IT and Productivity: A firm level analysis

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Abstract: In recent years, most industrial economies have witnessed a slowdown in productivity growth. Yet, societies are increasingly transformed by the adaption of information technology (IT). This is believed to increase production efficiency. An important challenge in the literature on returns from IT capital is the measurement of IT. Earlier research often uses data on IT at a high level of aggregation or based on surveys at mostly large companies. In this paper, we use a new and hitherto unexploited data set of all VAT transactions between firms, which allows us to trace IT purchases by firms. We develop a measure of IT capital at the firm level, which improves on earlier ones used in the literature and is available for the entire firm size distribution. Our rich firm level dataset allows us to look at various dimensions of industry and firm level heterogeneity in returns of IT capital. Furthermore we revisit the Solow Paradox and show how much of firm level TFP dispersion is explained by IT.

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1. Introduction

In recent years, most industrial economies have witnessed a slowdown in productivity growth. Therefore, a lot of research is done to identify the driving forces of productivity growth. One source of productivity growth that received a lot of attention the last two decades is the increasing importance of computers, robots and more in general information technology (IT) in the production process. Policy makers seem convinced of the potential of IT for productivity growth. The European Commission declared that "Europe needs download rates of 30Mbps for everybody and at least 50% of the Europeans should have internet connections above 100Mbps by 2020". However, not all academics agree on the potential of IT for productivity growth. Carr (2003) argues that IT is a commodity factor of production and also Gordon (2010) claims that business productivity improvements from IT are already in the past. On the other hand, Brynjolfsson and McAfee (2014) claim that the best is yet to come. In this paper we investigate returns from IT capital at micro level to contribute to this discussion at the macro level.

In most of the literature, IT refers to broad investments in office and computing investment and therefore does not capture precisely the extent of technological change, which may also be induced by software, especially the last decade. Moreover, IT measures are mostly only available at a high level of aggregation, either the 2 or 3-digit sector level. However, firm heterogeneity in returns to IT is likely to be substantial and cannot be captured at the sector level. This paper therefore first develops a measure of IT investment at the firm level, which improves on earlier ones used in the literature. To this end, we use a new and hitherto unexploited data set of all VAT transactions between firms in Belgium, which allows us to trace IT purchases by firms. In addition, we use import data at the product-firm level to capture IT purchases from abroad. This allows us to construct a firm specific measure of IT capital. Earlier work using firm level measures of IT relied on survey data, which typically cover limited samples of large firms and with a time invariant measure of IT (e.g. Brynjolfsson and Hitt, 2003). In contrast, our approach covers the full set of firms, small and large, and covers all transactions between firms. We merge this data with firm level company accounts data.. The result is a rich panel data set that allows us to use recent advances in the productivity literature to control for endogeneity from unobserved productivity. More specifically, we will follow Brynjolfsson and Hitt (1995, 2003) and estimate an augmented production function with IT capital and non IT capital inputs and use the control function approach of Ackerberg, Caves and Frazer (2015) and a novel estimator recently introduced by Collard-Wexler and De Loecker (2016) that also controls for measurement error in capital.

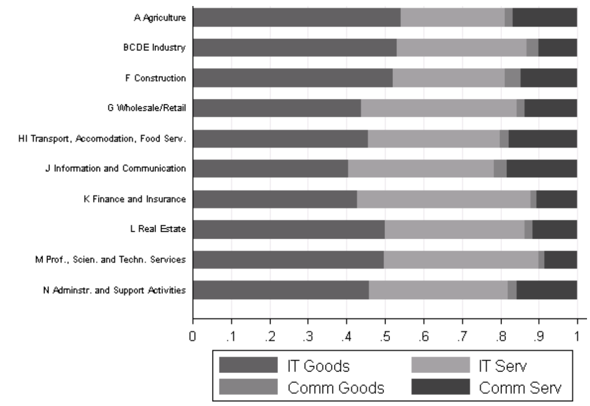
We exploit the various dimensions of our dataset to answer a number of questions that earlier work could not resolve. After benchmarking our results for Belgium with earlier findings for the U.S., we further disentangle industry and firm level heterogeneity in returns from IT capital. At the industry level, we find larger marginal products for IT capital in manufacturing industries than in services industries, indicating IT investments are particularly productivity enhancing in manufacturing industries. One reason for which the marginal product of IT capital is on average lower in services industries, is that services industries are on average more IT intensive than manufacturing industries. Next, we explore heterogeneity in returns from IT capital for firms of different sizes. Bloom et al. (2012) show that IT is complementary to management practices and as large firms have better management practices, the impact of IT investments could be larger for these firms. To the best of our knowledge, our paper is the first with IT capital measures across the entire firm size distribution. Our results show that there is indeed a size premium on returns from IT investment. Furthermore, we revisit the Solow paradox. Our inquiry on the revival of the Solow paradox refutes recent rejections of previous resolutions. We see IT capital contributing to output, and this effect is not only confined to the IT producing and IT using industries. Last, we investigated the impact of IT on TFP dispersion. We find that IT investments explain about 20 percent of the dispersion in measured productivity. In the cross section of small firms, IT investments explains more of the dispersion in TFP than in large firms. Taking into account measurement error in firm level TFP, IT and human capital explain up to half of the dispersion in TFP in the Belgian economy.

The rest of the paper is organized as follows. In the next section we discuss how we construct our measure of IT and describe the various data sets that we use. Section III explains our econometric model and the control function approach that we use. Section IV discusses the results and section V concludes.

2. Data

We combine three different data sets to obtain a firm level measure of IT capital and to estimate its impact on productivity. The first comes from the tax authorities and is based on all VAT declarations firms are legally required to report. From this dataset we can obtain for each active Belgian firm its supplier of inputs and investment goods as well as the value of these. Based on the detailed four digit primary NACE sector code of the supplier, we distinguish investments in IT, both goods and services, within these purchases. For example, if a firm makes a purchase from a supplier that has its primary activity in sector 4651 – *Wholesale of Computers and Software* - we classify this purchase as an investment in IT. In particular, we classify IT investments as purchases from firms active in the following narrowly defined 4-digit sectors. For IT goods: *2620 Computer and peripheral equipment, 4651 Wholesale of computers and software, 4741 Retail sale of computers and software and 5829 Other software publishing* and for IT services: *6200-6203 and 6209 Computer Programming, consultancy and related activities* and *6311-6312 Data processing, hosting and related services* (also see appendix D). We excluded all purchases related to communication technologies as well as information related services for our main analysis, but we will show robustness results in which we take these into account.[5] Figure 1 shows that it is the IT component which matters most as in most sectors the Communication component of ICT is not very important, except in the telecom sector. In most sectors the IT component of goods and services accounts for about 80% of total ICT purchases, while communication goods hardly matter. Next to the IT purchases that we obtain from the VAT transactions of the suppliers, we also have data on the VAT transactions of the buyers. From these we know how much each firms invests and how much intermediate inputs a firm buys. A breakdown from the supplier side to the buyer side that learns how much of the IT purchases are investments and how much are intermediate inputs, is not available in these sort of data. Appendix A provides more detail on the VAT data and a discussion on how we cope with the issues that are inherent to the data.

