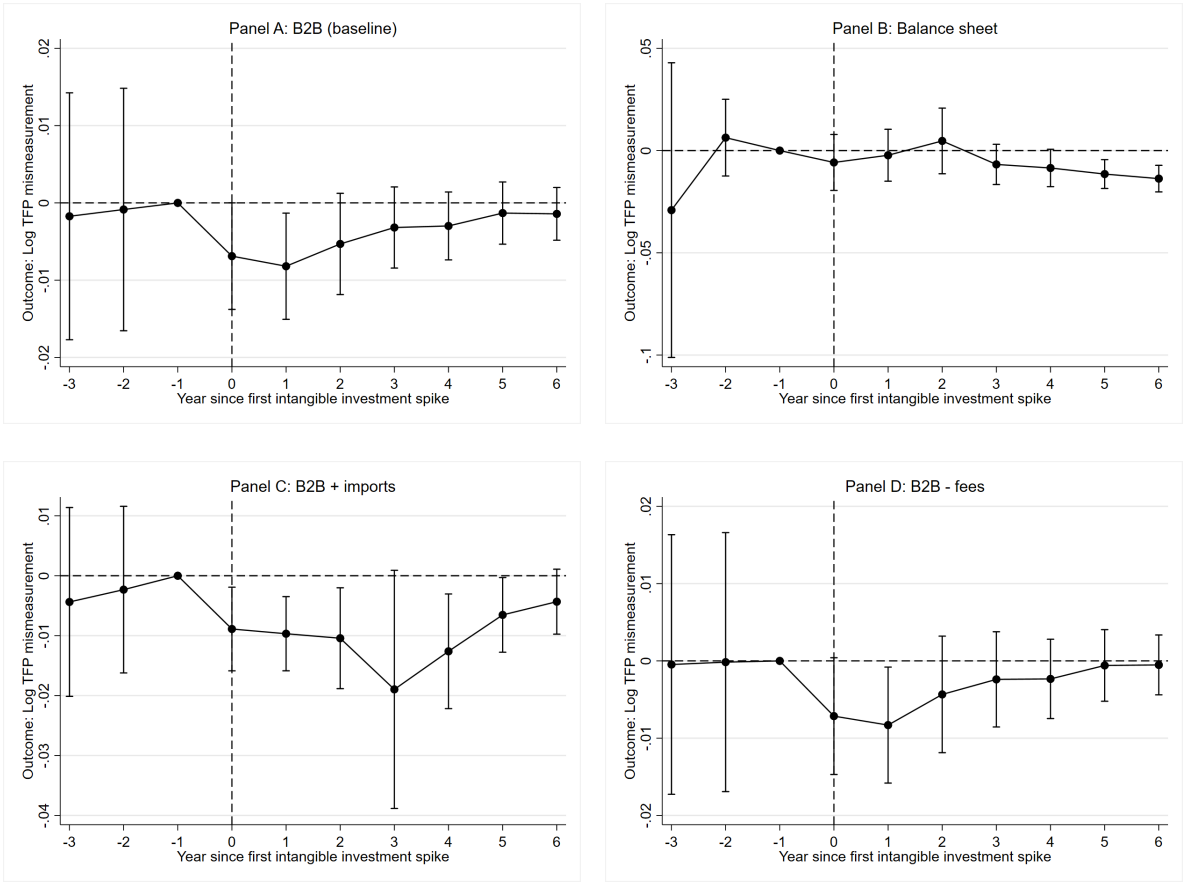
where $\mathbb{1}$ denotes the indicator function. Finally, we define an intangible investment event as the year when the firm has its *first* increase in intangible investment cost share that qualifies as a spike. Table F.3 shows the frequency for such spikes in our data and Figure F.4 shows the difference-in-differences results.

Table F.3: Intangible spike frequency by type

	Percentage of firms with event type			
Nr of spikes	*Baseline*	*Balance sheet*	*B2B - fee*	*B2B + imports*
0	64.0	76.3	68.6	63.7
1	26.7	17.0	21.8	27.0
2	7.3	5.3	7.4	7.4
3	1.6	1.3	1.9	1.6
4	0.3	0.1	0.3	0.3
5 or 6	0.0	0.0	0.1	0.0

Notes: N = 199,930.

Figure F.4: The impact of different measures of intangible capital on productivity mismeasurement



Notes: Productivity mismeasurement is defined as the difference between measured log TFP - intangibles-adjusted log TFP, both estimated at the 2-digit NACE industry level. All models are weighted by firm-level employment size in $\tau = -1$. Whiskers reflect 95% confidence intervals.

F.5 Changes in model specification

Here, we change our model specification in a number of ways. In particular, compared to our baseline estimates, Figure F.5 shows results when additionally matching firms age in years; additionally matching firms on firm size; and both.

Figure F.5: Robustness to matching on firm size and/or age

