"Intangible Investment, Labour Composition and Productivity"

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Intangible Investment, Labour Composition and Productivity WORK IN PROGRESS

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Abstract
We estimate the causal effects of intangible investments on labour, output and productivity at the firm-level. We apply an event-based approach, where events are measured by spikes in intangible investment and use a dataset that includes all non-financial firms in the Netherlands (2006-2019) and merges firm-level and employee-level data with a tailor-made dataset on intangibles. We find that investments in intangible assets appear to have little to no effect on several firm performance indicators, three years after the investment.

Keywords: intangibles, productivity, event study, causal effects, firm level

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1 Introduction

Both the capital stock and investments in intangibles have become increasingly important (Thum-Thysen et al., 2019; van Ark et al., 2009; Corrado et al., 2005, 2009), including in the Netherlands (Freeman, 2021). The Covid-19 pandemic has most likely increased the importance of intangible assets, with teleworking, online shopping and contactless payments, to name a few.

Intangible assets include R&D, software, databases, but also organizational capital, training and brand capital. Given their growing importance as well as the fact that intangible assets differ from tangibles assets, we need a better understanding of the firm level implications of these investments. However, analysis on the impact of intangible assets on firms is still limited. In addition, most studies on the impact of intangibles on firms lack an effective strategy for identifying the causal impact of intangibles on firms' performance indicators. The reason behind this is that it is difficult to distinguish firms that have become productive due to their investments into intangibles from those that were already productive and therefore invested in intangibles. Similarly, there can be other factors driving both intangible investments and productivity. To address this problem, we adapt the strategy of Bessen et al. (2019) and Bessen and Righi (2020), who use an event-based differences-in-differences design (DiD).

To obtain a more complete picture of the impact of intangible investments, it is important to take into account both smaller firms and sectoral differences. Berlingieri et al. (2018) find that the relationship between firm size and productivity is significantly weaker for the service sectors. This relates to findings of van Heuvelen et al. (2018) that smaller firms also frequently appear in the group of frontier firms (defined as the top decile of the productivity distribution), especially in service sectors. It is likely that intangible investments lead to different results in different sectors. For example, Bessen (2019) shows that technologically mature sectors tend to have a lower elasticity of demand and a weaker or negative employment response to innovation shocks. In addition, the intangible asset type and amount invested will differ per sector.

The main contribution of this project is twofold: First, we estimate the effect of intangible investments on firm level productivity, using accounting data of firms in non-financial sectors to perform an event study to identify causal effects of spikes in intangible investment. Second, we investigate how intangible investments differ between firm sizes and sectors.

We find that investments in intangible assets appear to have little to no effect on several firm performance indicators, three years after the investment. There seems to be no effect on output or productivity (labour productivity or TFP). The composition of the labor force (permanent or flexible contracts; education level) also does not change in that period and we see no change in wages. We see small differences between sectors.

The paper is structured as follows. We first provide an overview of the literature on intangibles at the macro and firm levels and studies that incorporate causality. In section 3 we introduce the data sources, which consist of six datasets obtained from Statistics Netherlands, including a custom dataset that consists of intangible assets at firm level. Section 4 explains our empirical approach, which explains the event-based and differences-in-differences design, where events are measured by spikes in intangible investments. The results section 5 presents the impact of intangibles on hours of fixed and flexible workers, skills composition, age composition, labour productivity and TFP. Section 6 discusses and concludes.

2 Literature overview

There is a large literature on intangibles, which can roughly be divided into two parts. First, we will discuss the macro literature that focuses on intangibles at the national or sectoral level. Secondly, we discuss and relate this work to the literature examining intangibles at firm level. A third section discusses the literature establishing causality between investments and firm performance.

2.1 Intangibles at the macro level

Because intangibles include a list of potential assets, intangibles are frequently defined by characteristics attributed to them. Haskel and Westlake (2017) use four S's to describe the properties of intangibles: Scalability, Sunkenness, Spillovers and Synergies. Scalability refers to the fact that intangibles are often non-rival goods that can be used by several users at the same time. Sunkenness implies that it is harder to retrieve the investment's cost by selling the created asset. Intangible investments often lead to Spillovers between firms, implying that it is easier for firms to profit from the intangible investments of other firms. Synergies occur through complementarities between asset types, both for tangible and intangible capital. This implies that assets become more valuable when firms combine them with other assets. The degree with which these characteristics are present differs over asset type, as intangibles are heterogeneous. Nonetheless, intangibles tend to have more complementarities than their tangible counterparts.

The increasing importance of intangible assets has been extensively documented in literature focusing on the macro and meso levels (Thum-Thysen et al., 2019; Corrado et al., 2005, 2009). Both the capital stock of intangibles and investments in intangibles have increased in most countries over time. Thum-Thysen et al. (2019) show that the growth of investments the intangible assets explicitly included in national accounts has outpaced investments in tangibles in the US and in EU-28. These assets include intangibles that a relatively easily capitalized: *intellectual property*, like patents and R&D, and *IT-capital*, like software and databases. These assets correspond to the assets included in our measure of intangibles. However, outside of the national accounts, more types of intangibles cn be distinguished that are not typically capitalized. These include further intellectual property like product design, but also economic competencies, like training of staff, brand-capital and management quality.

Corrado et al. (2009) show, using data on NA *and* non-NA intangibles, that investments in intangibles amounted to 11.7% of GDP in 2003 and were larger than investments in tangibles in the U.S. For Europe, the investments in intangible assets are lower than that of the US. In 2004, intangible investments amounted to 10.1% for the UK (Marrano and Haskel, 2007), 7.0% in Germany (Crass et al., 2009), 6-7% in France (Nayman and Delbecque, 2010) and 5.2% in Spain and Italy (van Ark et al., 2009). For the Netherlands, van Rooijen-Horsten et al. (2008) show this number was 7.2% in 2005, they point out that the importance of intangible investments differ across sectors. The intangible investments as a ratio of tangible investment have risen from 51% in 1987 to 99% in 2005 for the commercial sector. However, this increase was mostly driven by a drop in tangible investments.

An issue with the measurement of intangible capital stocks is the depreciation rate, which is difficult to pin down (Corrado et al., 2009). This is primarily due to the absence of market prices for intangible investments; intangibles are often intramural investments, i.e. produced and used within firms. Many studies use the depreciation rate and investment percentage of expensed costs provided in the literature (see for example Corrado et al. (2005, 2012)[1].

Because the characteristics of intangibles differ from tangible capital, the determinants of investment in intangibles differ too. Thum-Thysen et al. (2019) show that the regulatory framework and existing investment in human capital are more relevant determinants for intangibles, while financial conditions are more relevant for tangibles. In addition, they show that intangibles are more frequently funded internally and provide evidence for

[1] Some exceptions exist. In an effort to improve measurement, Ewens et al. (2019) use M&A's to estimate the depreciation rate of non-capitalized intangibles. They find an average annual depreciation rate for R&D of 33%, which is more than double the rate commonly used in the literature. Furthermore, it appears to differ greatly across sectors.

complementarities between different asset types.

Brynjolfsson et al. (2018) stress that general purpose technologies like artificial intelligence and ICT require significant complementary investments into intangibles. They show that accounting for the complementary intangible investments enhances the estimated productivity benefits of investment in new technologies. Taking these complementarities into account shows the productivity contribution of new technologies is likely underestimated in the initial stages of their introduction and overestimated at later stages. This leads to a *productivity J-curve*. This J-curve might be the reason why new technologies are hard to link directly to productivity effects. For example, David (1990) shows that in the case of electrification, it took around 30 years before the benefits where being fully reaped.

Further evidence for this idea comes from Hulten (2017) who shows that using an activity based model assigns more importance to labour skills and education. This is because inputs are assumed to be complementary. He suggests that when firms adopt new IT-enhanced equipment, the skills required of their labour change. Many other studies use frameworks without complementary inputs. Due to this, intangible assets may play a larger role in growth than generally documented.

2.2 Intangibles at the firm level

A stream of literature more closely related to the current research focuses on intangibles and their impact at the firm level. A key difference with macro of meso analyses is that those at the firm level yield estimates of private returns. Many firm level studies focus on single intangible assets. Furthermore, they often combine tangible and intangible capital, like in ICT, which combines tangible hardware capital and intangible software.

The focus has often been on single assets in R&D or ICT intensive sectors and mainly on large firms. There are only few studies that analyze multiple intangible assets and productivity at the firm level (see for example Chappell and Jaffe (2018) and Crass and Peters (2014)). Most of the multiple asset studies have focused on the estimation of the elasticity of the intangible assets and/or correlation regressions (i.e. Bontempi and Mairesse (2015); Lin and Lo (2015); Chappell and Jaffe (2018); Montresor and Vezzani (2016); Riley and Bondibene (2018)).

Ugur et al. (2016) provide a meta study on the relationship between R&D and firm productivity. They find that the firm level rates of return do not differ significantly from the sectoral social rate of returns. As such, they do not find evidence for large social returns over the private returns of R&D.

Cardona et al. (2013) provide an overview of the empirical literature on ICT and productivity, concluding ICT has a positive and significant effect on productivity. They state that aggregate and sectoral growth accounting exercises show larger differences of ICT effects between the US and Europe. Europe's slower productivity growth in the 1990s till mid-2000s is often attributed to weaker ICT investments than in the US. However, at a firm level there are no significant country differences.

Bloom et al. (2016) provide evidence that management is positively associated with higher productivity. They estimate a production function including a management indicator (z-score) input variable. They find a positive and significant elasticity for the management input. However, in a regression with only capital, labour and management as inputs, the effect of the management variable is probably overestimated, due to its correlation with other omitted unobservable intangible assets.

Finally, Crass and Peters (2014) note that their firm level regressions with multiple intangible assets yield smaller effects compared to other regressions that use a single type of intangible asset. This implies that single asset regressions might overestimate the positive effect of that asset type. The research on single asset types should therefore be interpreted as an upper bound estimate of the effect of that asset on productivity if synergy is crucial. Another disadvantage of single asset studies is that certain assets such as R&D and ICT are relatively more important in certain sectors, this would overstate differences in the use of intangibles between sectors.

2.3 Causality

Very few studies employ an effective strategy for identifying the causal impact of intangibles on firm performance indicators such as productivity or firm strategies such as employment. Bessen et al. (2019); Bessen and Righi (2020) address this endogeneity problem by using the observation that firms tend to invest at discrete intervals, or spikes, over time. These *investment spikes* can be used as an identification strategy to tease out the impact of investments on the performance of firms. Bessen et al. (2019) use a differences-in-differences method, relying on investment spikes into *automation* as treatment. They explore how automation is related to workers' jobs and pay. They find that, within 5 years after a firm's investment spike, older workers are 24% more likely to have left. Bessen and Righi (2020) use a similar method, taking advantage of spikes in the hiring of IT-personnel. The authors explore how these investments in IT affect firms' labour demand. They distinguish three channels through which this can happen, displacement, productivity, and markups. The first reduces labour demand by replacing workers with machines, the latter two are stated to increase labour demand. The results show labour demand is increased by IT investments. The authors argue that the markups channel is the most important, the effect of which dominates the other two channels. We follow both these papers and apply a very similar method to investment of intangibles, as outlined in more detail in the methodology section below.

3 Data

We construct a firm-level dataset that includes all non-financial firms that pay corporate tax in the Netherlands, covering the period 2006-2019. The data combines firm and employee level data. The data used in the analysis are based on six datasets obtained from Statistics Netherlands (CBS). The dataset consist of three firms level datasets and three employee level datasets. First, the business registry (ABR) dataset containing basic background data such as firm sector, events (birth, exit) and size. Due to major changes in the ABR, we only use data after the period 2006, yielding a panel of 14 years. Second, the non-financial firms (NFO) dataset contains accounting data of Dutch firms. The NFO data are, in CBS terminology, at the enterprise level. An enterprise can consist of multiple firms. In most cases the enterprise consists of one firm. The ABR links the enterprise to the firm level. Third, the Polisbus data contains employment data at the employee level. The Polibus data is the link between firms and employee level data. The data contains both the employee and the firm identifier enabling us to link employees to firms. With the Polisbus we add hours, contract type and wages to the firm data. Fourth, the Employee administrative data(GBA) is added. This dataset adds gender, age and ethnic background information to the data. Fifth, we add Education data (Hoogsteopltab). The education data contains the education code of the highest obtained and followed educational level. Finally, a custom made dataset by the CBS was added for intangible depreciation and goodwill.

The NFO dataset is at the enterprise level and the Polisbus data is at the employee level. When only some of the firms that comprise the enterprise have employee data, merging the datasets results in a partial match (around 2.0% of the firm-year observations). When matched employment data account for less than 90% of the total employment in fulltime equivalents (FTEs) for an enterprise, the enterprise is deleted from the sample. This results in keeping on average 84.2% of the firm observations each year. The match results in the greatest loss for small enterprises (10.5% of the enterprise observations). For larger enterprises (more than 20 FTE) the loss is minimal, as only 3.5% of the enterprise observations do not have corresponding labour hours. Next, we add other employee characteristics to the data.

First, the employee administrative data is added. This data matches fully with the Polisbus. Second, we add the education data. This data is a little more complicated to match to the firm level. The dataset contains the highest achieved and highest followed level of education of the Dutch population. Education abroad, education in private institutions and long corporate education and courses are underestimated. More than 2% of the population actually has a higher education level than observed in the sources. Therefore, the CBS has supplemented the data with a yearly rotating employees survey (the labour survey EBB). For older employees with a low education level and foreigners employed in the Netherlands that did not study in the Netherlands that have not appeared in the EBB the education data is potentially missing. The average (median) percentage of employee hours for which there is education data within a firm is 72% (78%). From the education data we construct the ICT and education variables.

The custom CBS data is the last dataset we employ. We used the dataset to separate depreciation rates for tangible and intangible capital, which we cannot do in the NFO dataset. The customised dataset starts in 2011. Also, firms with a book value of gross output that was less than 40 million goodwill could be separated from the other intangible assets. In the current paper we use this dataset mainly for underlying comparison and checks.

3.1 Intangible assets

The intangible assets on the balance sheet only comprise a subset of the total intangible investments and is therefore an incomplete measure of total intangible investments. A distinction is made between national accounts (NA) intangible assets and non-NA intangible investments, investments that appear as costs on the balance sheets (see for example Thum-Thysen et al. (2019) for an overview). Since intangible assets often have large synergies, we expect that other intangible investments are made when we observe a large increase in the intangible capital stock on the balance sheet of a firm.

Freeman (2021) shows, based on Streher et al. (2019), that macro-level NA-intangibles in the Netherlands in 2017 covered approximately 23% of all investments, and 45% of intangible investments. The remaining intangible investments are non-NA intangibles. Assuming NA-intangibles correspond to the balance sheets of firms, our measure of balance sheet intangible investments consist, on average, of three categories. With 64% of NA-intangible investment, software and databases are the most important. Another 34% is made up of R&D intangibles. The final 2% is covered by other intellectual property, like artistic originals.

Intangible assets on the balance sheet are defined as identifiable, non-monetary assets without physical appearance that is used for the production and delivery of goods or services. According to the guidelines for annual reporting (RJ 210.201) intangibles can only be capitalized on the balance sheet if they meet the following two conditions:

1. Economic benefits from the asset are expected to flow to firm.
2. The costs can be determined reliably.

Examples of intangible assets includes concessions, permits, patents, goodwill, R&D, and software. However, not all costs of an intangible investment appear on the balance sheet as intangible capital. In the case of software, the investment can appear as a cost or as an investment in intangible capital on the balance sheet. Costs of software that is produced in-house are difficult to determine reliably. Since the second condition often does not hold, most in-house developed software does not appear as an intangible asset on the balance sheet.