Figure 1: Distribution of the components of ICT by sector



[5] These include suppliers active in the following product branches: Communication equipment (2630), Wholesale trade of electronic and telecom equipment (4652) and Retail trade of telecom equipment (4742).

The second dataset refers to data on imports at the firm-product level and comes from the customs for imports coming outside the EU and the Intrastat trade survey for imports to Belgium coming from within the EU. The reason why we need this additional data is that suppliers of IT can be foreign and therefore we require information at the firm level how much IT is imported. We do this based on the detailed HS 6 digit codes.

The third dataset consists of the annual company accounts with detailed financial and operational data, which we use to estimate production functions. All incorporated firms in Belgium are required to submit company accounts to the National Bank of Belgium for tax purposes. We merge these three data sets, which gives us 1.5 million firm-year observations, of which around 60% have positive investment in IT. We have data for the period 2002-2013 for the whole private sector, so including both manufacturing and services sectors.

To construct IT capital stocks as well as non-IT capital stocks from the observed investment flows, we follow the perpetual inventory method. Appendix A provides more details about the exact procedure and presents IT intensity measures to show that our IT measure behaves as expected.

Table 1 provides summary statistics of the main firm level variables that we will be using in our analysis and that report the necessary variables for the estimations. The panel consists of 937386 firm-year observations over the period 2002-2013. The average firm employs 13.3 full time equivalent workers in our sample, but we have very small firms as well with less than one full time equivalent worker and large firms with more than 10000 workers. We will exploit these size differences in our analysis. Average value added is equal to 1.17 million euros, implying labor productivity in the average firm to be slightly less than 65000euros. The average non IT and IT capital stock are equal to 1.08 million and 128 thousand euros respectively. This means that an employee in the average firm has around 9625 euros IT capital to work with. The standard deviation is high, which indicates there are large differences at the firm level in terms of IT stock. So the aggregate picture hides a lot of firm level heterogeneity.

Table 1 Summary Statistics

	mean	Median	standard deviation
Value Added (X1000 €)	1170.3	166.4	17800
Non IT Capital (X1000 €)	1079.7	97.5	33000
IT capital (X1000 €)	127.5	3.9	2951.2
Employment	13.3	2.5	183.3
Non-IT Investment (X1000 €)	145.4	4.1	4061.7
IT investment (X1000 €)	43.3	0.7	1084.8

3. Econometric Model

In order to estimate the return from IT, we rely on an augmented Cobb Douglas production function. Tambe & Hitt (2012) adapt this production function by distinguishing between IT labor and non IT labor. We take a similar approach and distinguish between IT capital and non IT capital. By considering IT capital as a separate input in the production function next to non IT capital, our approach is closest to the work of Brynjolfsson & Hitt (1996, 2003), with the advantage that our sample of firms is much larger, contains both small and large firms and does not rely on survey data. Also, we add robustness checks that allow for endogenous productivity growth, alternative data generating processes and mismeasurement in the capital stocks.

Our augmented production function treats IT capital and non IT capital as separate inputs. The log-linearized Cobb-Douglas production function then looks as follows:

$$y_{it} = \beta_l l_{it} + \beta_{IT} k_{it}^{IT} + \beta_{NIT} k_{it}^{NIT} + \omega_{it} + \epsilon_{it} \tag{1}$$

In which the i and t subscripts refer to firm and year. y_{it} refers to a firm value added. l_{it}, k_{it}^{IT} and k_{it}^{NIT} refer respectively to firm labor, IT capital and non IT capital. ω_{it} is the firm's Total Factor Productivity (TFP). Econometricians do not observe a firm's TFP. This gives rise to the well-known simultaneity bias (Marschak & Andrews, 1944), i.e. firms typically adjust their capital and labor inputs in function of their productivity and this prevents one from obtaining unbiased estimates for β_l, β_{IT} and β_{NIT} with an OLS estimation of equation (1). To overcome this simultaneity bias, we use a semiparametric estimator. This approach was introduced by Olley & Pakes (1996, henceforth OP), the idea is to control for the unobserved productivity residual with other variables through which firms signal their productivity. The OP model relies on the firm's investment demand to control for the unobserved productivity. Levinsohn & Petrin (2003, henceforth LP) rely on the demand for material inputs instead of investment demand to proxy for unobserved productivity because investments are lumpy and often badly reported. Ackerberg, Caves and Frazer (2015, henceforth ACF) discuss how to ensure unbiased identification of the OP and LP estimators. Collard-Wexler and De Loecker (2016, henceforth CWDL) build on these models and propose an estimator that relies on the firm's materials demand to proxy for unobserved productivity and that is robust to measurement error in capital. We will use and modify the ACF estimator, which is currently the workhorse model in the literature. We will also use the novel estimator introduced by CWDL. For consistency, we rely on material demand in both estimators.[6]

[6] We also experimented with a control function based on the Olley and Pakes (1996) model with non IT investment demand, this did not change our findings regarding the output elasticity of IT capital.

The ACF estimation is based on the assumption that material expenditures are monotonically increasing in productivity, conditional on the other state variables. We can then substitute ω_{it} in equation (1) with the inverse of a non-parametric function of materials and the state variables, $\omega_{it} = f^{-1}(k_{it}^{IT}, k_{it}^{NIT}, l_{it}, m_{it})$. In a first step, we estimate the following equation:

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_{IT} k_{it}^{IT} + \beta_{NIT} k_{it}^{NIT} + f^{-1}(k_{it}^{IT}, k_{it}^{NIT}, l_{it}, m_{it}) + \epsilon_{it} \\ &= \tilde{\phi}_t(l_{it}, k_{it}^{IT}, k_{it}^{NIT}) + \epsilon_{it} \end{aligned} \tag{2}$$

In which m_{it} refers to material expenditures of firm i in year t. From this first step, we identify ϵ_{it}, which is the true orthogonal residual that represents e.g. machine breakdowns. The second assumption is that productivity evolves according to a first order Markov process. Productivity is then a function of its lagged value and an unexpected shock:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{3}$$

The parameters of the production function are identified from using the following moment conditions on this unexpected shock in productivity:

$$E\left[(\xi_{it})\begin{pmatrix} l_{it} \\ k_{it}^{IT} \\ k_{it}^{NIT} \end{pmatrix}\right] = 0 \tag{4}$$

These moment conditions are the result of assumptions on the timing of the input decisions. First, as is common in the literature, we assume that it takes one year to order and install capital goods. Consequently, investments entering the capital stock in period t where decided based on the information available in year $t-1$ and are by definition unrelated to the unexpected productivity shocks in t. Second, we make a similar assumption for labor, namely that it takes one period to hire new workers. This is a more strict assumption than is common in the literature, but can be justified by the large extent of hiring and firing costs in Belgium (see as well Konings and Vanormelingen, 2015) and can lead to more precise estimates (Ackerberg et al., 2015). We also estimated the production function while allowing IT investments to be dependent on contemporaneous shocks in productivity as these are likely to be more flexible than non-IT capital investments. To this end, we replace k_{it}^{IT} by its lagged value in the moment conditions.