Another example are costs of a website. A website that is only used for the promotion of products cannot be an intangible investment on the balance sheet, as condition one does not hold. However, if individuals can buy or place orders on the site then certain costs of the website can appear as an intangible investment. Even in this case not all costs can appear as intangible capital on the balance sheet. For example, developing a graphic design, application and infrastructure development and content development can appear as an intangible capital, while planning, exploitation, updating, administration sales or overhead and content design for promotion cannot.

Training of employees cannot be booked as intangible investment as the first condition does not hold, as people can move on to other jobs. For R&D, a distinction is made between research and development. The research costs are not seen as an intangible investment, while the development can appear as an intangible investment. Since a clear distinction between research and development is often difficult to make, there is some room for discretion on where to book the costs.

Goodwill might be used to value intangible investments, which appear as costs on the balance sheet can be determined (See Ewens et al., 2019). The goodwill is the valuation of intangible capital, added to the balance sheet when the firm is taken over or merges. Goodwill is the difference between the book value of the assets of the firm and the price paid for it in a takeover. Therefore, goodwill can be an indication of intangible capital gained for the new firm, which is still an investment.

For all these reasons, balance sheet intangibles will give an incomplete picture of the intangible investments made by a firm. The intangible assets on the balance sheet are likely to be an underestimation of the total intangible investments made. However, when intangible investments are large, at least some of it will be recorded on the balance sheet as intangibles assets. The reason is that assets depreciate over a longer time period, while expenditures do not have this advantage. It is the moment that a firm invests in intangible assets that is of the the utmost importance, not the exact level. It is highly conceivable that other intangible investments are made at the same time when intangible assets appear on the balance sheet due to synergies.

3.2 Measurement of intangible investment

In this paper we exploit the concentration in certain years, or "lumpiness", of investments in intangible capital. Investments in intangible capital are likely more lumpy than investment in regular, tangible capital for two reasons. Firstly, the market value of intangible assets is more uncertain than that of, for instance, land or factories (see Haskel and Westlake, 2017). This is called the "sunkenness of intangible assets". Sunkenness implies it is difficult to sell an asset to retrieve the initial investment cost. This feature implies that investing in intangibles comes with higher uncertainty and irreversibility than investments in tangible assets. High uncertainty leads to lumpy investments when they are irreversible and have nonconvex adjustment costs (Pindyck, 1990; Rothschild, 1971).

Secondly, intangible assets are known to have synergies with other (intangible and human capital) assets. Synergies arise from complementarities between asset types. Therefore, investing in a single intangible asset will not automatically improve productivity of the firm. Full utilization of intangible assets often requires complementary investments. The synergies between intangible assets should lead to the clustering of investment to maximize the benefits. Therefore, only large intangible investments are expected to lead to observable changes within the firms Bessen and Righi (2020).

The analysis revolves around large intangible investment, henceforth spikes. We follow the methodology of Bessen et al. (2019). The spike has to be an event that is large for the firm. The first step for constructing the spike variable is creating an intangible investment series. Intangible investment (I_t^a) can be defined using the capital accumulation rule.

$$I_{it}^a = IC_{it} - IC_{it-1} + ID_{it} \tag{1}$$

Where IC is the intangible capital stock and ID the depreciation of the intangible asset. The main drawback of this definition is that it needs depreciation data, which start in 2011. Given that it is not the exact size of the investment that matters, but the fact that the event is big for the firm the following investment proxy variable (I_{it}^b) is employed.

$$I_{it}^b = IC_{it} - IC_{it-1} \tag{2}$$

This definition gives an underestimation of the investment as depreciation is not accounted for. None the less the investment proxy is very similar to the investment variable obtained through the capital rule. We compared the identified spikes with and without depreciation over the period 2011-2019. In 91% of the cases the spikes identified by the investment proxy are also identified when using investment. Therefore, the investment proxy is used to identify spikes.[2] This definition of intangible investment allows us to start the analysis in 2006 (instead of 2011). The investment proxy allows for the possibility that investment is negative as we cannot account for depreciation. Therefore, negative investments are equated to zero.

3.3 Intangible capital stock and investment descriptives

The number of observations for which we observe intangible capital is 15.3% of the sample (see Table 1). For the majority of the observations no intangible capital appears on the balance sheet. For 3.8% of the observations we see an positive investment in intangible assets. Firms often do not invest in intangibles for an extended period, and when they do, it will be a large investment, which then depreciates over time. Therefore, the number of years that positive intangible assets appears on the balance sheet is notably larger than the number of years that positive investments in intangible capital are made. For the observations in which we do observe positive investments, the mean (median) investment is relatively large around €7,2 million (73,400).

The size of intangible capital stock and the investment share differs across the sectors (see Table 2). We see that the size of intangible capital stock is the highest for the Manufacturing and Information and communication sector, although the investment share is notably higher for the latter sector (12.6%) than that of manufacturing (2.3%). This difference can be explained by the higher stocks of tangible capital that is often present in the Manufacturing sector. The Agricultural and the Accommodation and food service activities sector both have a relatively low investment share. The lowest mean intangible capital stock level is observed for the Professional, scientific and technical activities sector.

Intangible capital stock and the investment share increase with firm size (see Table 3). Large firms have notably more intangible capital stock on the balance sheet and the investments also constitute a larger percentage of average total capital.

[2] The percentage of spikes identified by the investment variable that are not identified by the investment proxy (i.e. false negatives) is 20.7%

Table 1: Distribution of intangible capital and investment

	All observations		*Investment> 0*	
	Intangible capital	Investment share	Intangible capital	Investment share
p5	0	0.0%	2.1	0.1%
p10	0	0.0%	5.0	0.2%
p25	0	0.0%	18.7	1.7%
median	0	0.0%	73.4	10.3%
p75	0	0.0%	274.4	46.0%
p90	17.6	0.0%	1,110.3	141.2%
p95	80.0	0.0%	3,442.0	247.4%
mean	590.4	5.3%	7,293.0	143.4%
% of N with 0	84.7%	96.2%	0.0 %	0.0 %
Observations	2,018,636	2,018,636	74,713	74,713

Notes: The Intangible capital is in 1000's euros, the investment share as a percentage of average total capital. Negative investments are equated to zero.

Table 2: Intangibles per sector

Sectors	Intangible capital *Mean*	Investment share *Mean*	N
Agriculture, Forestry and Fishing (A)	106.1	0.5%	54,301
Manufacturing (C)	2,081.7	2.3%	188,203
Construction (F)	183.1	1.2%	200,244
Wholesale and retail trade (G)	498.3	4.2%	541,122
Transportation and storage (H)	515.6	2,4%	82,426
Accommodation and food service activities (I)	154.0	1,6%	72,150
Information and communication (J)	1,967.2	12.6%	155,054
Professional, Scientific and Technical activities (M)	80.4	7,7%	608,415
Administrative and support activities (N)	688,873	7.2%	1116,721
Total	590.4	5.3%	2,018,636

The Intangible capital is in 1000's euros, the investment share as a percentage of average total capital. Negative investments are equated to zero.

Table 3: Size of intangible capital stock

FTE	Mean (1000 Euros)	Median (1000 Euros)	N
0-9	32.5	5.1%	1,539,789
10-19	68.0	3.7%	228,807
20-49	176.3	5.8%	160,016
50-99	612.2	4.4%	50,760
100-199	2,765.1	17.1%	21,209
200-499	9,569.9	22.5%	11,099
>500	129,675.5	26.4%	6,956
Total	590.3	5.5%	2,018,636

The Intangible capital stock is in 1000's euros, the investment share as a percentage of average total capital. Negative investments are equated to zero.

3.4 Dependent variable construction

Next we discuss the construction of the dependent variables that we use in the analysis. The definitions of the dependent variables can be seen in Table 4.[3]

The only variables that cannot be constructed directly from the data are the TFP and markup variables. The calculation of TFP and markups requires the estimation of a production function. We specify that gross output is a function of labour (in working hours), materials and capital (defined as the sum of tangible and intangible capital). We apply a control function approach to account for the endogeneity problem that arises from the correlation between the productivity shock known to the firm and its demand for flexible inputs (the estimation methodology is in detail described in van Heuvelen et al. 2021).

We start by estimating sector-specific Cobb Douglas (CD) functions. Given the relatively short time period, we reasonably assume that the parameters are time invariant per sector. This CD function is restrictive in that it assumes that the output elasticities are the same both for all firms (within a sector) and years. We also compute TFP from the more flexible Translog production function, which includes the quadratic terms and the interaction term between labour and capital. Although the parameters remain time invariant, output elasticities will vary over firms and years.[4]

Under the assumption that the input of materials can be flexibly adjusted (i.e. without adjustment costs), the markup is calculated as the ratio of the output elasticity of materials

[3] In Appendix Table A.2 the definition of other variables is given.

[4] We drop observations of firms for which estimated output elasticities are negative.

Table 4: Dependent variable construction

Variable name	Definition
ln(output)	Natural logarithm of gross output.
Mean education level	The weighted (by hours) mean education level of the employees in the firm.
High educated hours (%)	The percentage of hours worked by employees with at least a HBO diploma.
ICT total hours	The total hours worked by individuals that enjoyed a ICT education within the estimation period.
TFP Cobb-Douglas	The natural logarithm of TFP estimated with the restricted profit function with a Cobb-Douglas production function.
TFP Translog	The natural logarithm of TFP estimated with the restricted profit function with a Translog production function.
Labour productivity	Gross output divided by labour hours.
Labout productivity VA	Value added divided by labour hours.
Markup	The firm level markup estimated using the production function approach applied in van Heuvelen et al. (2021).
Mean age	The mean age of the employees of the firm weighted by hours.
Std. dev. of age	The standard deviation of the age of the employees of the firm weighted by hours.
Median age	Median age of the employees of the firm weighted by hours.
Flex hours	The number of hours worked by employees with a flexible contract.
Fixed hours	The number of hours worked by employees with a fixed contract.
Wage	Total wage cost divided by the number of hours.

and its cost share. We use the estimated elasticity of the CD production function (see the detailed explanation in van Heuvelen et al., 2021).

4 Methodology

4.1 Empirical approach

We apply an events based approach. The main challenges for empirically identifying firm-level impact of intangible investment are finding a control group and distinguishing intangible investment events at the firm-level. We apply a methodology that uses investment spikes for both these challenges (see Bessen et al., 2019; Bessen and Righi, 2020). This method exploits the "lumpiness" of investment, that is, investment is observed in spikes (See Olley and Pakes, 1996). As outlined in the data section, investment in intangible capital is likely more lumpy than investments in tangible capital due to the features specific to intangibles. There are two papers that are methodologically closely related to the approach we adopt.

The first paper is that of Bessen et al. (2019). This methodology uses large events that take place within a firm, so called spikes, to set up an difference-in-difference (DiD) analysis. Bessen et al. (2019) use automation cost spike in order to identify changes in work processes. They define an automation cost spike as a year in which the automation costs relative to operating costs (excluding automation), averaged across all years, are at least three times the average firm-level. They have an events based set-up in which firms that spike four years later are used as potential control firms. They stress that non-spiking firms are often inherently different and therefore should be excluded from the control group. The analysis of Bessen et al. (2019) is at the employee level. They employ a matching strategy to insure that similar firms and employees are being compared.

The second paper is that of Bessen and Righi (2020). They use a similar method, but with a different identification strategy, to evaluate the effect of investments in (in-house) software on firm level outcomes like productivity and the labour share. They postulate that standard software packages will not give a firm a competitive advantage as all firms can buy this type of software. However, differences in software developed by the firm (in-house software) can make a difference as competitors do not have it. They link the development of in-house software to the number of IT employees that work for a firm. Bessen and Righi (2020) define a spike in software as a year when the percentage growth rate in the IT share exceeds 30%. The IT share is the percentage of IT employees in the total workforce. Their analysis is at the firm level. Bessen and Righi (2020) do not explicitly match observations but attempt to control for unobserved heterogeneity by adding an extra control variable to the DiD regression. The extra control variable they add is productivity estimated with a control function approach. This variable incorporates productivity and demand shocks. If the adoption is correlated with productivity or demand shocks that also effect labour, the estimates will be biased. By adding this control variable Bessen and Righi (2020) hope to fully control for endogeniety of technology adoption. The reason why this is of more importance in the Bessen and Righi (2020) paper is because non-spiking firms are included in the control group.[5]

The Bessen et al. (2019) strategy has stronger identification by relying on firm matching and a sample that only consist of spiking firms. However, the strategy of Bessen and Righi (2020) is less demanding of the time series dimension of the data. For our analysis we follow Bessen et al. (2019) more closely.

By applying the methodology of Bessen et al. (2019), we exploit the lumpiness of investment to establish causal links between intangible investments, labour composition, labour input, output and productivity. A spike is defined as a short surge in investment expenditures within one year. Therefore, this spike can be used as a shock to assess how investment affects the labour composition and productivity of a firm. The investment spike is a firm specific measure intended to identify significant intangible investments at the firm level. We can estimate a DiD model for which we match firms with observed spikes in intangible investment with firms in the control group without spikes.

4.2 Definition of spikes

An important step in the Bessen et al. (2019) methodology is the definition of the spike. Bessen et al. (2019) define a year with a spike as a year where the automation costs ratio is at least three times as large as average automation cost ratio (excluding the year it is being compared to). Bessen and Righi (2020) define a spike as a year when the growth rate in the IT share exceeds 30%. The IT share is the percentage of IT employees in the total workforce. We define investment spikes as follows.

$$spike_{i\tau} = \mathbb{1}\left\{ \frac{I^b_{i\tau}}{\overline{K}_i} \geqslant 3 \times \frac{\overline{I}^b_{i,t\neq\tau}}{\overline{K}_i} \right\} \tag{3}$$

[5]Bessen and Righi (2020) use Compustat data that is matched with LinkedIn data. Compustat data contains publicly listed firms, which are often relatively large. The firms for which they can match the LinkedIn data increases from 25% in 1990 to 54% in 2012. The employee level data is obtained from Google for public profiles on LinkedIn from June to November of 2013. Therefore, skills that might be obtained in the future are attributed to individuals in the past. By using obtained skill in 2013 the link between the IT spike and the dependent variables, labour and output, my have reverse causal issues, as it is not known when the IT skills are obtained.

where $\mathbb{1}\{\dots\}$ denotes the indicator function, $I^b_{i\tau}$ real intangible investments and $\overline{K}_i$ average capital stock. A firm has a spike in intangible investment if the intangible investment in year τ divided by the average capital stock is three times larger than the average investment (excluding year τ) divided by the average capital. The three times is an arbitrary choice in the definition. However, the lumpiness of the investment data basically ensures that same spikes will, in most cases, be identified if this value is slightly decreased (to 2) or increased (to 4). Note that this is a firm specific measure, intended to identify intangible investments that are large for the firm. When a firm with multiple spikes is identified the first spike in the sample is taken.

We now document the existence and frequency of intangible investment spikes. Table 5 shows that 88% of the firms never spike in intangible investments, whereas the remaining 12% spike at least once. The majority of firms that spike, only spike once (85%). Therefore, relatively few firms make large investments in intangible capital when they do they usually only make this investment once. Table 5 supports the usefulness of our spike definition. If all firms spike frequently, the underlying data is probably not "lumpy" or the spike definition is incorrect. In our case the "lumpy" intangible investment data drives the descriptives and therefore the descriptives are less sensitive for variations in the definition.

Table 5: Firm-level intangible spike frequency

Nr. of spikes	Frequency	Precent
0	300,738	88.1%
1	34,684	10.2%
2	5,581	1.6%
3	507	0.1%
4	9	0.0%

The percentage of firms that spike differs per size category (see Table 6). Larger firms are increasingly more likely to spike than firms that are smaller. For the smallest firms (0-9) only 8.5% spike, while the largest firms (>500) almost always show a spike in intangible investment (70.9%). The probability that a firm spikes increases with size.

Not only are larger firms more likely to spike, but when they spike they also invest significantly more (see Table 7). For the smallest firms the median investment is €21,300. For the largest firms the median investment is almost €7 million. The median is always

Table 6: Spiking firms per size category

FTE	Spiking	Total	Percentage
0-9	23,397	275,461	8.5%
10-19	6,014	32,327	18.6%
20-49	6,127	21,846	28.0%
50-99	2,445	6,617	37.0%
100-199	1,268	2,842	44.6%
200-499	915	1,558	58.7%
> 500	615	868	70.9%
Total	40,781	341,519	12.40%

notably smaller than the mean implying that the investment distribution has a long right tail. This indicates that there are many firms that invest significantly more than the median.

Table 7: Size of intangible investment when a firm spikes

FTE	Mean (1000 Euros)	Median (1000 Euros)	N
0-9	276.2	21.3	25,709
10-19	225.0	42.6	7,532
20-49	855.8	78.3	7.295
50-99	1021.1	145.3	3,211
100-199	14,388.4	253.4	1,655
200-499	17,698.2	866.8	1,183
>500	174,965.5	6,876.5	818
Total	4,349.7	40.5	47,403

Although the type of the intangible investment probably differs per sector, we still see that firms in all sectors invest in intangible assets. The amount of firms that spike does differ per sector. The manufacturing sector has the highest percentage of firms that spike in intangible investment, while relatively few firms spike for the construction sector.

Table 8: Spiking firms per sector

Sectors	Spiking	Total	Percentage
Agriculture, Forestry and Fishing (A)	1,124	9,242	12.2%
Manufacturing (C)	4,846	28,209	17.2%
Construction (F)	2,826	32,167	8.8%
Wholesale and retail trade (G)	11,368	86,945	13.1%
Transportation and storage (H)	1,344	13,135	10.2%
Accommodation and food service activities (I)	1,635	13,789	11.9%
Information and communication (J)	4,653	27,961	16.6%
Professional, Scientific and Technical activities (M)	10,193	108,705	9.4%
Administrative and support activities (N)	2,792	21,366	13.1%
Total	40,781	341,519	12.4%

4.3 An event study DiD design

We outline our empirical design to use intangible investment spikes for identification. First, the intangible investment spikes are by construction a big event for the firm. The idea is that the major event helps distinguish the effect from other factors by making the signal, the intangible investment, strong compared to the noise, other factors.

Secondly, the timing of the intangible investment is assumed to be essentially random conditioned on observables. This assumption allows us to use firms that spike in a later year as a control group for firms that spike earlier. An events based approach that exploits the timing of the spike to distinguish between the treatment and control group. The treatment group consist of firms that spike between 2010-2014 and the control group of firms that spike between 2015-2019. Firms that invest heavily in intangible capital a few years apart should have similar characteristics and can therefore serve as a counterfactual. For the treatment group we define a control group of firms that spikes at least four years after the the treatment firm. Therefore, the spike observation of the control firm never enters the comparison. Like Bessen et al. (2019) we also believe that spiking and non-spiking firms are often inherently different. Comparing spiking to non-spiking firm is therefore likely to be problematic as observed and unobserved difference between the firms could drive the results. Finding a suitable control group for the spiking firms would be challenging. Restricting the sample to consist of only spiking firms ensures that similar firms are being compared.

Third, we match firms on sector and labour size group. We want to ensure that the results are not driven by sectoral and size composition differences between the two groups. Therefore, an (coarsened) exact match is done on the data (by sector, and labour size group) to create a one-on-one match in the sample.[6] We match the treatment and control group on the $t = -3$ observation of the treatment group. To make a comparison between treatment and control firms we use a balanced sample and therefore firms must be operational throughout the whole period (2007-2019). It can be the case that a firm that is operational throughout the whole time period has missing data for a certain variable in one of more years. Only treated firms for which we observe 3 year before and 3 years after the spike for the dependent variable are kept in the sample when running the DiD analysis. Similarly, a corresponding matched control firm must also have no missing dependent variable data for the overlapping time period. Since we use three years before the spike in order to check for pre-trends we can only use firms that spike on or after 2010. Table 9 shows that treatment and control groups are very similar a year before the treatment firms spikes (t=-1).

Table 9: Treatment and control group mean comparison

	edu. mean	High edu. (%)	intangible investment share	revenue (ln)	labour hours (ln)	TFP (ln)	Firm age	N
Treatment	4.0	26.0%	5.0%	9.3	11.6	1.5	13.0	2,102
Control	4.0	26.0%	4.3%	9.3	11.6	1.5	13.7	2,012

Our firm-level event study specification is given below:

$$y_{it} = \alpha + \alpha_j + \alpha_i + \sum_{t=-2}^{3} \gamma_t \times I_t + \sum_{t=-2}^{3} \delta_t \times I_t \times treat_i + \lambda X_{it} + \varepsilon \tag{4}$$

Where i indexes firms, t time to spike and j year. y_{it} is the dependent variable (i.e. productivity, output and labour hours). $treat_i$ is the treatment indicator, equal to 1 if the firms is experiencing a spike at time zero. I_t are indicators for time relative to the spike year. X_{it} are control variables, in our case firm age, labour size group and a dummy indicating whether or not the a firm is part of a multinational. The regression includes year (α_j) and firm level (α_i) fixed effects.

[6]The matching is done on 2-digit SBI code, in our case 52 sectors (see Appendix Table A.1 for a complete list). The labour size group consist of the following 15 groups in terms of FTE's: 0, 1, 2,(3-4), (5-9), (10-19), (20-49), (50-99), (100-149), (150-199), (200-299), (200-299) , (300-499), (500-999), (1000-1999), (2000-∞)

Two additional steps have been made in order to enable us to run a Difference-in-difference (DiD) analysis. First, a minimum threshold is applied on the absolute value of the intangible investment spike which must be more than €10,000. This minimum threshold deletes around 12.4% of the observations mostly small firms, as the mean and median are notably higher than the threshold (See Table 7). This minimum value thresholds ensures that the intangible investment is sufficiently large and therefore can lead to measurable effects for the firm.

Second, the firms in the sample have, on average, 10 or more employees (in FTE's). The data of smaller firms is relatively noisy and often causes problems for the parallel trend assumption in the dependent variable. It is also inherently more difficult to identify relevant spikes for smaller firms. We deem the data for larger firm to be more reliable and less noisy when it comes to intangible assets and therefore only use this sample.[7] However, these firms are also the firms that dominate the sample in terms of output, value added and employment.[8] The sample is restricted to larger firms. We restrict firms to have an average of at least 10 FTE employees over the whole time period.

The number of observations in the spike descriptives differ from that used in the final analysis. The reason for this is that the steps that we take, that enable us, to run the DiD influences the number of firm. The main restriction, that of a balanced sample, greatly reduces the number of firms to of around 6500. From this balanced sample, firms that spike before 2010 cannot enter de DiD analysis, but do enter the descriptives. The second major step that influences the number of firms is the employment size requirement. Other steps, like the threshold and matching, do very little after the other two steps have been taken, in terms of number of firms. For the final analysis we remain with a sample of around 4200 firms. If large intangible investments have notable causal effects on firms then we expect to find it with this sample.

5 Results

We estimate regressions with and without year specific effects before and after the spikes, as well as with and without control variables. We consider three control variables: the age of the firm, the size measured by the log of output and a dummy variable that equals one

[7]Here we do not deviate from the literature as both Bessen and Righi (2020) and Bessen et al. (2019) use data that by construction is tilted towards larger firms. Bessen et al. (2019) use is production statistics of the CBS which contains nearly all large firms and a non representative sample of smaller firms. Bessen and Righi (2020) use Compustat data that contains only publicly listed firm, which are often relatively large. In our case it implies that we use around 1/3 of the spiking firms within our sample.

[8]The larger firms represent around 97% of output, value added and employment of the spiking firms.

if the firm is part of a multinational.[9] All regressions control for unobserved heterogeneity by including fixed effects for years and sectors. Standard errors are clustered by industry and year. Full estimation results can be found in the Appendix Tables. The discussion in this section focuses on the specification with year-specific effects (δ) and the three control variables.[10]

5.1 Impact on hours of fixed and flexible workers

When the expansion of intangible capital substitutes for labour, a fall in total working hours is expected. In contrast, the number of working hours might increase following the growing size of the firm (see the effects of automation in e.g. Bessen et al. (2019) and Grossman and Oberfield (2021)). The left panel of Figure 1 shows simple averages of total working hours (ln) for the treatment and the matched control groups, without controlling for fixed effects. We observe a similar pre-spike trend in hours worked in both groups. In the year of and one year after the spike the number of working hours seems to increase more for the spiking firms. Thereafter, the growth in average hours seems to slow down.

The right panel gives the estimated δ-coefficients, with the 95% confidence interval. Remember the effect three years before the spike is normalised at zero ($\delta(-3) = 0$). The placebo effects in $t = -2$ and $t = -1$ are not significantly different from zero at the 5%-level. Since only the effect one year after the spike is significant, we find that the intangible investment has no effect on working hours after three years.[11]

Next, we analyse if total hours of workers with a fixed or a flexible contract respond differently. The number and hours of flexible workers are more easily adjusted than for fixed workers. However, when higher investments in intangibles imply an expansion of firm specific human capital, hiring more workers with a fixed contract becomes more attractive. We find that none of the pre- and post-spike δ-coefficients are estimated significantly for both contract types, except for $\delta(-1)$ for flexible contract hours (see Tables A.4 and A.5). Findings are similar when we consider the fraction of fixed contract hours in total working hours (see Table A.6).

5.2 Impact on skill composition of workforce

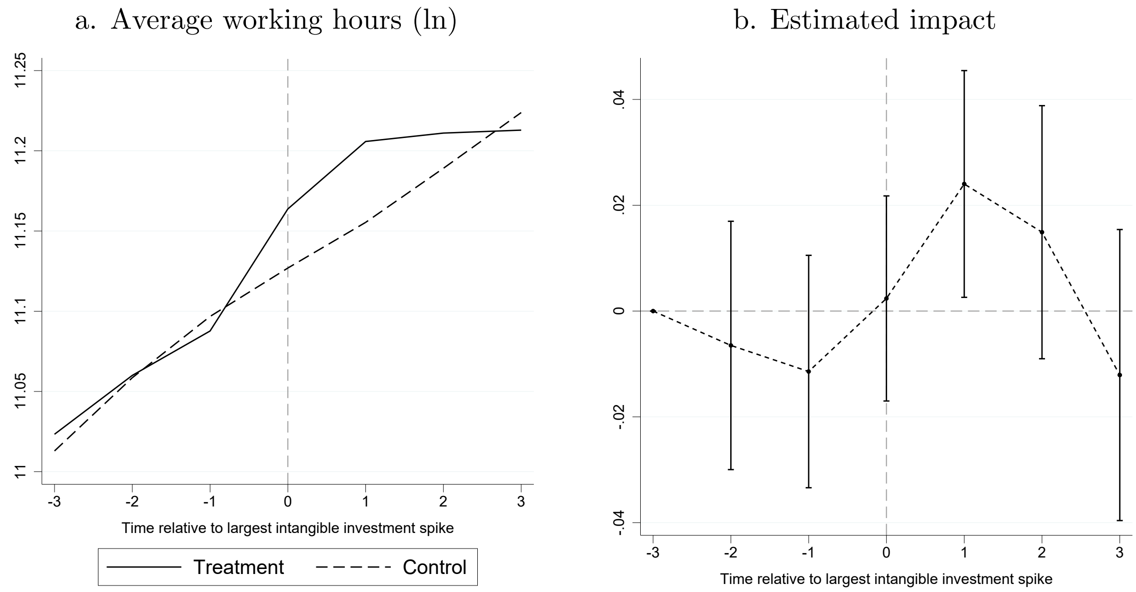
We conjecture that an increase in intangible investments is associated with an increase in the share of highly educated employees (see e.g. Haskel and Westlake, 2017). We first

[9]When the dependent variable is output, the log of employment is taken as size variable

[10]This case is found in the last column of the estimation Tables. The findings on the 'treatment' effects are in general robust to dropping the control variables (see the third column).

[11]Findings are similar without the three control variables, except that $\delta(0)$ is significant (see Table A.3).

Figure 1: Impact on total working hours (ln)



study the impact on the average level of education (see the definition in Section 3). The development of the averages in Figure 2 indicates a common, rising pre-spike trend for the treatment and control group, which continues after the spike for both groups. This pattern is confirmed by the insignificant δ-coefficients.

As an alternative measure, we consider the fraction of hours worked by highly educated employees (as defined in Section 3). Figure 3b shows that this fraction is larger for 'treated' firms in every year (with p-values for $\delta(-2)$ and $\delta(+2)$ equal to 5.1% and 7.2%, respectively).

Finally, we restrict the analysis to working hours and number of employees who have finished an ICT-related study (see the description in Section 3). The average change in working hours of ICT employees is not significantly different between the treatment and control firms, both before and after the spike (see Figure 4 and Table A.9). All coefficients remain insignificant when we regress on the number of ICT employees (Table A.10).