In a recent paper, Collard Wexler and De Loecker (2016, henceforth CWDL) argue that capital stocks are particularly sensitive to measurement error. First, when constructing the capital stock using the PIM method, we assumed a common depreciation rate for all firms while this probably varies across firms and vintage of the capital stock. Second, since we do not observe the initial capital stock, we approximated it using a measure for the IT intensity of the firm and the book value of all tangible fixed assets. This procedure is likely to introduce as well measurement error in the capital stock. CWDL propose a novel estimator that deals with this measurement error while controlling for unobserved productivity in the production function. To preserve the linear structure of the estimation equation, they suggest to write productivity as an AR(1) process. The counterpart of equation (2) with the CWDL extension is then:

$$y_{it} = \beta_l l_{it} + \beta_{IT} k_{it}^{IT} + \beta_{NIT} k_{it}^{NIT} + \theta_{IT} k_{it-1}^{IT} + \theta_{NIT} k_{it-1}^{NIT} + \theta_l l_{it-1} + \theta_m m_{it-1} + \xi_{it} + \epsilon_{it} \tag{5}$$

In which m_{it-1} refers to lagged material demand and the θ parameters combine the productivity persistence and production parameters. CWDL suggest to instrument the capital stock variables with lagged investments.[7] The idea is that the investment variables contain less measurement error than the stock variables. This gives rise to the following moment conditions for identification:

$$E\left[(\xi_{it} + \epsilon_{it}) \begin{pmatrix} l_{it} \\ i_{it-1}^{IT} \\ i_{it-1}^{NIT} \\ i_{it-2}^{IT} \\ i_{it-2}^{NIT} \\ l_{it-1} \\ m_{it-1} \end{pmatrix}\right] = 0 \tag{6}$$

With i_{it}^{IT} and i_{it}^{NIT} the investments in IT capital goods and non IT capital goods, which we have detailed information on from the VAT transactions data.[8] In our main specification, we model IT capital as a stock variable. The premises is that IT capital is part of the production isoquant, i.e. IT capital can be substituted with other production inputs. While this is the standard approach in the literature, it could be argued that IT investments induce a shift of the production function, i.e. enable to produce more output with the same set of inputs. We enrich our model to allow for this data generating process as suggested by Doraszelski and Jaumandreu (2013) and De Loecker (2013). In appendix B we show results on this alternative data generating process and on how we model IT capital.

7 Galuščák and Lízal (2011) propose a similar approach to account for measurement error in capital. Instead of investments, they instrument the capital stock with depreciation, employment and intermediate inputs.

8 It is important to note that this procedure will correct for measurement error due to imprecisely observing the depreciation rate and the initial capital stock but not for measurement error in the investment variables themselves.

4. Results

4.1 Aggregate results

This section reports results for the private sector as a whole and explores sector and firm-level heterogeneity in returns to IT. Figure A1 shows a scatterplot on the relation between IT capital and output. Table 2 reports production function estimates for the private sector as a whole. All specifications control for industry and year fixed effects. The first column shows pooled OLS results. The second columns displays the ACF estimator. Lastly, we also report results for the CWDL estimator that corrects for measurement error in the capital variables.

Table 2: Results Private Sector (NACE 1-82)

Value Added Production Function	OLS	ACF	CWDL
Labor	0.6868***	0.6189***	0.4942***
	(0.0014)	(0.0035)	(0.0063)
Non IT Capital	0.1621***	0.2257***	0.3150***
	(0.0012)	(0.0048)	(0.0657)
IT Capital	0.1027***	0.1032***	0.1497***
	(0.009)	(0.0027)	(0.0364)
# obs	973386	897119	319549
Industry & Year FE	YES	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

The coefficients are reasonable and returns to scale are close to one. The correction for measurement error in the capital stocks in column (4) increases the capital coefficients upwards as expected. The IT capital output elasticity is estimated in the range 0.10-0.15, so increasing the IT capital stock with 1% increases value added on average with 0.10-0.15%. This is higher than in earlier work, see table A1 in appendix for a comparison with earlier studies.

While output elasticities have the advantage of being independent of the units in which outputs and inputs are measured, they cannot be easily compared with studies on other samples that have different average levels of IT investments or other factor input shares. Therefore, we follow Tambe & Hitt (2012) and Brynjolfsson (1996) and compute the marginal product of the inputs.[9] The IT capital input share $\frac{K^{IT}}{VA}$ is on average 8.31% of value added, this is comparable to Brynjolfsson and Hitt (1995) who found an input share of 9.35% for IT capital and IT labor together. Based on the estimated output elasticities of IT capital , $MP_{K^{IT}} = \beta_{IT}\left(\frac{K^{IT}}{Y}\right)^{-1} = \frac{0.1032}{0.0831} = 1.24$. For non-IT

[9] The marginal product of IT capital is equal to the output elasticity of IT capital multiplied by the ratio of output to IT capital. Formally, $MP_{K^{IT}} = \frac{\delta Y}{\delta K^{IT}} = \frac{\delta Y}{\delta K^{IT}}\frac{K^{IT}}{Y}\frac{Y}{K^{IT}} = \beta_{IT}\frac{Y}{K^{IT}} = \frac{\beta_{IT}}{\frac{K^{IT}}{Y}}$. Estimates for β_{IT} are shown in table 1. To obtain $\frac{K^{IT}}{Y}$, we use the same sample as for the estimation of the production function for consistency. We calculate the IT capital input share for each observation and take the mean of the resulting distribution. Because some firms have very low value added or very low IT capital, we winsorize this ratio at the 1% level to avoid bias from outliers.

capital and labor, the input shares are respectively 1.31 and 0.65, so $MP_{K^{NIT}} = \frac{0.2257}{1.3131} = 0.17$ and $MP_{\mathrm{L}} = \frac{0.6189}{0.6507} = 0.95$. The marginal product of non-IT capital is 0.17 while the marginal product of IT capital is 1.24. So investing an additional euro in IT capital increases value added on average with 1.24euro. Our estimates are higher than those of Brynjolfsson and Hitt (1996), who found the marginal product of IT capital to be 81% for a sample of 1121 large US firms between 1987-1991, indicating that the returns from IT investments are higher nowadays than in the early nineties. The marginal product tells how much the last dollar of IT capital contributed to value added. Infra-marginal investments generally have a higher rate of return, so our results indicate that the average return from investing in IT capital even higher than 124%. However, the net contribution of IT capital to value added also depends on the user costs that are associated to maintaining IT capital. According to the EU KLEMS data, IT capital depreciates at a rate of 32% per year, while non-IT capital only depreciates at 8% per year. As a result, the net rate of return from IT capital is about 92% while the net rate of return of non-IT capital is about 9%.[10] Altogether, our results indicate excess returns from IT capital compared to non-IT capital.