5.3 Impact on output

Gross output is measured by revenues deflated by a sector price index. Figure 5 shows that the average output increases gradually for the group of control firms. After a strong increase in the year of the spike, average output of the 'treated' firms more or less stabilises, implying that the difference with the control group increases. The common trend

Figure 2: Impact on the average education level of the employees

a. Average education level b. Estimated impact

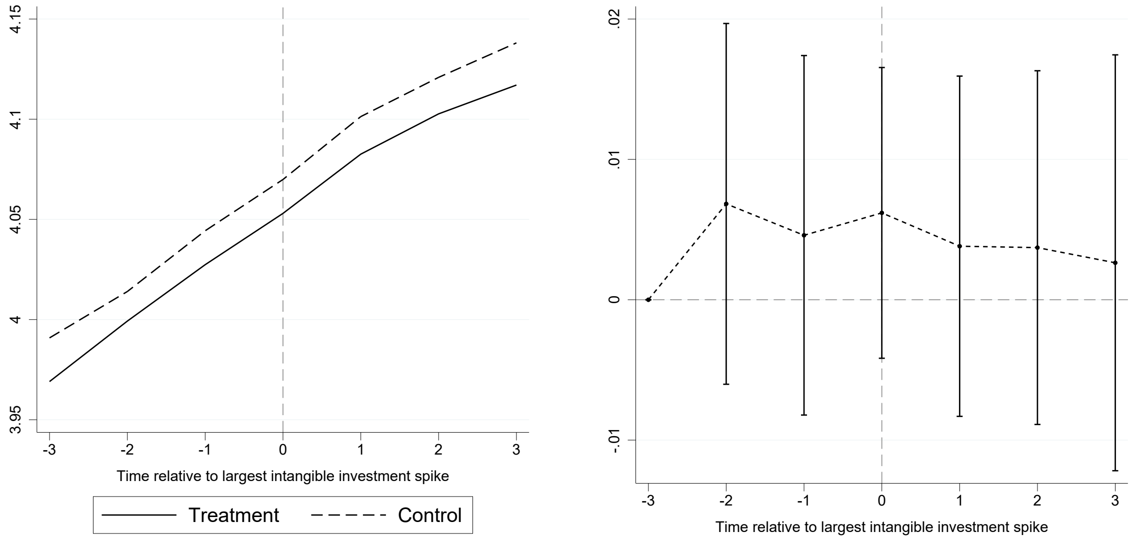


Figure 3: Impact on the fraction of hours worked by highly educated employees

a. Fraction in working hours b. Estimated impact

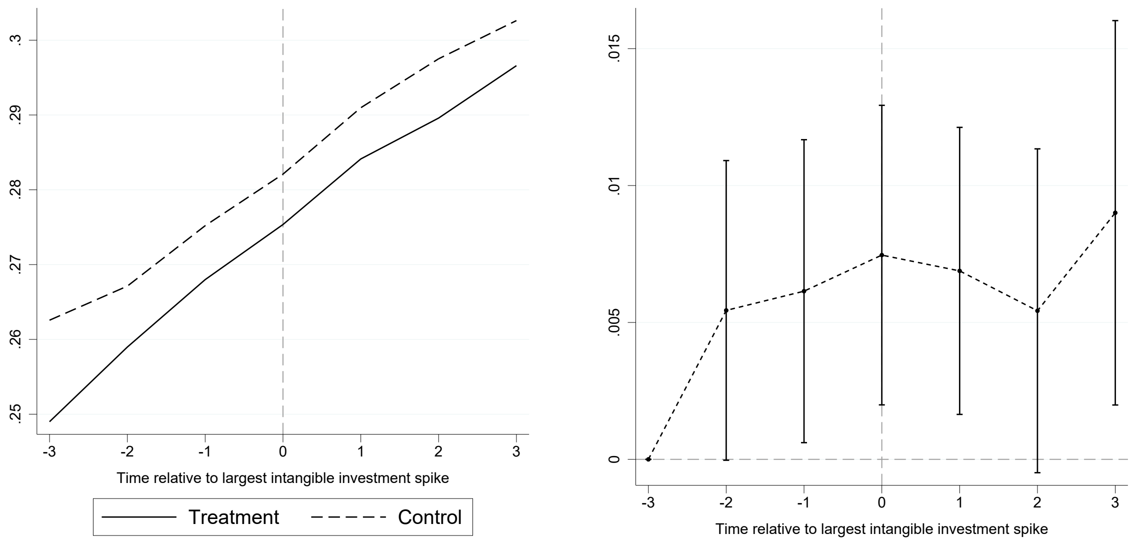
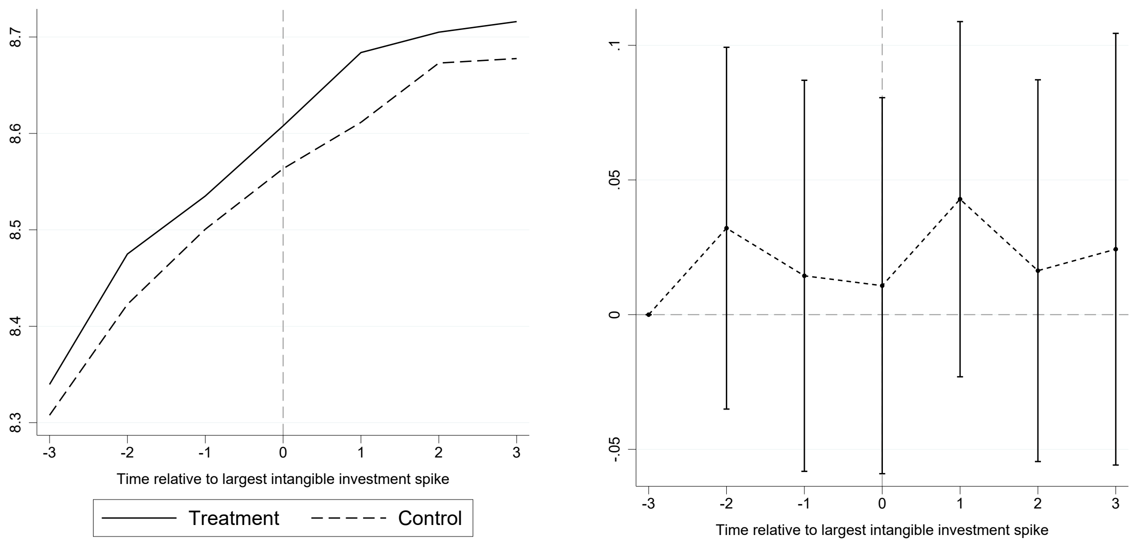


Figure 4: Impact on the hours worked by employees with an ICT-study (ln)

a. Working hours

b. Estimated impact

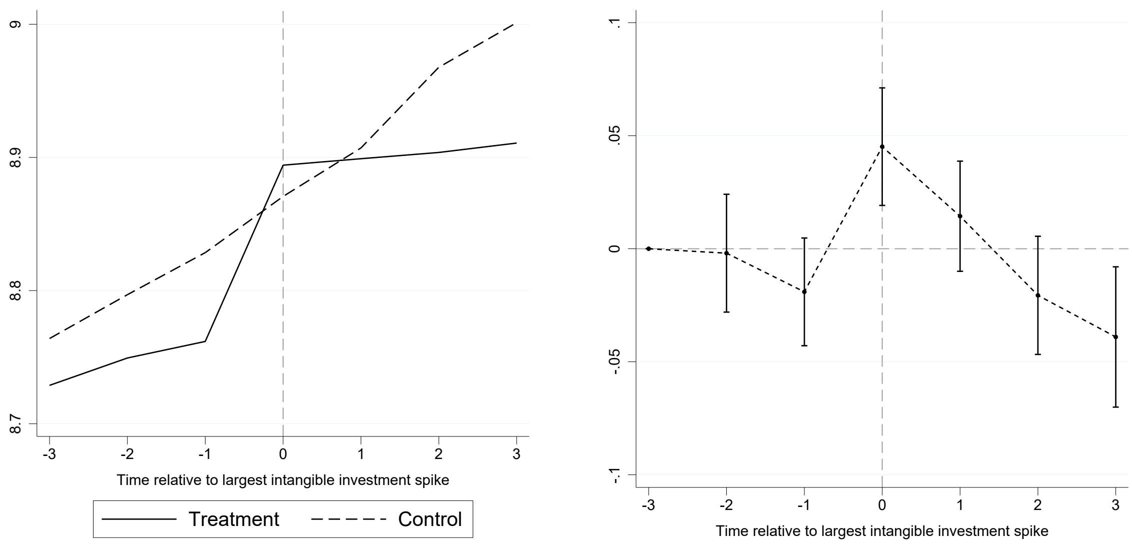


assumption is supported by the small and insignificant coefficients $\delta(-2)$ and $\delta(-1)$. A positive effect at $t = 0$ becomes negative and significant in $t = +3$.

Figure 5: Impact on output (ln)

a. Average output (ln)

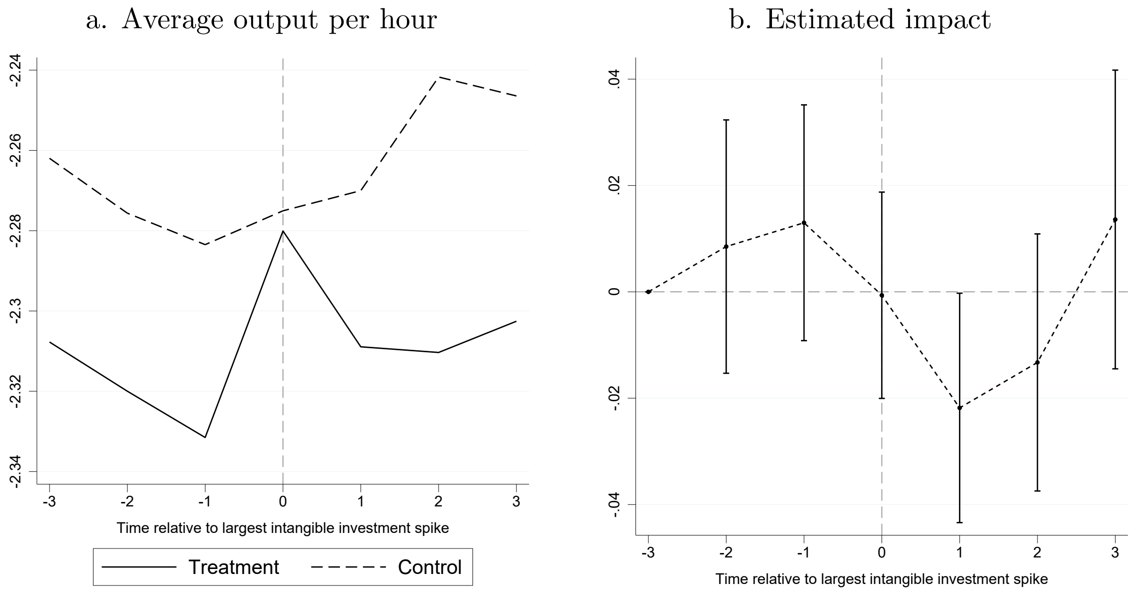
b. Estimated impact



5.4 Impact on labour productivity

The ratio of, previously discussed, gross output and total working hours gives a measure of labour productivity. Figure 6a suggests a different development between both groups. The common trend assumption is supported by the non-significant $\delta(-2)$ and $\delta(-1)$ coefficients. After a fall in the first year after the spike, average productivity of the spiking firms slowly recovers, but the last two δ-coefficients are not significant.[12] When we alternatively consider value added per working hour, the pattern of the δ-coefficients is similar (Table A.13). Labour productivity is driven by changes in the capital/labour ratio and in Total Factor Productivity (TFP). As the first determinant is known to increase after an investment spike (with unaffected working hours), we now focus on the impact on TFP.

Figure 6: Impact on output per working hour



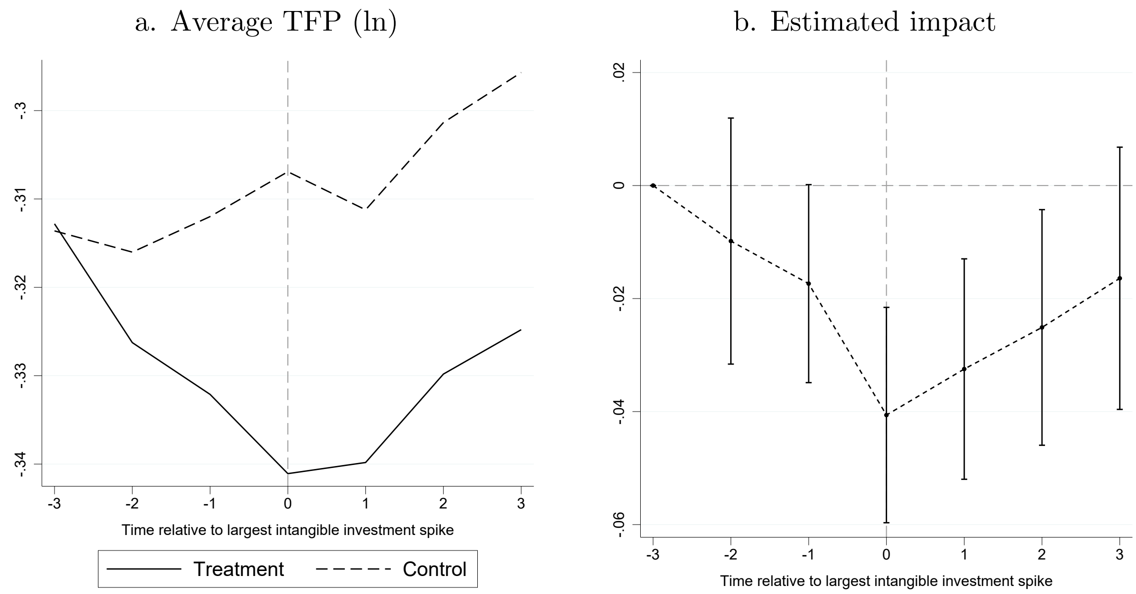
5.5 Impact on TFP

We start by presenting the effects on TFP calculated from estimating sector-specific Cobb Douglas (CD) functions. The asymmetric pre-spike trends in Figure 7 points at problems with the common trend assumption. Average TFP falls well before the spike for the spiking firms, while it recovers rather slowly thereafter. These findings are supported by

[12]With control variables, the negative $\delta(+1)$ is significant. Significance shifts to a positive $\delta(0)$ when control variables are excluded; see Table A.12.

the negative and significant estimates of the δ-coefficients. When considering the more flexible Translog production function, Figure 8 again raises concerns about the control group, while all the δ-coefficients are highly non-significant.

Figure 7: Impact on TFP (ln) with CD production function



In the last section we will elaborate on explanations of our general findings. We now specifically comment on the perhaps, disappointing TFP outcomes. Since TFP is not directly observed, a production function needs to be estimated. We assume in this estimation that all firms in a sector apply the same production technology. One might argue that firms that invest strongly in intangibles switch to another vintage of technology. As a consequence, the production function, and thus TFP, might differ between firms that use little or much intangible capital. In the future we try to explore the consequences of different production functions for groups of firms.

5.6 Impact on wage cost

The real wage cost per hour is obtained by deflating by a sector price index. Bessen et al. (2019) estimate the wage effects of automation. Figure 9 shows a fall in wage costs in both groups and insignificant δ-coefficients before the spike ($t < 0$). In the year of the spike, the real wage cost strongly increases for the spiking firms, and $\delta(0)$ is significantly positive. The following wage effects remain positive at a lower significance level (except the last one).

Figure 8: Impact on TFP (ln) with Translog production function

a. Average TFP (ln)

b. Estimated impact

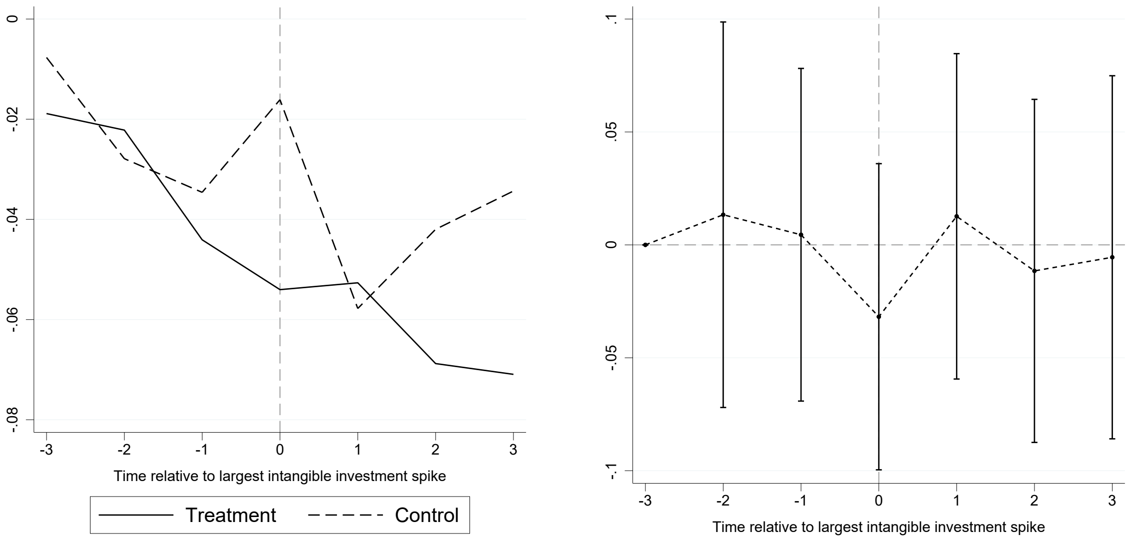
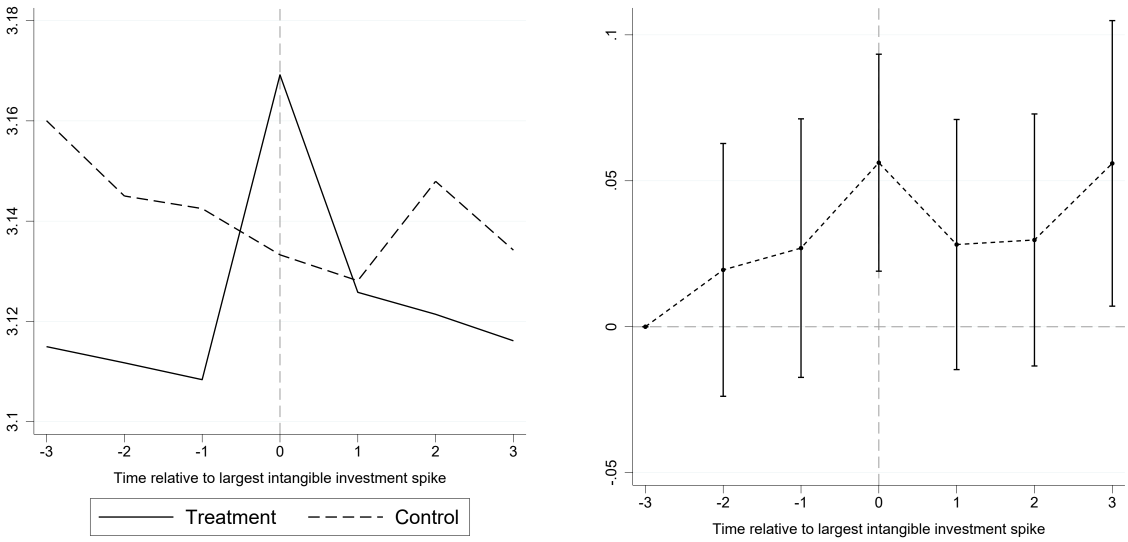


Figure 9: Impact on real wage cost (ln)

a. Average wage cost (ln)

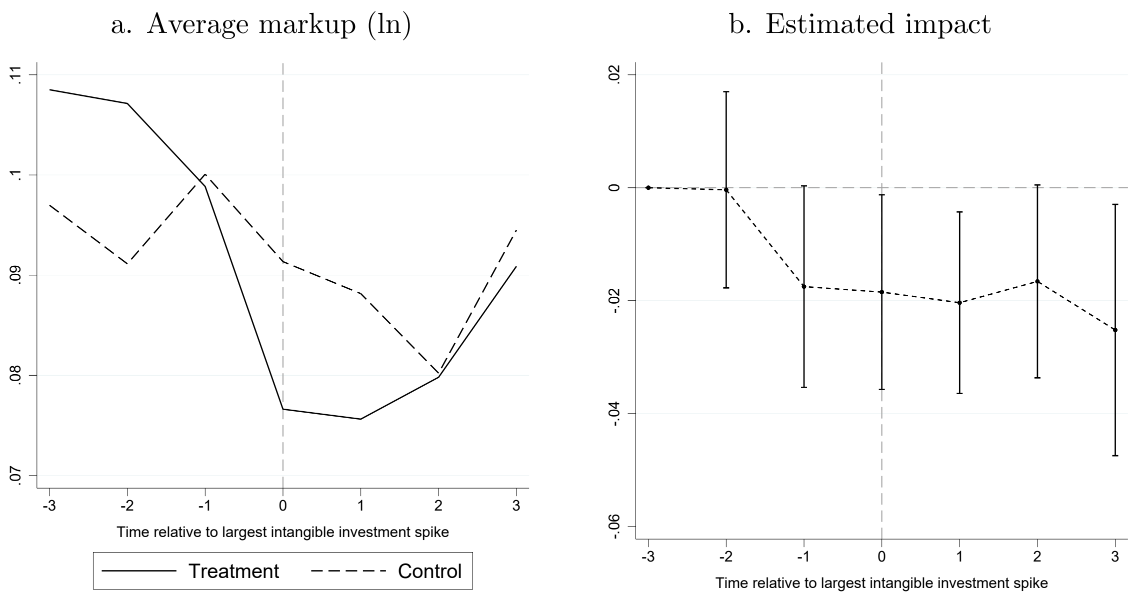
b. Estimated impact



5.7 Impact on markup

We calculate the markups, based on the estimated output elasticities of materials in a gross output CD production function (see van Heuvelen et al., 2021). Bessen and Righi (2020) report that IT spikes increase markups. Pre-spike developments in average markups seem different between both groups in Figure 10, although the δ-coefficients at $t = -2$ and $t = -1$ are not significantly different for zero (with a latter p-value of 5.4%). At and after the spike, we find that markups fall for firms in the treatment group.

Figure 10: Impact on markup (ln)



5.8 Differences between Manufacturing and Service sectors

One limitation we face is that we do not know in what type(s) of intangible capital the firm has invested. Different types of intangible investment can lead to very different effects and can also differ in the timing of the effect on the dependent variable. To test whether this might play a role in our data, we look at sectoral heterogeneity, as firms in a more homogeneous group are more likely to make similar investments. The relatively small sample size limits the number of groups in which the sample can be split. Therefore, we split the sample into a service sector and a non-service sector (henceforth the manufacturing sector as this makes up the majority of the non-service sector). We restrict the sectoral analysis to two dependent variables, working hours and output (see

Tables A.18 and A.19).

We find that underneath the aggregate results there are sectoral differences. For total hours worked the differences with the main result are relatively small. Pre-spike developments in working hours seem similar between both groups for manufacturing and the service sectors (see Figure 11 and Figure 12). In fact, both manufacturing and services show a similar trend over time. However, only for services the temporary increase in working hours, after the spike, is significant. For the manufacturing sector we do not observe any significant effects.

For output we find different effects for the manufacturing and service sectors. Pre-spike developments in output seem relatively similar between both groups for manufacturing and the services (see Figure 13 and Figure 14). For services the large intangible investment leads to a significant output decline in t=2 and t=3, which is similar to the aggregate result. However, for manufacturing we see that the investment spike leads to a temporary significant output *in*crease at $t = 0$ and $t = 1$.

Given that a simple split between manufacturing and services already leads to results that differ from the base results indicates that sectoral heterogeneity and therefore intangible investment heterogeneity can make a difference. Although investment heterogeneity could potentially explain part of the null effects in the aggregate results, it is highly unlikely to be the whole explanation given the wide scope of dependent variables.

Figure 11: Impact on working hours in Manufacturing (ln)

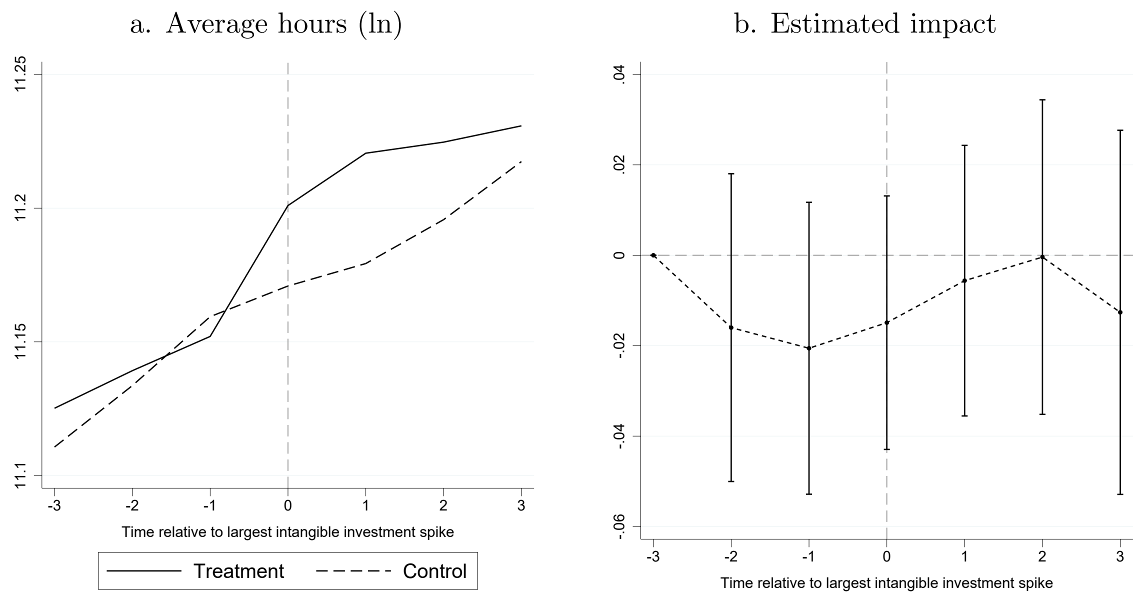


Figure 12: Impact on working hours in Services (ln)

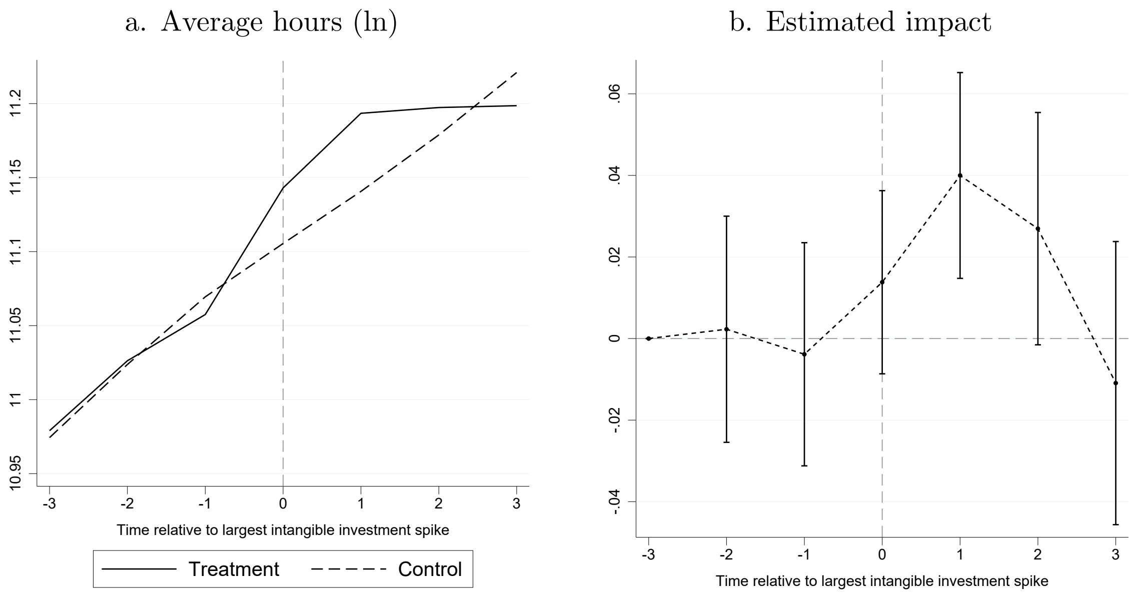


Figure 13: Impact on output in Manufacturing (ln)

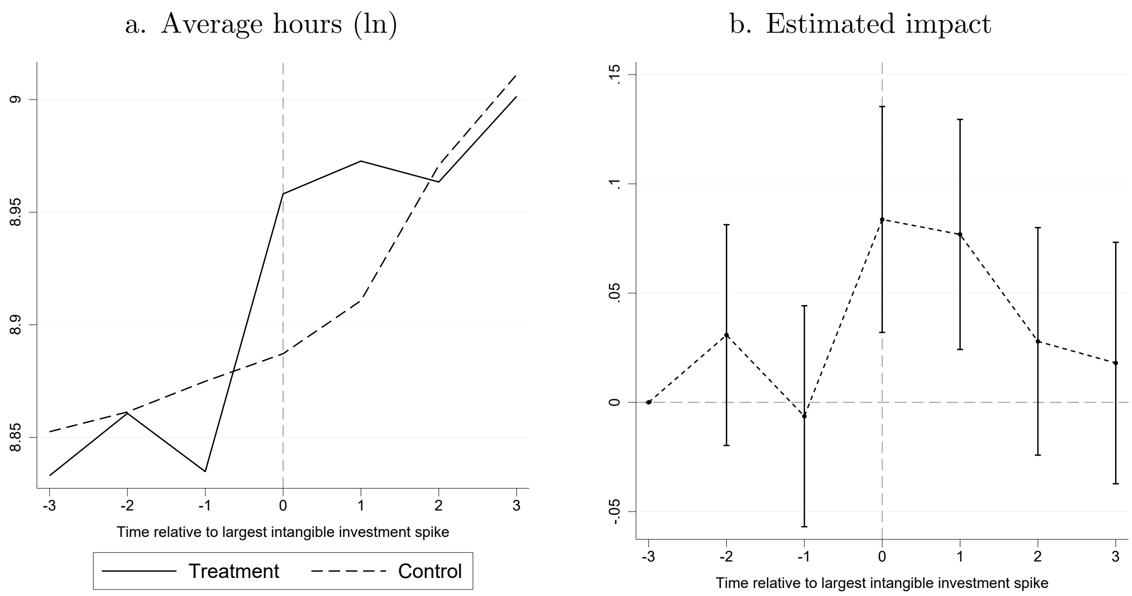
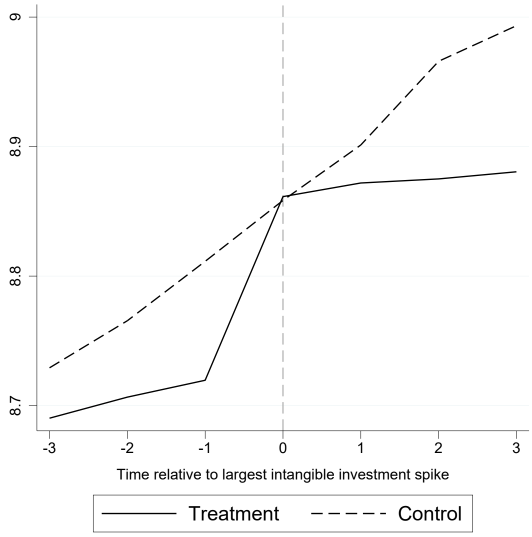
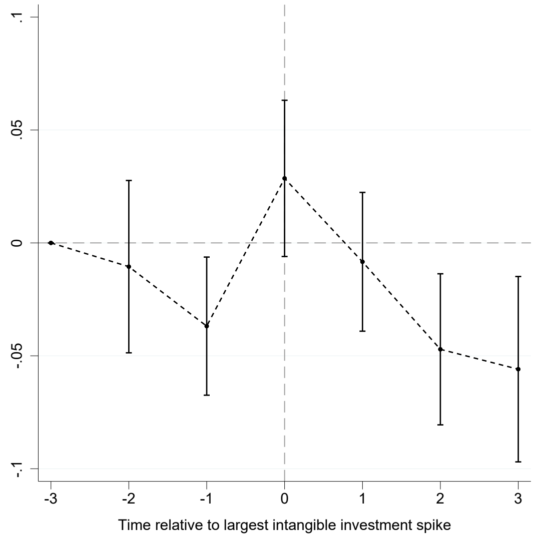


Figure 14: Impact on output in Services (ln)

a. Average hours (ln)



b. Estimated impact



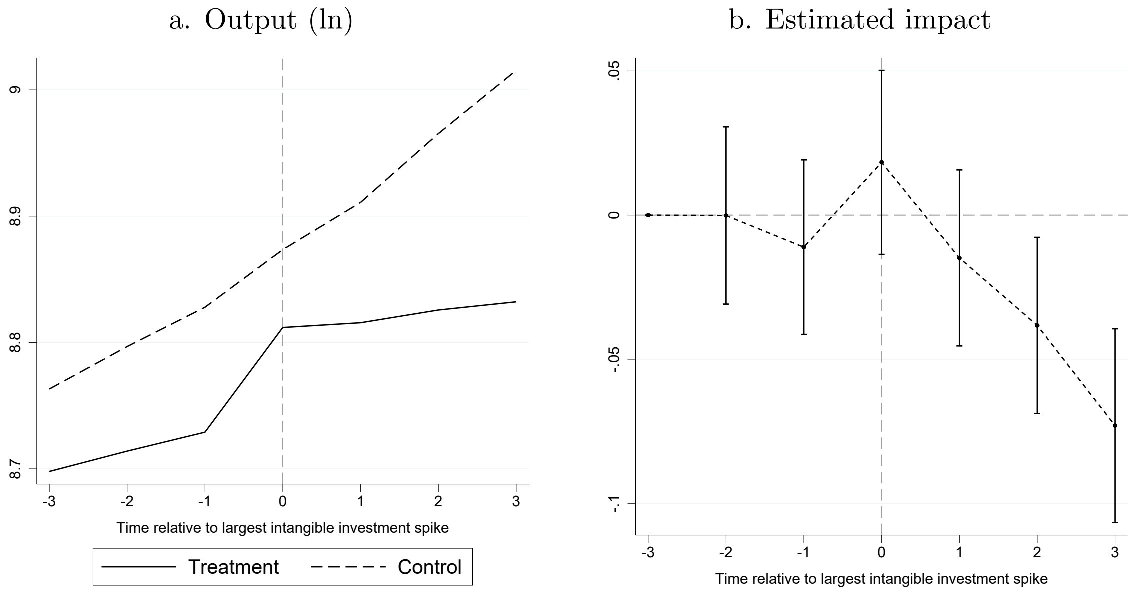
5.9 Goodwill spikes

Goodwill is an intangible investment for which the impact on the firm might be more ambiguous. Spikes that are dominated by expenditures on goodwill correspond with a merger or acquisition. Since we have a balanced sample, we know that the merger or acquisition does not lead to an exit or the creation of a new firm. However, a merger or acquisition can lead to short-term negative effects as a reorganisation and/or other changes have to be implemented. We check whether the base results are driven by goodwill spikes by excluding all firms for which the spike coincides with a merger or acquisition. This results in losing around 1/4 of the total observations. We find that most results are robust to excluding goodwill spikes. We will therefore only discuss the results for variables for which we do find notable differences (see Table A.20).