A possible important caveat is that we have no information on necessary additional intangible investments, like innovations in business methods and organizational structure, that may be required in order the new IT capital to be productive (Brynjolfsson, Hitt and Yang (2002), Brynjolfsson & Hitt (2003), Bresnahan et al., 2002; Tambe & Hitt, 2012 and the references cited therein). As a result, the net rate of return for IT capital could be substantially lower. Although our dataset does not allow for robustness checks on this issue, we believe our findings would not change because of three reasons. First, adjustment costs are primarily a concern for large firms, who were typically the focus of earlier research on IT capital because of data availability. Earlier work argues that adjustment costs for complementary assets increase with firm size because of increasing difficulties to change work routines and coordinating tasks (Ito, 1995). Small firms are generally more flexible since they have less firm specificity embedded in their internal organization. Therefore, small firms are less prone to adjustment costs from investments in IT capital. As figure A2 shows, two thirds of the firms in our sample employ less than 10 employees. Since our production function estimates are based on unweighted regressions, the findings regarding the output elasticity and marginal product of IT capital probably not hinge on potential adjustment costs. In section 4.2, we elaborate further on firm size differences. Second, adjustment costs are not necessarily a bad thing. As Brynjolfsson & Yang (1999) explicate, even though the implementation of IT capital may cost up to ten times

[10] The marginal product of an input can be interpreted as its gross rate of return, whereas the net rate of return is defined as the marginal product minus the depreciation rate.

more than the installation of other physical assets, these organizational changes – new routines, a new organizational form, new supplier relations - that firms undertake create a competitive advantage and barriers for competitors. From that point of view, adjustment costs could be regarded as building intangible capital for the firm. Third, even if one regards adjustment costs as a negative complement to IT investments, the net rate of return from IT capital is likely to be still larger than zero after accounting for such costs.

4.2 Industry Heterogeneity

As pointed out by Tambe & Hitt (2012), limited availability of data in earlier work prohibited sectoral comparisons. Our data contains information on firm level IT investments for the entire private sector. As shown in figure 2, the results pooled over all sectors mask obviously important heterogeneity across sectors. Tables 3 and 4 show split sample results for manufacturing and services sectors as a first step in disentangling this heterogeneity.

Table 3: Results Manufacturing Sectors (NACE 10-33)

Value Added Production Function	OLS	ACF	CWDL
Labor	0.7347***	0.6494***	0.5999***
	(0.0042)	(0.0115)	(0.0180)
Non IT Capital	0.1700***	0.2374***	0.2012*
	(0.0032)	(0.0143)	(0.1057)
IT Capital	0.0994***	0.1049***	0.1481**
	(0.0022)	(0.0062)	(0.0583)
# obs	132462	120959	56056
Industry & Year dum.	YES	YES	YES

Note: *** is significant at 1% level. ** is significant at 5% level. * is significant at 10% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

Table 4: Results Services Sectors (NACE 45-82)

Value Added Production Function	OLS	ACF	CWDL
Labor	0.6906***	0.6302***	0.4502***
	(0.0026)	(0.0059)	(0.0108)
Non IT Capital	0.1631***	0.2134***	0.4366***
	(0.0023)	(0.0082)	(0.1443)
IT Capital	0.0836***	0.0913***	0.1758**
	(0.0017)	(0.0054)	(0.0704)
# obs	279058	252751	75547
Industry & Year FE	YES	YES	YES

Note: *** is significant at 1% level. ** is significant at 5% level. * is significant at 10% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

The output elasticity of IT capital is slightly higher for manufacturing industries.[11] Also the marginal product of IT capital is higher in the manufacturing sector, namely 1.53 in the

[11] The CWDL estimates however show the opposite. However, the non IT capital coefficient for services industries is exceptionally high, which casts doubt on the robustness of the CWDL estimator.

manufacturing sector compared to 0.80 in the services sector. The marginal products of non-IT capital and labor are respectively 0.19 and 0.95 for the manufacturing sector and 0.14 and 0.97 for the services sector.[12] There are two possible explanations for such high marginal product of IT capital in the manufacturing industry: either user costs and adjustment costs from increasing IT capital are large such that firms retain from investing in IT capital, either there is a market failure that results in manufacturing firms underinvesting in IT capital. To gain deeper understanding in industry heterogeneity, we estimate the augmented production function at a more disaggregated level. Table 5 shows provides further details on differences in the output elasticity and the marginal product of IT capital across industries.

Table 5: Results Value Added Production Function - ACF Estimator

Industry (NACE codes)	**Labor**	**Non IT Capital**	**IT Capital**	**IT input share**	**Marginal Product IT**
Agriculture, Forestry and Fishing (1-3)	0.40	0.45	0.06	0.05	1.19
Mining and Quarrying (5-9)	0.38	0.45	0.13	0.03	3.93
High Tech Manufacturing (21; 26; 30)	0.74	0.18	0.12	0.07	1.73
Other Manufacturing (10-33 except Hightech)	0.64	0.25	0.10	0.07	1.43
Utilities (35-39)	0.52	0.32	0.10	0.04	2.33
Construction (41-43)	0.62	0.24	0.10	0.04	2.57
Wholesale and Retail (45-47)	0.60	0.21	0.12	0.10	1.26
Transportation and Storage (49-56)	0.56	0.17	0.04	0.05	0.74
Information and Communication (58-63)	0.64	0.18	0.18	0.23	0.77
Financial and Insurance (64-66)	0.68	0.18	0.08	0.13	0.63
Real Estate (68)	0.51	0.34	0.08	0.17	0.49
Professional, Scientific and Technical activities (69-75)	0.63	0.17	0.11	0.15	0.72
Administrative and Support activities (77-82)	0.65	0.23	0.11	0.10	1.12
Average	0.60	0.24	0.10	0.08	1.38

Note: The results in this table are from the ACF estimator. All regressions include industry and year fixed effects. Standard errors are clustered at the firm level. All estimates are significant at the 1%, except for the IT capital variables of Agriculture, Forestry and Fishing and Mining and Quarrying that are significant at the 5% level and the labor and non IT capital variables of Mining and Quarrying that are insignificant.

The manufacturing industries have lower IT intensity, as measured by the ratio of IT capital to value added, than the services industries. Because the output elasticity of IT capital is relatively high in manufacturing industries compared to the average output elasticity of IT capital in services industries, the marginal product of IT capital is higher for manufacturing industries. An interesting finding is that the marginal product is high for utilities and construction industries. Also for mining and quarrying industries this is the case, but given that the number of observations for these industries is low and the production function coefficients are insignificant, we do not want to make strong claims on this result.

[12] For the manufacturing sector, $MP_{K^{IT}} = \frac{0.1049}{0.0687} = 1.53$; $MP_{K^{NIT}} = \frac{0.2374}{1.2181} = 0.19$; $MP_L = \frac{0.6494}{0.6817} = 0.95$ and for the services sector $MP_{K^{IT}} = \frac{0.0913}{0.1145} = 0.80$; $MP_{K^{NIT}} = \frac{0.2134}{1.5094} = 0.14$; $MP_L = \frac{0.6302}{0.6511} = 0.97$.