We first consider the effect on output. Figure 15 shows that the pre-spike trend between treatment and control group is similar. However, the results without goodwill spikes show a significant negative impact on output in t=2 and t=3, compared to a significant positive effect in t=0 and only a significant negative effect in t=3 in the base outcomes. Therefore, after leaving goodwill out of the analysis, intangible investments have a clearer negative effect on output.

For working hours we again find significant negative effects. Figure 16 shows that the

Figure 15: Impact on output (ln) without goodwill spikes



pre-spike trend is very similar, while the treatment and control group start deviating after the spike. The regression results tell the same story. The large intangible investment has a negative effect on working hours, which becomes significant in t=3. The negative impact of intangible investments is more pronounced, both for working hours and output, when goodwill spikes are excluded from the sample.

The TFP CD results without goodwill spikes are similar to the main results. However, the pre-spike trends are more symmetric, giving more confidence that the common trend assumption holds. Large intangible investments have a significant negative effect on TFP CD at t=0, which quickly becomes less negative and insignificant (see Figure 17).[13]

The labour productivity result without goodwill spiking firms is also different from the base result. The pre-spiking trend between the groups is again similar. Figure 18 shows that, unlike TFP, there is a significant positive effect on labour productivity at t=3. When the control variables are not added to the regression, the labour productivity effects are negative but not significant. In most regressions including the control variables does not alter the results greatly, labour productivity is the only exception.

The result for real wage cost are also more pronounced when goodwill spiking firms are excluded. The pre-spiking trends are asymmetric but rather flat for both groups. Intangible investments have significant positive and persistent effects on the wage cost.

[13]For TFP Translog the results remain insignificant.

Figure 16: Impact on working hours (ln) without goodwill spikes

a. Working hours (ln) b. Estimated impact

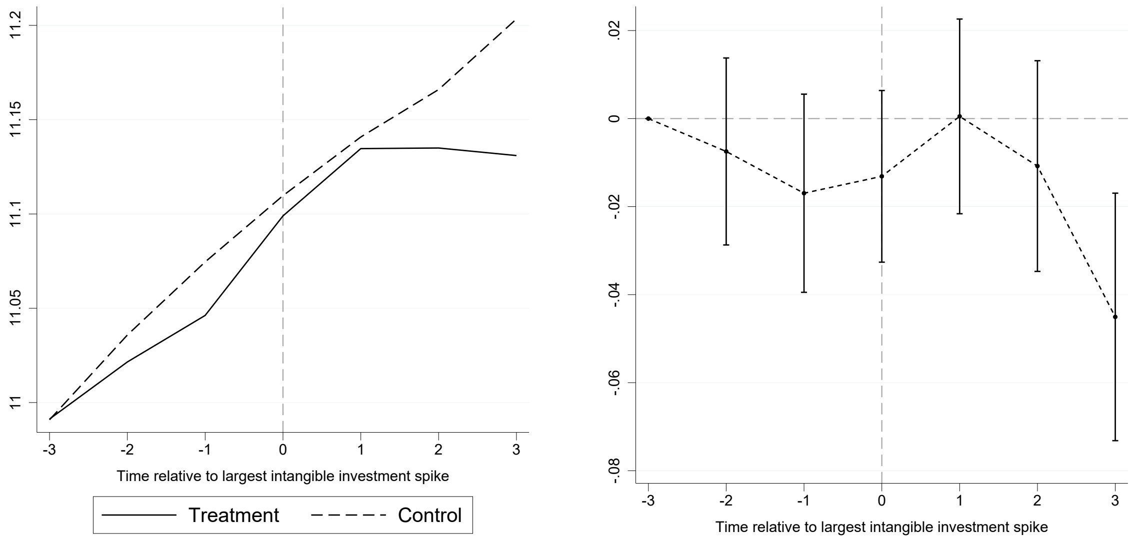


Figure 17: Impact on TFP (ln) with CD production function, without goodwill spikes

a. TFP (ln) b. Estimated impact

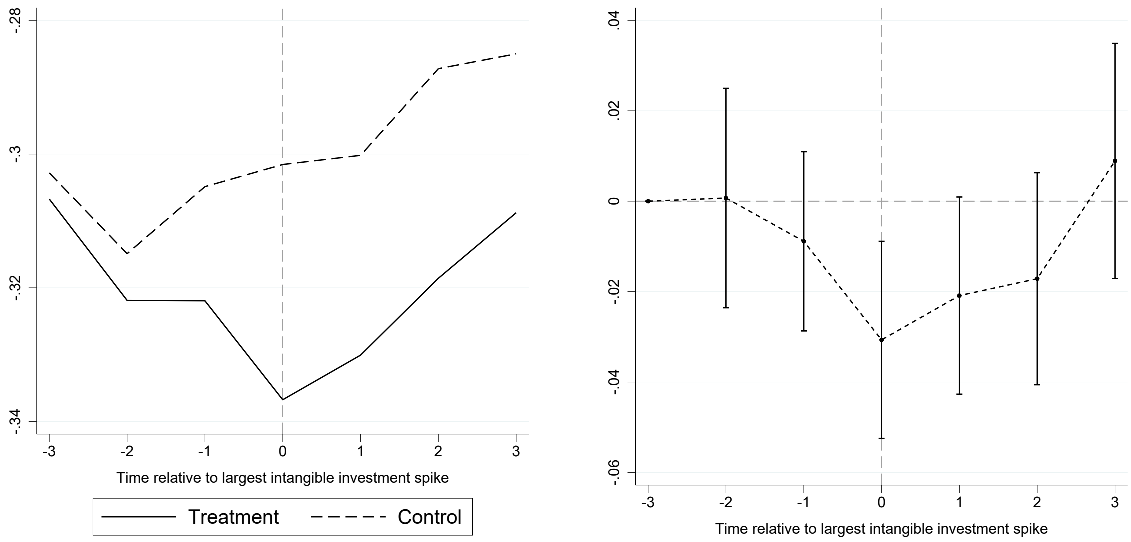
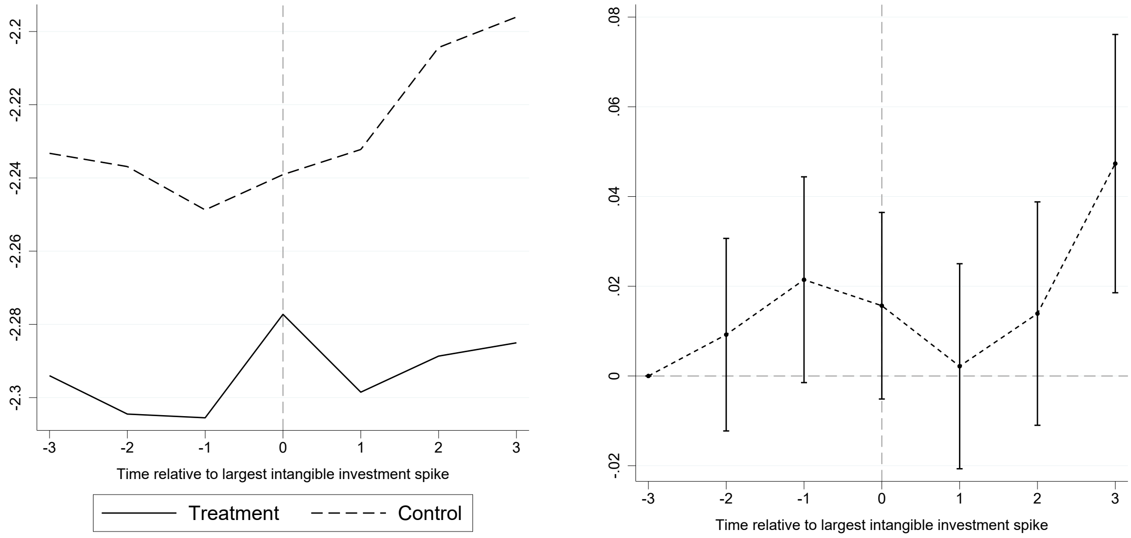


Figure 18: Impact on labour productivity (ln) without goodwill spikes

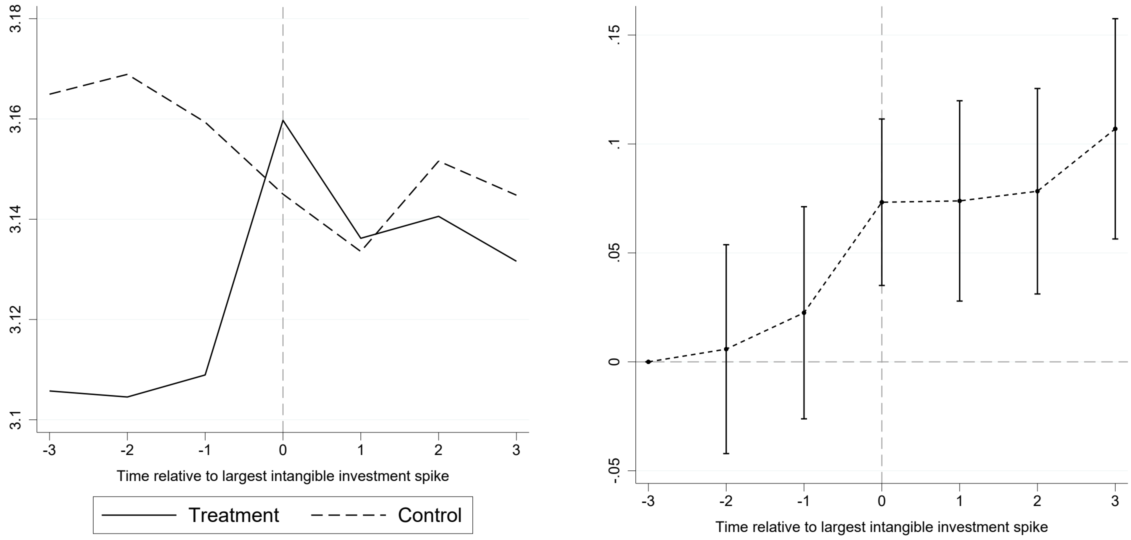
a. Labour productivity (ln) b. Estimated impact



This is slightly different than the base result where the effect on wage costs are not significant in t=1 and t=2, and effects are smaller.

Figure 19: Impact on real wage cost (ln) without goodwill spikes

a. Average wage cost (ln) b. Estimated impact



6 Discussion & Conclusion

In sum, we find a dominance of insignificant effects within three years of investments in intangibles, while significant results are found for output and real wage costs. The dominance of insignificant results, as wel as the negative effects for output, are unexpected. We list a number of reasons that might explain these outcomes:

- Our sample might include too few firms, following the balanced sample and minimum firm size restiction. We will experiment with less strict approaches resulting in larger samples and check the sensitivity of our findings.
- The time period is too short with three years after the spike. One might argue that it takes more than three years before large investment projects yield favourable effects on output and productivity. Running against this argument are the uncertain economic lives and large depreciation rates of many intangibles (see Haskel and Westlake, 2017).
- Estimation might suffer from an endogeneity bias. Bessen and Righi (2020) argue that IT adoption might be correlated with unobserved productivity and demand shocks. They estimate the dif-in-dif regression together with control functions to account for these shocks. However, they report that in their case the estimates hardly change after controlling for unobserved productivity and demand shocks, suggesting that the bias in the impact coefficients is not substantial.
- We report average 'treatment' effects, which might hide differences between firms. One might argue that large benefits are restricted to some firms, like first-movers. We will pay more attention to heterogeneous aspects in future work.
- We only have data on the total value of intangible investments, without knowing the distinction between different types. We cannot study whether effects on e.g. productivity differ between different types of intangibles. As a first sensitivity analysis, we consider two subsamples consisting of firms in service and non-service sectors, respectively. As these sectors likely invest in different intangibles, differences between outcomes might follow from heterogeneous intangibles. We indeed find that in particular output effects are different between both sectors. In addition, we are able to identify expenditures on a particular intangible, goodwill, related to a merger or acquisition. When goodwill spikes are excluded from the sample, we find more pronounced negative effects on working hours and output.

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Appendix

Table A.1: Description of sector codes (2-digit SBI 2008)

SBI	Description
1	Crop and animal production, hunting and related service activities
	Manufacturing
10	Manufacture of food products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacture of study and study products
18	Printing and reproduction of recorded media
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
	Construction
41	Construction of buildings
42	Civil engineering
43	Specialized construction activities

Table A.1: Continued

SBI	Description
	Services
45	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Wholesale trade, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines
50	Water transport
52	Warehousing and support activities for transportation
53	Postal and courier activities
55	Accommodation
56	Food and beverage service activities
58	Publishing activities
59	Motion picture, video and television program production, sound recording and music
60	Programming and broadcasting activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
71	Architectural and engineering activities; technical testing and analysis
72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
77	Rental and leasing activities
78	Employment activities
79	Travel agency, tour operator and other reservation service and related activities
80	Security and investigation activities
81	Services to buildings and landscape activities
82	Office administrative, office support and other business support activities

Table A.2: Variable definitions

Output variable	
Revenues	Net sales minus returned goods, payed damages and discounts
Value added	Revenues − Materials
Labour	
Labour hours	Number of payed working hours
Labour costs	Wages and social security contributions
Wage	Gross salary
Capital	
Capital stock	Tangible fixed assets + Intangible assets − Depreciation
Tangible fixed assets	These are the physical assets intended for the sustainable support of a company's business operations (end of period and before depreciation). Examples: buildings, machines, installations, computers, transport equipment.
Intangible fixed assets	An identifiable non-monetary asset without physical form used for the production and delivery of goods or services, rental to third parties or for administrative purposes (end of period and before depreciation). Examples: licenses, patents, goodwill.
Depreciation	Accounting for impairment resulting from wear and tear (e.g. buildings, machinery, inventory), price drops (e.g. stocks) or other causes. In the dataset it is not possible to separate depreciation of tangible and intangible assets.
Other variables	
Materials (i.e. Production costs)	This concerns the (raw) material consumption and the purchase value of the commodities and other operating expenses included in net sales. Other operating expenses include all costs, insofar as they do not relate to wages, depreciation and interest expenses.
Investment	$capital_t - capital_{t-1} + depreciation_t$
Deflator	The nominal values of the variables are deflated by the appropriate sector prices obtained from the input-output tables from the national accounts. We use the following variables to construct a deflator. 1. The capital deflator uses gross fixed capital formation. 2. The value added deflator uses gross value added in basic prices. 3. The labour cost deflator uses wages and employer social security contributions. 4. The revenue deflator uses total revenues. 5. The materials deflator uses consumption at purchasing price. All the inputs and outputs are in terms of 2010 prices.