For the services industries, the output elasticity of IT capital is highest for the Information and Communication industries. This is consistent with Bosworth and Triplett (2007), who show that productivity growth from IT capital within the services sector was highest for these industries. However, since also IT intensity is highest in these industries, the marginal product of IT capital is below the average for the information and communication industries. Abstracting from potential discrepancies in adjustment costs across industries, creating output growth through investments in IT will be hardest in these industries that have the a relatively high IT intensity compared to the output elasticity of IT capital. The high IT intensity in services industries compared to the manufacturing industries explains why the marginal product is on average lower for services industries. The wholesale and retail industries and for administrative and support activities industries are notable exceptions as they have marginal products of IT capital that are above 1. Together these industries account for 23% of employment and 21% of Belgian GDP. Investing an additional euro in IT capital in these industries, results in a gross rate of return of respectively 1.26 and 1.12euros.

4.3 Firm Heterogeneity

Most, if not all, of the previous literature has focused on large firms, often using survey data, but it is unclear whether the earlier findings can be generalized for the population of small firms, who represent the bulk of the economy. Tambe and Hitt (2012) indicate this to be a major shortcoming in the literature on IT and productivity. The returns and costs from IT investments that large firms experience may not reflect the experiences of smaller firms. As shown in figure A2, our dataset comprises both small and large firms. The median firm in our sample employs only 2.5 full time equivalents and the mean of firm employs 13.3 full time equivalents. In this section we fill this caveat in the literature. Table seven divides the population of firms into seven bins according to firm size. For each bin, table 7 shows the results of a split sample estimation of the production function and the marginal product of IT capital.

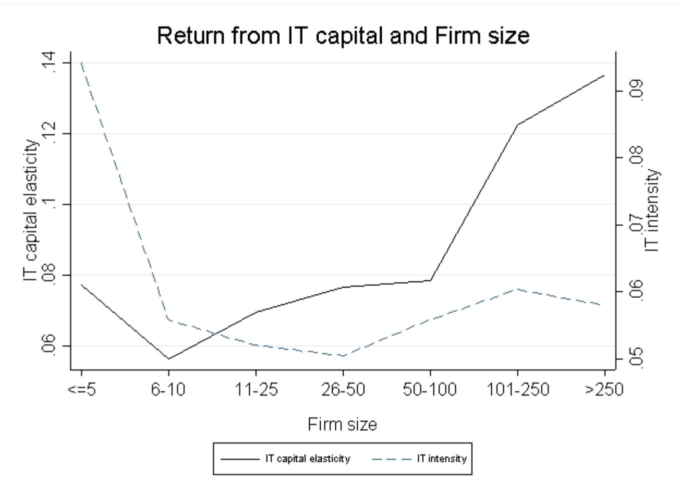
Table 7: Results Value Added Production Function – ACF Estimator

Firm size	# obs	Labor	Non IT Capital	IT Capital	IT input share	Marginal Product IT
<= 5 employees	535681	0.4843	0.2350	0.0770	0.0942	0.8179
6-10 employees	11946	0.7637	0.1790	0.0562	0.0558	1.0078
10-25 employees	97564	0.8025	0.1507	0.0693	0.0521	1.3317
26-50 employees	40680	0.8665	0.1494	0.0766	0.0504	1.5175
50-100 employees	15784	0.8370	0.1205	0.0784	0.0559	1.4022
100-250 employees	10197	0.8167	0.1323	0.1224	0.0604	2.0277
> 250 employees	5941	0.7770	0.1500	0.1366	0.0578	2.3581
Average		0.7640	0.1236	0.0881	0.0610	1.4947

Note: The results in this table are from the ACF estimator. All regressions include industry and year fixed effects. Standard errors are clustered at the firm level. All estimates are significant either at the 1% level. As in section 4.1, the IT input share average is based on winsorized IT input shares at the 1% level to avoid outlier biases.

Some interesting findings emerge when comparing the results for different firm sizes. In section 4.1, which presents results for the entire population of firms, we found an average IT input share of 0.0831 and a marginal product of IT capital equal to 1.24. As is apparent from table seven, there is heterogeneity in firm size underlying these results. The IT input share reported in section 4.1 seems to be driven by the large tail of small firms in the population. For firms with less than five employees, the IT capital input share is on average 9.4% while for firms with more than five employees, the IT input share is between 5-6%. It is puzzling that the output elasticity of IT capital increases with firm size while the IT input share decreases with firm size. Because of the widening gap between the output elasticity and the IT input share, the marginal product of IT capital increases with firm size. This supports the hypothesis that large firms benefit more from IT. Figure 4 shows this graphically.

Figure 3:

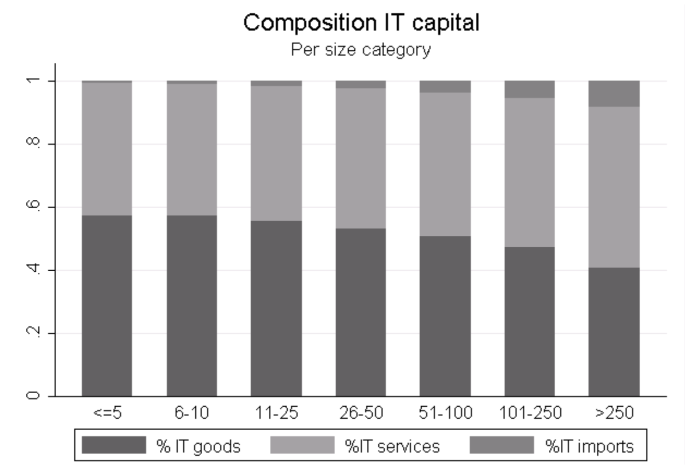


Initially, the output elasticity of IT capital decreases with firm size. Firms with less than five employees have a higher output elasticity for IT capital than firms with 10-25 employees. The trend reverses once firms have more than 25 employees. One theory we believe to be consistent with our results is that small firms have a flexible organizational structure and informal procedures on IT investments. When being small, this agility is beneficial for the firm. The more people are employed in a firm, the more the need arises for organizational structures and formal procedures on IT investments to guarantee results. Mid-sized firms with 5-25 employees are in the grey area where this need arises but formal organization and implementation is often neglected, which could explain lower returns on IT capital for these firms. Once the firm reaches the threshold of 50 employees, the returns from IT capital increase substantially. Firms that exceed this size typically have an IT department or at least personnel that is responsible for following up on the efficiency of the IT structure and making necessary investments to maintain and improve IT systems. An alternative reason for which the trend could reverse for firms with more than 50 employees, is that the output elasticity of IT capital reflects more than just returns from IT capital only. More specifically, the output elasticity could also partly reflect unmeasured complementary assets such as management practices or intrinsic ability of the firm (Bloom et al., 2014). If this is not controlled for, the average return from IT capital could be biased upwards and partly reflecting these omitted variables. Earlier studies of Brynjolfsson and Hitt (1995) already indicated the importance of controlling for individual firm differences in productivity. They found that controlling for individual firm effects accounts for up to half of the productivity benefits attributed to IT. Most earlier studies rely on fixed effects estimators to control for firm effects. While this controls for unobserved heterogeneity in productivity, it also controls for the returns from the part of the IT stock that is persistent over time. Therefore fixed effects estimators are likely to substantially underestimate the returns from IT capital. By applying the ACF and CWDL estimators we control for unobserved differences in firm level productivity and allow this unobserved heterogeneity to vary over time. To the best of our knowledge, this methodology is the state of the art in the production function literature to be robust to potential biases in the IT capital output elasticity from unmeasured intrinsic ability of the firm and management quality. Broersma, McGuckin and Timmer (2003) control for unobserved productivity by including wages as control variable in the production function. As good management is usually costly, wages can proxy for omitted management quality. We find that including wages hardly changes the IT capital coefficient, so our control function approach seems to work well.[13]

Our results indicate there is a size premium in returns on IT capital. Note that there are some implicit assumptions we make on the cost side to arrive at this conclusion. As we have no data on firm level IT depreciation rates, complementary investments and adjustment costs (e.g. training personnel when new IT systems are introduced), we assume such costs to be uncorrelated with firm size. To gain deeper understanding in this size premium, it is useful to compare the composition of IT capital in the different size groups. Figure 4 disentangles IT investments, which are at the basis of the IT capital stocks, for the different size groups.

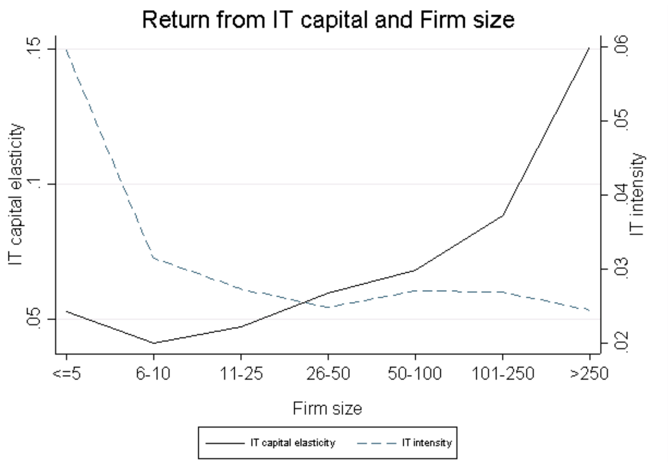
[13] Including wages does however result in lower labor coefficients. This is not surprising since wages also serve as proxy for labor quality.

Figure 4:



The share of IT goods in IT investments, and hence in IT capital, decreases with firm size, while the share of IT services and IT imports increase with firm size. This is an interesting insight itself, but can it explain the size premium in returns on IT capital? If so, the output elasticity of IT capital should not increase with firm size if the capital stock is constructed solely on the basis of IT goods, so neglecting IT services and IT imports. Taking this approach to construct the IT capital stock does not alter our findings. Figure 5 is a replication of figure 3 in which the IT capital stock was constructed solely on the basis of investments in IT goods.

Figure 5:



Our results show that the size premium in returns on IT capital is robust to omitted variable bias and that it cannot be explained by differences in the decomposition of IT capital. Appendix C1 shows robustness for our results based on a random coefficient production function.

4.4 The Solow Paradox

Early work in the literature on returns from IT capital was driven by the famous quote of Robert Solow (1987) *"You can see the computer age everywhere but in the productivity statistics"*. This quote received much attention from academics because productivity growth indeed started to decline right at the moment computer investments took off. By the end of the nineties, the majority of the academics agreed on the importance of IT for productivity (in particular authors as Jorgenson, Stiroh, Brynjolfsson, Stiroh and Ho, Oliner and Sichel, van Ark, Timmer and Mahony). However, recently the resolution of the productivity paradox was questioned by Houseman et al. (2015) who showed that it is crucial to distinguish between IT producing and IT using industries. They found that productivity growth rates in the U.S. between 1997 and 2007 fall by almost half when computer producing industries are excluded. Also Acemoglu et al. (2014) found that IT producing industries drive the positive impact of IT investments on labor productivity. They conclude that the statement of IT to improve productivity in all industries may be exaggerated.

Our detailed micro data allows to investigate the Solow paradox for the Belgian case. There are several issues on IT input and IT output, that confound the measurement of returns from IT investments in earlier studies, to which our study is robust, or in any case more robust. On the input side, measurement error or unreliable measures for IT capital prohibited to construct an accurate measure of IT capital. As designated in section 2 and appendix A, our dataset allows to advance on the issue of measurement error on the input side. On the output side, an often quoted resolution to the paradox is that it is uncertain how long it takes before IT investments pay-off (Brynjolfsson, 1993; Triplett, 1999). In appendix B.8 we experiment with an IT capital stock without depreciation. In this way, old IT investments get more weight than in the baseline specification. This IT measure should be robust to the critique of lagged returns from IT capital. Another often quoted issue to validate the productivity paradox is that the return from IT capital not necessarily translates into higher value added. Often, the returns from IT investments are higher quality or variety of products, better service and responsiveness. At aggregate industry levels, this can result in a redistribution of value added rather than an increase in value added (Brynjolfsson and Yang, 1996). Another argument related to this is that IT capital potentially has become a commodity factor of production, a cost that must be paid by all but provides distinction to none (Carr, 2003). While these issues arise when assessing the impact of IT on productivity at the industry level, our micro-data does not suffer from these issue since our estimator exploits heterogeneity in IT capital at the firm level to estimate the impact of IT capital on productivity.[14] Our assessment of returns from IT capital is robust to

[14] Some issues remain. For example, IT investments could enable a firm to provide a better service. As our output measure is value added, we only capture the benefits from IT to the extent that there is heterogeneity in returns in terms of value added from IT capital. If better service becomes a commodity in the industry and there is no heterogeneity at

mismeasurement on the input side, potential lagged effects of IT investments and the criticism that IT investments would induce a redistribution of value added rather than an increase in value added. As detailed in section 4.1 and robustness checks in appendix B, we find that IT capital contributes to output expressed in value added. Our results furthermore show that the net rate of return from IT investments is larger than zero. While Houseman et al. (2015) and Acemoglu et al. (2014) suggest that it are only a subset of industries, namely those that produce IT related goods or use IT intensively, that benefit from IT, we find positive returns from IT capital across industries. So we do see IT in the productivity statistics and can refute the Solow paradox.