Table A.3: Estimation results for total working hours (ln)

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0236	0.0068	0.0146	0.0059				
$\bar{\gamma}$	0.0205	0.0067	0.0053	0.0055				
$agefirm$			0.0264	0.0026			0.0291	0.0026
$\ln(size)$			0.3565	0.0199			0.3561	0.0199
$multinat$			0.0186	0.0082			0.0181	0.0082
$\delta(-3)$								
$\delta(-2)$					-0.0090	0.0125	-0.0065	0.0119
$\delta(-1)$					-0.0195	0.0129	-0.0114	0.0112
$\delta(0)$					0.0264	0.0107	0.0024	0.0099
$\delta(+1)$					0.0400	0.0121	0.0240	0.0109
$\delta(+2)$					0.0115	0.0129	0.0149	0.0122
$\delta(+3)$					-0.0214	0.0137	-0.0121	0.0140
$\gamma(-3)$								
$\gamma(-2)$					0.0384	0.0097	-0.0023	0.0077
$\gamma(-1)$					0.0810	0.0102	-0.0026	0.0063
$\gamma(0)$					0.1238	0.0118	-0.0044	0.0061
$\gamma(+1)$					0.1694	0.0137	-0.0031	0.0064
$\gamma(+2)$					0.2195	0.0161	-0.0072	0.0080
$\gamma(+3)$					0.2674	0.0177		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	28406		27334		28406		27334	
N firms	4058		4056		4058		4056	
log likelihood	-395.7231		4399.2734		-372.2059		4413.0361	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.4: Estimation results for total hours of workers with fixed contract (ln)

	(1) coeff.	std. error	(2) coeff.	std. error	(3) coeff.	std. error	(4) coeff.	std. error
$\bar{\delta}$	0.0229	0.0087	0.0174	0.0081				
$\bar{\gamma}$	0.0090	0.0091	-0.0019	0.0090				
$agefirm$			0.0197	0.0035			0.0229	0.0037
$\ln(size)$			0.2778	0.0210			0.2774	0.0209
$multinat$			0.0425	0.0149			0.0418	0.0150
$\delta(-3)$								
$\delta(-2)$					-0.0279	0.0206	-0.0242	0.0187
$\delta(-1)$					-0.0379	0.0205	-0.0327	0.0188
$\delta(0)$					-0.0023	0.0185	-0.0170	0.0168
$\delta(+1)$					0.0330	0.0184	0.0253	0.0169
$\delta(+2)$					-0.0009	0.0207	0.0052	0.0196
$\delta(+3)$					-0.0259	0.0219	-0.0264	0.0211
$\gamma(-3)$								
$\gamma(-2)$					0.0451	0.0126	0.0078	0.0098
$\gamma(-1)$					0.0802	0.0150	0.0083	0.0104
$\gamma(0)$					0.1089	0.0156	0.0006	0.0096
$\gamma(+1)$					0.1312	0.0175	-0.0121	0.0095
$\gamma(+2)$					0.1721	0.0198	-0.0119	0.0097
$\gamma(+3)$					0.2109	0.0216		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	27118		26080		27118		26080	
N firms	3874		3873		3874		3873	
log likelihood	-9186.4208		-7593.3768		-9174.7280		-7582.7510	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.5: Estimation results for total hours of workers with filexible contract (ln)

	(1) coeff.	std. error	(2) coeff.	std. error	(3) coeff.	std. error	(4) coeff.	std. error
$\bar{\delta}$	0.0280	0.0165	0.0339	0.0162				
$\bar{\gamma}$	0.0559	0.0195	0.0318	0.0184				
$agefirm$			0.0475	0.0079			0.0525	0.0080
$\ln(size)$			0.3884	0.0311			0.3868	0.0310
$multinat$			-0.0161	0.0259			-0.0142	0.0257
$\delta(-3)$								
$\delta(-2)$					-0.0655	0.0350	-0.0593	0.0342
$\delta(-1)$					-0.0690	0.0327	-0.0608	0.0306
$\delta(0)$					-0.0084	0.0332	-0.0247	0.0317
$\delta(+1)$					0.0097	0.0328	0.0058	0.0317
$\delta(+2)$					-0.0196	0.0351	-0.0034	0.0339
$\delta(+3)$					-0.0491	0.0367	-0.0015	0.0396
$\gamma(-3)$								
$\gamma(-2)$					0.1590	0.0270	0.0845	0.0236
$\gamma(-1)$					0.2485	0.0250	0.1068	0.0171
$\gamma(0)$					0.3227	0.0297	0.1076	0.0194
$\gamma(+1)$					0.3760	0.0359	0.0928	0.0221
$\gamma(+2)$					0.4166	0.0408	0.0573	0.0226
$\gamma(+3)$					0.4343	0.0457		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	21238		20397		21238		20397	
N firms	3034		3033		3034		3033	
log likelihood	-19689.0039		-18245.6382		-19656.7344		-18217.6819	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.6: Estimation results for fraction of fixed contract hours in total working hours

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	-0.0009	0.0027	-0.0023	0.0028				
$\bar{\gamma}$	-0.0044	0.0031	-0.0040	0.0032				
$agefirm$			-0.0050	0.0009			-0.0055	0.0009
$\ln(size)$			0.0050	0.0033			0.0050	0.0033
$multinat$			0.0035	0.0048			0.0033	0.0048
$\delta(-3)$								
$\delta(-2)$					-0.0001	0.0056	-0.0003	0.0056
$\delta(-1)$					-0.0068	0.0055	-0.0069	0.0054
$\delta(0)$					-0.0069	0.0053	-0.0078	0.0052
$\delta(+1)$					-0.0026	0.0051	-0.0034	0.0051
$\delta(+2)$					-0.0033	0.0060	-0.0040	0.0060
$\delta(+3)$					0.0000	0.0062	-0.0029	0.0069
$\gamma(-3)$								
$\gamma(-2)$					-0.0077	0.0036	-0.0027	0.0034
$\gamma(-1)$					-0.0111	0.0037	-0.0017	0.0031
$\gamma(0)$					-0.0182	0.0038	-0.0040	0.0031
$\gamma(+1)$					-0.0249	0.0042	-0.0063	0.0031
$\gamma(+2)$					-0.0255	0.0048	-0.0025	0.0034
$\gamma(+3)$					-0.0287	0.0052		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N	28406		27332		28406		27332	
N firms	4058		4056		4058		4056	
log likelihood	20753.8369		20124.4862		20760.0267		20130.1936	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.7: Estimation results for average education level

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	-0.0009	0.0034	0.0004	0.0034				
$\bar{\gamma}$	-0.0017	0.0034	-0.0014	0.0032				
$agefirm$			0.0212	0.0011			0.0208	0.0011
$\ln(size)$			-0.0176	0.0035			-0.0176	0.0035
$multinat$			0.0046	0.0053			0.0046	0.0053
$\delta(-3)$								
$\delta(-2)$					0.0070	0.0064	0.0068	0.0065
$\delta(-1)$					0.0049	0.0066	0.0046	0.0065
$\delta(0)$					0.0049	0.0052	0.0062	0.0053
$\delta(+1)$					0.0031	0.0060	0.0038	0.0062
$\delta(+2)$					0.0036	0.0063	0.0037	0.0064
$\delta(+3)$					0.0008	0.0067	0.0026	0.0075
$\gamma(-3)$								
$\gamma(-2)$					0.0158	0.0047	-0.0032	0.0044
$\gamma(-1)$					0.0377	0.0048	-0.0007	0.0038
$\gamma(0)$					0.0541	0.0049	-0.0030	0.0034
$\gamma(+1)$					0.0759	0.0054	0.0000	0.0037
$\gamma(+2)$					0.0932	0.0064	-0.0012	0.0039
$\gamma(+3)$					0.1144	0.0067		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N	29092		28013		29092		28013	
N firms	4156		4154		4156		4154	
log likelihood	17694.3857		17205.5484		17695.7572		17206.7279	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.8: Estimation results for fraction of hours worked by highly educated employees

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0028	0.0015	0.0032	0.0015				
$\bar{\gamma}$	-0.0031	0.0015	-0.0027	0.0014				
$agefirm$			0.0067	0.0006			0.0059	0.0007
$\ln(size)$			-0.0097	0.0021			-0.0096	0.0021
$multinat$			0.0023	0.0024			0.0024	0.0024
$\delta(-3)$								
$\delta(-2)$					0.0054	0.0028	0.0054	0.0028
$\delta(-1)$					0.0064	0.0028	0.0061	0.0028
$\delta(0)$					0.0068	0.0028	0.0075	0.0028
$\delta(+1)$					0.0067	0.0027	0.0069	0.0027
$\delta(+2)$					0.0056	0.0030	0.0054	0.0030
$\delta(+3)$					0.0075	0.0032	0.0090	0.0036
$\gamma(-3)$								
$\gamma(-2)$					0.0025	0.0021	-0.0026	0.0019
$\gamma(-1)$					0.0084	0.0023	-0.0016	0.0018
$\gamma(0)$					0.0124	0.0026	-0.0024	0.0017
$\gamma(+1)$					0.0180	0.0029	-0.0015	0.0018
$\gamma(+2)$					0.0234	0.0035	-0.0009	0.0019
$\gamma(+3)$					0.0301	0.0038		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N	29092		28013		29092		28013	
N firms	4156		4154		4156		4154	
log likelihood	41786.5564		40550.1536		41791.6647		40555.7495	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.9: Estimation results for hours worked by ICT-employees (ln)

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0073	0.0210	0.0083	0.0192				
$\bar{\gamma}$	0.0450	0.0195	0.0278	0.0195				
$agefirm$			0.0534	0.0073			0.0525	0.0072
$\ln(size)$			0.2785	0.0254			0.2757	0.0252
$multinat$			0.0033	0.0233			0.0048	0.0230
$\delta(-3)$								
$\delta(-2)$					0.0203	0.0336	0.0321	0.0342
$\delta(-1)$					0.0025	0.0378	0.0144	0.0369
$\delta(0)$					0.0124	0.0384	0.0108	0.0355
$\delta(+1)$					0.0405	0.0355	0.0429	0.0335
$\delta(+2)$					0.0001	0.0368	0.0163	0.0360
$\delta(+3)$					0.0064	0.0387	0.0243	0.0407
$\gamma(-3)$								
$\gamma(-2)$					0.1206	0.0261	0.0436	0.0231
$\gamma(-1)$					0.2179	0.0261	0.0696	0.0214
$\gamma(0)$					0.3003	0.0299	0.0797	0.0220
$\gamma(+1)$					0.3611	0.0316	0.0748	0.0202
$\gamma(+2)$					0.4259	0.0366	0.0691	0.0221
$\gamma(+3)$					0.4160	0.0388		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	10234		9815		10234		9815	
N firms	1462		1460		1462		1460	
log likelihood	-7322.6153		-6749.6612		-7302.0065		-6732.4585	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.10: Estimation results for numbers of ICT-employees

	(1) coeff.	std. error	(2) coeff.	std. error	(3) coeff.	std. error	(4) coeff.	std. error
$\bar{\delta}$	0.3892	0.5926	0.6421	0.5942				
$\bar{\gamma}$	0.0161	0.7756	-0.2533	0.6782				
$agefirm$			0.5104	0.2972			0.3459	0.2323
$\ln(size)$			2.2408	0.4779			2.2823	0.4936
$multinat$			0.5834	0.5608			0.5886	0.5603
$\delta(-3)$								
$\delta(-2)$					-0.1622	0.7473	-0.1445	0.7034
$\delta(-1)$					-0.3292	0.7926	-0.2714	0.8421
$\delta(0)$					-0.2916	0.7888	-0.4657	0.8479
$\delta(+1)$					-0.1987	0.6976	-0.3089	0.6923
$\delta(+2)$					1.6516	1.7789	1.7308	1.6049
$\delta(+3)$					-0.2594	1.4853	1.2459	1.3322
$\gamma(-3)$								
$\gamma(-2)$					0.3064	0.4581	-0.0130	0.3496
$\gamma(-1)$					0.6564	0.5537	0.0335	0.4394
$\gamma(0)$					1.2346	0.7066	0.2752	0.5224
$\gamma(+1)$					1.8656	0.9118	0.5954	0.6159
$\gamma(+2)$					2.1514	1.0065	0.4648	0.5583
$\gamma(+3)$					2.6835	1.6031		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	29092		28003		29092		28003	
N firms	4156		4154		4156		4154	
log likelihood	-142601.6223		-135699.5623		-142599.0652		-135696.3290	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.11: Estimation results for output (ln)

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0151	0.0100	0.0096	0.0075				
$\bar{\gamma}$	0.0498	0.0103	0.0300	0.0089				
$agefirm$			0.0116	0.0038			0.0207	0.0038
$\ln(size)$			0.5970	0.0132			0.5957	0.0132
$multinat$			0.1393	0.0153			0.1385	0.0153
$\delta(-3)$								
$\delta(-2)$					-0.0124	0.0172	-0.0020	0.0133
$\delta(-1)$					-0.0315	0.0153	-0.0191	0.0121
$\delta(0)$					0.0586	0.0159	0.0452	0.0132
$\delta(+1)$					0.0271	0.0157	0.0144	0.0124
$\delta(+2)$					-0.0288	0.0162	-0.0206	0.0133
$\delta(+3)$					-0.0552	0.0194	-0.0390	0.0158
$\gamma(-3)$								
$\gamma(-2)$					0.0344	0.0127	-0.0050	0.0091
$\gamma(-1)$					0.0703	0.0140	-0.0118	0.0093
$\gamma(0)$					0.1143	0.0179	-0.0130	0.0096
$\gamma(+1)$					0.1591	0.0202	-0.0172	0.0090
$\gamma(+2)$					0.2273	0.0228	0.0025	0.0091
$\gamma(+3)$					0.2639	0.0259		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	29428		28321		29428		28321	
N firms	4204		4202		4204		4202	
log likelihood	-12715.4369		-7725.2596		-12682.0163		-7702.5914	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.12: Estimation results for output per working hour