4.5 IT and TFP dispersion

So far, we have shown that the returns to IT capital are positive and substantial. In this section we derive how important IT is in explaining productivity dispersion. To get a sense on how much of the variation IT explains, we investigate how much of the 90-10 TFP spread can be accounted for by IT investments per worker. We compare the explained spread in productivity from IT investments with the spread in productivity explained by human capital. We focus on these two determinants because they are prominent drivers of productivity dispersion amongst firms, see Syverson (2011).[15] As we compared returns from IT capital in Belgium mostly with returns from IT capital in the United States throughout the paper, we continue to do so in this part of our analysis. To this end, we apply the same analysis as Bloom et al. (2017) and show their results next to ours.

Table 9: Drivers of TFP dispersion

Dependent variable is demeaned TFP	Belgium			United States		
	(1)	(2)	(3)	(1)	(2)	(3)
IT investments per worker	0.0742***		0.0693***	0.015***		0.008***
	(0.0010)		(0.0010)	(0.003)		(0.002)
Skills (% employees highly educated)		0.1566***	0.1015***		0.527***	0.126**
		(0.0043)	(0.0043)		(0.060)	(0.057)
Share of 90-10 explained	0.1982	0.0360	0.2083	0.0752	0.111	-
# firms	131900	131900	131900	17843	17843	17843

Note: *** is significant at 1% level. Standard errors are clustered at the firm level. The Belgian regressions are OLS regressions with as dependent NACE 4 industry demeaned TFP. IT investments per worker are equal to log(IT purchases / FTE employment) and skills is equal to the ratio of highly educated employees to total employees. The US regressions are OLS regressions with as dependent NAICS 6 industry demeaned TFP. IT investments are investments in computers per employee and skills are measured by the share of employees with a college degree. The 'share of 90-10 explained' is obtained by multiplying the regression coefficient of the variable of interest with the 90-10 distribution spread of this variable and dividing this by the 90-10 spread of the dependent (TFP). Specification (3) of the United States cannot be directly compared to its counterpart of Belgium since the United States analysis also includes management and R&D as drivers of TFP, which we have no data on.

the firm level, then there will not be a value added premium for better service quality. As we only measure the returns in terms of value added and ignore e.g. consumer surplus from better service quality, we could still underestimate the actual returns from IT capital.

[15] Other important factors are R&D expenditures and management practices. As we have no firm level measures of these factors in our dataset, we abstract from these.

IT investments per worker explain about 20% of the dispersion in productivity amongst firms, which is close to what Bloom et al. (2017) find for management. Human capital only explains about 4% in productivity dispersion amongst firms, while it explains around 11% of TFP dispersion in the U.S. Together, IT and human capital explain about one fifth of productivity dispersion in the Belgian economy. Given that 50% of firm-level TFP is measurement error (Collard-Wexler, 2011; Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry, 2016), these findings suggest that IT and human capital actually explain nearly half of total productivity dispersion in the economy.

It stands out that the share of TFP dispersion that is explained by IT investments per worker is substantially larger in our Belgian data than in Bloom et al. (2017) for the U.S. They find that IT explains for only about 8% of firm level TFP dispersion. Part of this discrepancy can be explained by the difference in firm size between the samples. The average firm size in the study of Bloom et al. (2017) is 167 employees, while in our sample this is only 13.3 employees. When we drop firms with less than 50employees from our sample, the coefficient on IT investments per worker from model (3) decreases from 0.0693 to 0.0247 while the coefficient on the skills variable increases from 0.1015 to 0.3164. The share of the 90-10 spread in TFP explained by IT investments drops from 0.1982 to 0.1471 while the share of 90-10 spread in TFP explained by human capital increases from 0.0360 to 0.2075. These results are closer to those reported by Bloom et al. (2017). Altogether, IT investments and human capital explain a large part of firm level TFP dispersion. IT investments explain relatively more of the dispersion in TFP in small firms compared to large firms while human capital explains relatively more of the dispersion in TFP in large firms than in small firms.

5. Conclusion

Our society is increasingly transformed by IT, therefore it is important to understand the economic impact of IT. This paper provides new firm level evidence on returns from IT capital, which is possible by using a hitherto unexploited dataset. More specifically, we merged VAT transactions data on IT expenditures with IT import data and annual accounts data, resulting in a sample of 232.866 private sector firms that we observe for the period 2002-2013. The data on IT expenditures covers both tangible and intangible IT purchases. This is a more comprehensive measure of IT capital than in earlier studies, which often relied on the number of computers per worker and hence exclude the intangible component of IT capital, e.g. Bloom et al. (2010). Another interesting feature of our dataset is that all firms with limited liability are included, so the dataset contains both small and large firms, while earlier work was mostly, if not all, on large firms. We use the Perpetual Inventory Method to construct an IT capital stock and a non IT capital stock for each firm. An augmented production function is estimated using state of the art techniques to avoid biases from unobserved heterogeneity in productivity. More specifically, we use the Ackerberg, Caves and Frazer (2015) and Collard-Wexler and De Loecker (2016) estimators to this end.

We find robustness for an output elasticity of IT capital around 0.10. This is higher than in earlier studies, where the output elasticity of IT capital was usually estimated around 0.05-0.06 (Cardona et al., 2013). The gap between the output elasticity of IT capital and its input share is substantial, and higher than for other production factors. This results in a higher marginal product for IT capital than for other production inputs, a finding that is consistent with earlier studies on IT capital. The novelty in our study, apart from how we construct the IT capital stock, is that we can determine the micro origins of these excess returns in terms of industry and firm heterogeneity. We show that both at the industry and firm level, there are differences in the output elasticity and marginal product of IT capital. We find that marginal product of IT capital is higher in manufacturing industries than in services industries and that there is a size premium in returns on IT capital. These findings are robust to potential endogeneity from omitted firm specific unobserved heterogeneity in productivity. Furthermore, we revisit the Solow paradox. Our inquiry on the revival of the Solow paradox refutes recent rejections of previous resolutions, we do see IT capital contributing to output, and this effect is not only confined to the IT producing and IT using industries. Last, we investigated the impact of IT on TFP dispersion. We find that IT investments explain about 20 percent of the dispersion in measured productivity. In the cross section of small firms, IT investments explains more of the dispersion in TFP than in large firms. Taking into account measurement error in firm level TFP, IT and human capital explain up to half of the dispersion in TFP in the Belgian economy.