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0039	0.0076	-0.0140	0.0059				
$\bar{\gamma}$	0.0200	0.0087	-0.0059	0.0055				
$agefirm$			-0.0267	0.0025			-0.0295	0.0026
$\ln(size)$			0.6510	0.0200			0.6513	0.0200
$multinat$			-0.0220	0.0086			-0.0216	0.0086
$\delta(-3)$								
$\delta(-2)$					0.0014	0.0183	0.0085	0.0121
$\delta(-1)$					-0.0023	0.0149	0.0130	0.0113
$\delta(0)$					0.0407	0.0155	-0.0006	0.0099
$\delta(+1)$					0.0069	0.0153	-0.0218	0.0110
$\delta(+2)$					-0.0229	0.0170	-0.0133	0.0123
$\delta(+3)$					-0.0104	0.0184	0.0136	0.0143
$\gamma(-3)$								
$\gamma(-2)$					-0.0034	0.0121	0.0022	0.0077
$\gamma(-1)$					-0.0086	0.0117	0.0027	0.0063
$\gamma(0)$					-0.0105	0.0136	0.0043	0.0061
$\gamma(+1)$					-0.0164	0.0157	0.0027	0.0064
$\gamma(+2)$					0.0020	0.0162	0.0068	0.0079
$\gamma(+3)$					-0.0138	0.0189		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	28392		27321		28392		27321	
N firms	4056		4054		4056		4054	
log likelihood	-7645.4459		4414.3506		-7631.1411		4428.4063	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.13: Estimation results for value added per working hour

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	-0.0084	0.0068	-0.0187	0.0067				
$\bar{\gamma}$	0.0116	0.0088	-0.0051	0.0075				
$agefirm$			-0.0176	0.0028			-0.0211	0.0029
$\ln(size)$			0.4194	0.0154			0.4196	0.0154
$multinat$			-0.0095	0.0138			-0.0091	0.0139
$\delta(-3)$								
$\delta(-2)$					0.0086	0.0149	0.0137	0.0139
$\delta(-1)$					-0.0014	0.0155	0.0124	0.0143
$\delta(0)$					0.0270	0.0140	0.0036	0.0121
$\delta(+1)$					-0.0153	0.0144	-0.0305	0.0135
$\delta(+2)$					-0.0257	0.0151	-0.0204	0.0136
$\delta(+3)$					-0.0098	0.0149	0.0133	0.0145
$\gamma(-3)$								
$\gamma(-2)$					-0.0014	0.0115	0.0021	0.0092
$\gamma(-1)$					-0.0057	0.0110	0.0019	0.0080
$\gamma(0)$					-0.0119	0.0133	-0.0009	0.0077
$\gamma(+1)$					-0.0059	0.0153	0.0102	0.0083
$\gamma(+2)$					0.0056	0.0159	0.0147	0.0080
$\gamma(+3)$					-0.0111	0.0177		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	27902		26862		27902		26862	
N firms	3986		3985		3986		3985	
log likelihood	-6373.700		-2453.236		-6362.663		-2442.930	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.14: Estimation results for TFP with CD production function (ln)

	(1) coeff.	(1) std. error	(2) coeff.	(2) std. error	(3) coeff.	(3) std. error	(4) coeff.	(4) std. error
$\bar{\delta}$	-0.0202	0.0050	-0.0204	0.0049				
$\bar{\gamma}$	0.0005	0.0051	-0.0052	0.0049				
$agefirm$			-0.0062	0.0059			-0.0072	0.0057
$\ln(size)$			0.1448	0.0201			0.1452	0.0202
$multinat$			-0.0182	0.0094			-0.0184	0.0094
$\delta(-3)$								
$\delta(-2)$					-0.0110	0.0110	-0.0098	0.0111
$\delta(-1)$					-0.0209	0.0093	-0.0174	0.0089
$\delta(0)$					-0.0350	0.0100	-0.0406	0.0097
$\delta(+1)$					-0.0294	0.0101	-0.0325	0.0099
$\delta(+2)$					-0.0293	0.0106	-0.0251	0.0106
$\delta(+3)$					-0.0299	0.0112	-0.0164	0.0118
$\gamma(-3)$								
$\gamma(-2)$					-0.0026	0.0091	-0.0013	0.0078
$\gamma(-1)$					-0.0030	0.0118	0.0011	0.0064
$\gamma(0)$					-0.0046	0.0166	0.0014	0.0068
$\gamma(+1)$					-0.0128	0.0212	-0.0047	0.0063
$\gamma(+2)$					-0.0076	0.0264	-0.0007	0.0072
$\gamma(+3)$					-0.0070	0.0312		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	27972		26899		27972		26899	
N firms	3996		3994		3996		3994	
log likelihood	2894.82641		3753.60362		2900.36596		3762.02274	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.15: Estimation results for TFP with Translog production function (ln)

	(1) coeff.	(1) std. error	(2) coeff.	(2) std. error	(3) coeff.	(3) std. error	(4) coeff.	(4) std. error
$\bar{\delta}$	-0.0191	0.0174	-0.0152	0.0174				
$\bar{\gamma}$	0.0054	0.0177	-0.0013	0.0175				
$agefirm$			-0.0099	0.0098			-0.0098	0.0095
$\ln(size)$			0.1136	0.0206			0.1139	0.0206
$multinat$			-0.0696	0.0336			-0.0698	0.0337
$\delta(-3)$								
$\delta(-2)$					0.0169	0.0444	0.0133	0.0434
$\delta(-1)$					0.0017	0.0386	0.0045	0.0375
$\delta(0)$					-0.0267	0.0349	-0.0318	0.0345
$\delta(+1)$					0.0163	0.0367	0.0126	0.0367
$\delta(+2)$					-0.0156	0.0390	-0.0115	0.0386
$\delta(+3)$					-0.0254	0.0400	-0.0055	0.0409
$\gamma(-3)$								
$\gamma(-2)$					-0.0186	0.0302	-0.0095	0.0273
$\gamma(-1)$					-0.0258	0.0323	-0.0098	0.0243
$\gamma(0)$					-0.0160	0.0357	0.0085	0.0235
$\gamma(+1)$					-0.0630	0.0411	-0.0310	0.0241
$\gamma(+2)$					-0.0479	0.0475	-0.0102	0.0240
$\gamma(+3)$					-0.0402	0.0531		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	23576		22704		23576		22704	
N firms	3368		3367		3368		3367	
log likelihood	-25048.6055		-23741.6217		-25046.6297		-23739.7222	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.16: Estimation results for real wage cost (ln)

	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$\bar{\delta}$	0.0347	0.0104	0.0261	0.0094				
$\bar{\gamma}$	0.0115	0.0099	-0.0084	0.0088				
$agefirm$			-0.0190	0.0037			-0.0224	0.0037
$\ln(size)$			0.4550	0.0328			0.4551	0.0327
$multinat$			-0.0041	0.0203			-0.0037	0.0204
$\delta(-3)$								
$\delta(-2)$					0.0118	0.0239	0.0195	0.0220
$\delta(-1)$					0.0109	0.0231	0.0269	0.0225
$\delta(0)$					0.0810	0.0216	0.0562	0.0189
$\delta(+1)$					0.0428	0.0229	0.0282	0.0218
$\delta(+2)$					0.0185	0.0232	0.0297	0.0220
$\delta(+3)$					0.0270	0.0255	0.0560	0.0249
$\gamma(-3)$								
$\gamma(-2)$					-0.0170	0.0140	-0.0116	0.0121
$\gamma(-1)$					-0.0216	0.0137	-0.0076	0.0106
$\gamma(0)$					-0.0293	0.0149	-0.0086	0.0086
$\gamma(+1)$					-0.0365	0.0187	-0.0094	0.0115
$\gamma(+2)$					-0.0175	0.0185	0.0036	0.0098
$\gamma(+3)$					-0.0277	0.0208		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	28406		27324		28406		27324	
N firms	4058		4056		4058		4056	
log likelihood	-17317.4951		-14141.4119		-17309.3027		-14135.6625	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.17: Estimation results for markup (ln), CD output elasticities

	(1) coeff.	std. error	(2) coeff.	std. error	(3) coeff.	std. error	(4) coeff.	std. error
$\bar{\delta}$	-0.0166	0.0050	-0.0139	0.0051				
$\bar{\gamma}$	-0.0041	0.0059	0.0031	0.0053				
$agefirm$			0.0063	0.0020			0.0083	0.0023
$\ln(size)$			-0.1450	0.0208			-0.1451	0.0208
$multinat$			-0.0203	0.0109			-0.0205	0.0108
$\delta(-3)$								
$\delta(-2)$					0.0045	0.0097	-0.0004	0.0088
$\delta(-1)$					-0.0128	0.0093	-0.0175	0.0091
$\delta(0)$					-0.0263	0.0091	-0.0185	0.0088
$\delta(+1)$					-0.0241	0.0085	-0.0204	0.0082
$\delta(+2)$					-0.0119	0.0087	-0.0166	0.0087
$\delta(+3)$					-0.0151	0.0103	-0.0252	0.0113
$\gamma(-3)$								
$\gamma(-2)$					-0.0056	0.0073	-0.0038	0.0059
$\gamma(-1)$					0.0070	0.0082	0.0055	0.0062
$\gamma(0)$					0.0014	0.0095	0.0002	0.0062
$\gamma(+1)$					0.0008	0.0109	-0.0006	0.0066
$\gamma(+2)$					-0.0118	0.0124	-0.0101	0.0072
$\gamma(+3)$					-0.0006	0.0143		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	29260		28166		29260		28166	
N firms	4180		4178		4180		4178	
log likelihood	2990.7065		4474.6169		2996.2970		4479.1395	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.18: Estimation results for working hours in Manufacuring and Services sectors (ln)

	Manufacturing				Services			
	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$agefirm$			0.0170	0.0053			0.0330	0.0026
$\ln(size)$			0.3016	0.0259			0.3595	0.0255
$multinat$			0.0121	0.0190			0.0237	0.0100
$\delta(-3)$								
$\delta(-2)$	-0.0089	0.0182	-0.0160	0.0173	-0.0022	0.0153	0.0023	0.0141
$\delta(-1)$	-0.0219	0.0169	-0.0206	0.0164	-0.0166	0.0166	-0.0039	0.0139
$\delta(0)$	0.0156	0.0150	-0.0149	0.0142	0.0329	0.0132	0.0138	0.0114
$\delta(+1)$	0.0268	0.0161	-0.0056	0.0152	0.0481	0.0154	0.0400	0.0128
$\delta(+2)$	0.0145	0.0174	-0.0004	0.0177	0.0139	0.0165	0.0269	0.0145
$\delta(+3)$	-0.0011	0.0194	-0.0126	0.0204	-0.0270	0.0184	-0.0109	0.0176
$\gamma(-3)$								
$\gamma(-2)$	0.0206	0.0127	-0.0051	0.0110	0.0403	0.0114	-0.0051	0.0088
$\gamma(-1)$	0.0543	0.0154	-0.0014	0.0102	0.0888	0.0115	-0.0058	0.0063
$\gamma(0)$	0.0803	0.0184	0.0004	0.0096	0.1368	0.0137	-0.0070	0.0067
$\gamma(+1)$	0.1065	0.0216	-0.0006	0.0104	0.1888	0.0156	-0.0051	0.0070
$\gamma(+2)$	0.1397	0.0258	-0.0033	0.0122	0.2413	0.0185	-0.0110	0.0085
$\gamma(+3)$	0.1696	0.0298			0.2955	0.0202		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	7574		7256		19768		19067	
N firms	1082		1082		2824		2822	
log likelihood	1012.3421		1828.9475		-832.7470		2678.9723	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.19: Estimation results for output in Manufacuring and Services sectors (ln)

	Manufacturing				Services			
	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$agefirm$			0.0169	0.0069			0.0212	0.0047
$\ln(size)$			0.5209	0.0254			0.6179	0.0165
$multinat$			0.1648	0.0336			0.1289	0.0181
$\delta(-3)$								
$\delta(-2)$	0.0189	0.0299	0.0308	0.0257	-0.0201	0.0246	-0.0105	0.0194
$\delta(-1)$	-0.0205	0.0296	-0.0064	0.0257	-0.0529	0.0196	-0.0368	0.0155
$\delta(0)$	0.0905	0.0293	0.0837	0.0262	0.0418	0.0210	0.0286	0.0176
$\delta(+1)$	0.0815	0.0304	0.0768	0.0267	0.0096	0.0206	-0.0084	0.0156
$\delta(+2)$	0.0121	0.0292	0.0279	0.0264	-0.0519	0.0206	-0.0471	0.0170
$\delta(+3)$	0.0099	0.0317	0.0180	0.0280	-0.0739	0.0257	-0.0559	0.0208
$\gamma(-3)$								
$\gamma(-2)$	0.0308	0.0199	0.0070	0.0164	0.0261	0.0183	-0.0154	0.0133
$\gamma(-1)$	0.0616	0.0212	0.0055	0.0153	0.0697	0.0187	-0.0171	0.0125
$\gamma(0)$	0.0778	0.0265	-0.0157	0.0140	0.1175	0.0231	-0.0181	0.0126
$\gamma(+1)$	0.1107	0.0332	-0.0213	0.0162	0.1701	0.0259	-0.0182	0.0114
$\gamma(+2)$	0.1748	0.0395	0.0042	0.0152	0.2451	0.0278	0.0066	0.0117
$\gamma(+3)$	0.1988	0.0460			0.2843	0.0311		
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	7924		7602		20328		19599	
N firms	1132		1132		2904		2902	
log likelihood	-2462.2047		-1337.8779		-9496.0899		-5955.0654	
cluster var	sector * year		sector * year		sector * year		sector * year	

Table A.20: Estimation results without goodwill spikes and with control variables

	ln(output)		ln(working hours)		ln(TFP CD)		ln(labour productivity)	
	(1)		(2)		(3)		(4)	
	coeff.	std. error	coeff.	std. error	coeff.	std. error	coeff.	std. error
$agefirm$	0.0233	0.0041	0.0288	0.0025	-0.0099	0.0065	-0.0277	0.0025
$\ln(size)$	0.5743	0.0152	0.3270	0.0196	0.1673	0.0229	0.6656	0.0199
$multinat$	0.1521	0.0187	-0.0078	0.0103	-0.0214	0.0116	0.0012	0.0103
$\delta(-3)$								
$\delta(-2)$	-0.0001	0.0156	-0.0075	0.0108	0.0007	0.0123	0.0092	0.0109
$\delta(-1)$	-0.0111	0.0154	-0.0170	0.0115	-0.0089	0.0101	0.0215	0.0117
$\delta(0)$	0.0183	0.0162	-0.0131	0.0099	-0.0307	0.0111	0.0157	0.0106
$\delta(+1)$	-0.0148	0.0155	0.0005	0.0113	-0.0209	0.0111	0.0022	0.0116
$\delta(+2)$	-0.0383	0.0156	-0.0108	0.0122	-0.0171	0.0119	0.0139	0.0127
$\delta(+3)$	-0.0730	0.0171	-0.0451	0.0143	0.0089	0.0132	0.0473	0.0146
$\gamma(-3)$								
$\gamma(-2)$	-0.0058	0.0110	-0.0053	0.0073	-0.0137	0.0092	0.0040	0.0072
$\gamma(-1)$	-0.0171	0.0114	-0.0033	0.0064	-0.0054	0.0065	0.0017	0.0065
$\gamma(0)$	-0.0176	0.0114	-0.0014	0.0062	-0.0075	0.0076	-0.0003	0.0062
$\gamma(+1)$	-0.0240	0.0100	0.0014	0.0068	-0.0075	0.0074	-0.0028	0.0068
$\gamma(+2)$	-0.0094	0.0106	-0.0074	0.0071	0.0047	0.0077	0.0068	0.0071
year FE	yes		yes		yes		yes	
firm FE	yes		yes		yes		yes	
N obs.	21163		20540		20288		20540	
N firms	3143		3051		3014		3051	
log likelihood	-5286.4658		4203.7693		3417.9045		4121.3459	
cluster var	sector * year		sector * year		sector * year		sector * year	