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Additional Tables

Table A1: Overview other studies elasticity of IT capital

Authors	Elasticity	Unit	Data		Region	N/year
			Start	End		
Our paper	+-0.10	Firm	2002	2013	Belgium	120000
Van Reenen et al. (2010)	0.023	Firm	1998	2008	Europe	1900
Black and Lynch (2001)	0.05	Firm	1987	1993	U.S.	638
Black and Lynch (2004)	0.296	Firm	1993	1996	U.S.	284
Bresnahan et al. (2002)	0.035	Firm	1987	1994	U.S.	300
Brynjolfsson and Hitt (1995)	0.052	Firm	1988	1992	U.S.	n.a.
Brynjolfsson (1996)	0.044	Firm	1987	1991	U.S.	702
Brynjolfsson and Hitt (2003)	0.058	Firm	1987	1994	U.S.	1324
Dewan and Min (1997)	0.09	Firm	1988	1992	U.S.	773
Gilchrist et al. (2001)	0.021	Firm	1986	1993	U.S.	580
Brynjolfsson and Hitt (1996b)	0.048	Firm	1988	1992	U.S.	370
Lichtenberg (1995)	0.098	Firm	1988	1991	U.S.	1315
Tambe and Hitt (2011)	0.041	Firm	1987	2006	U.S.	1800
Bertschek and Kaiser (2004)	0.152	Firm	2000	2000	Europe	212
Bloom et al. (2010)	0.015	Firm	1995	2003	Europe	4809
Hempell et al. (2004)	0.041	Firm	1996	1998	Europe	972
Hempell (2005a)	0.06	Firm	1994	1999	Europe	1177
Mahr and Kretschmer (2010)	0.13	Firm	2000	2008	Europe	182
Hempell (2005b)	0.049	Firm	1994	1999	Europe	1222
Loveman (1994)	-0.06	Firm	1978	1984	Worldwide	60
Basant et al. (2006)	0.115	Firm	2003	2003	Asia	266
McGuckin and Stiroh (2002)	0.17	Industry	1980	1996	U.S.	10
Stiroh (2002a)	-0.071	Industry	1973	1999	U.S.	18
Acharya and Basu (2010)	0.031	Industry	1973	2004	Worldwide	384
O'Mahony and Vecchi (2005)	0.066	Industry	1976	2000	Worldwide	55
Venturini (2009)	0.138	Country	1980	2004	Europe	15
Dewan and Kraemer (2000)	-0.013	Country	1985	1993	Worldwide	36
Koutroumpis (2009)	0.012	Country	2002	2007	Worldwide	22
Madden and Savage (2000)	0.162	Country	1975	1990	Worldwide	43
Röller and Waverman (2001)	0.045	Country	1970	1990	Worldwide	21
Sridhar (2007)	0.15	Country	1990	2001	Worldwide	63

Source: Cardona et al. 2013

Additional Figures

Figure A1:

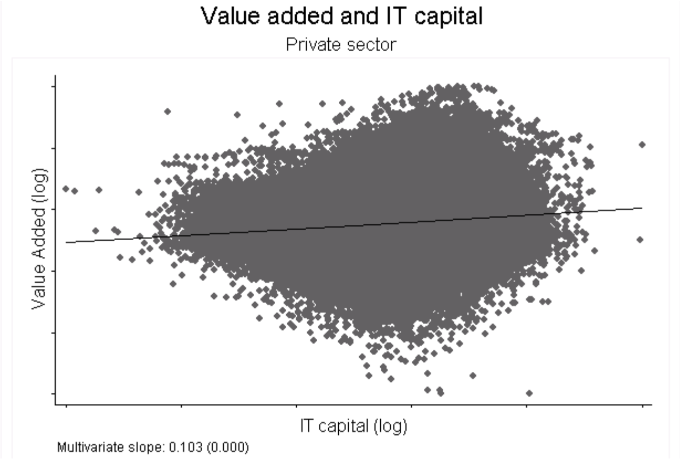
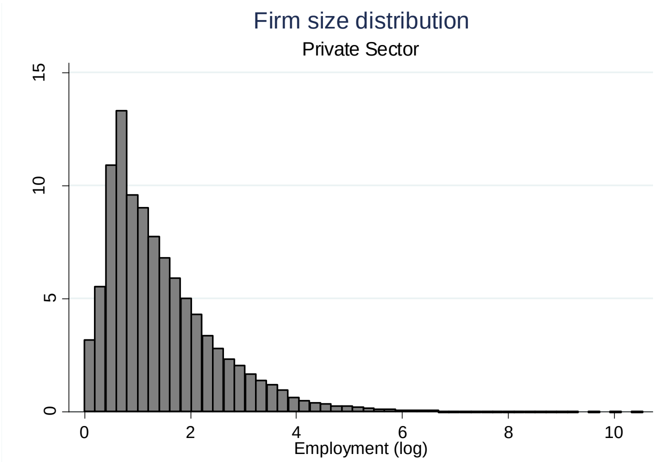


Figure A1 shows the positive relation between value added and IT capital after removing variation in value added from non-IT capital, labor and industry- and time-fixed effects for the entire private sector. The graph shows a positive association between IT capital and added value, with a slope coefficient around 0.10. It is also apparent that there is a lot of heterogeneity underlying this effect, this is discussed in the sections on industry and firm heterogeneity.

Figure A2



Notes: Histogram of firm size of all firms in private sector for which we can obtain IT capital. Employment figures from the social balance sheets only include those who are in the personnel register of the firm. Managers and directors are often not included in the personnel register. To correct for this, we add one full time equivalent for each firm.

Appendix A: Data

A 1. VAT transaction data

We use VAT declarations, yearly customer filings and import data at the product-firm level to construct non-IT and IT capital stocks at the firm level. Each firm with limited liability is obliged to report to the federal public service of finance all its purchases and sales for tax purposes. These declarations are a rich source of information, from which we can deduce how much non-IT and IT investments firms make. This will in turn allow us to construct non-IT and IT capital stocks (see section B 2.).

On their VAT declaration, firms have to specify how much assets they bought in Belgium or abroad. This is a direct measure for the total investments of a firms. Combining this information with the IT investments of the firm allows to obtain non IT investments. IT investments are obtained from the VAT customer listings firms have to hand in each year. In this listing, firms have to report the VAT number and total sales of each customer.[16] Of course, this also learns how much the customers bought. We exploit this information to obtain IT purchases for each customer. More specifically, we use the customer listings of firms that are active in NACE codes of IT goods and IT services industries (see appendix D). From their customer listings, we deduce how much IT goods and IT services each of its customers bought. For each customer, we sum its IT purchases over all IT producing firms. This sum is our firm level measure for Belgian IT investments. We add to this the IT purchases from abroad, which we retrieve from the customs for imports coming outside the EU and the intrastat trade survey for imports to Belgium coming from within the EU, to obtain the IT investments of the firm. By deducting IT investments from total investments, we retrieve non-IT investments of the firm.

Figure A2a shows how ICT purchases as a fraction of total revenue matters in the various 2-digit NACE manufacturing sectors in Belgium and Figure A2b plots the same for the service sectors. We aggregated the firm level ICT purchases and firm level sales up to the level of the 2-digit primary NACE sectors they belong to. We can note that ICT producing sectors have a relatively higher ICT intensity than other sectors. Other sectors in manufacturing that are intensive users are Manufacturing of Printing and Reproduction of Recorded Media and Manufacturing of Other Transport Equipment. In services we see that especially the computer related services have high ICT intensities, as expected, but also financial services tend to be relatively intensive in the use of ICT.

[16] Natural persons are excluded. The customer listing serves taxation purposes, hence firms only have to report customers in this listing that are also subject to the VAT system, so basically all firms with limited liability.

Figure A2a: Distribution of IT intensity in Manufacturing

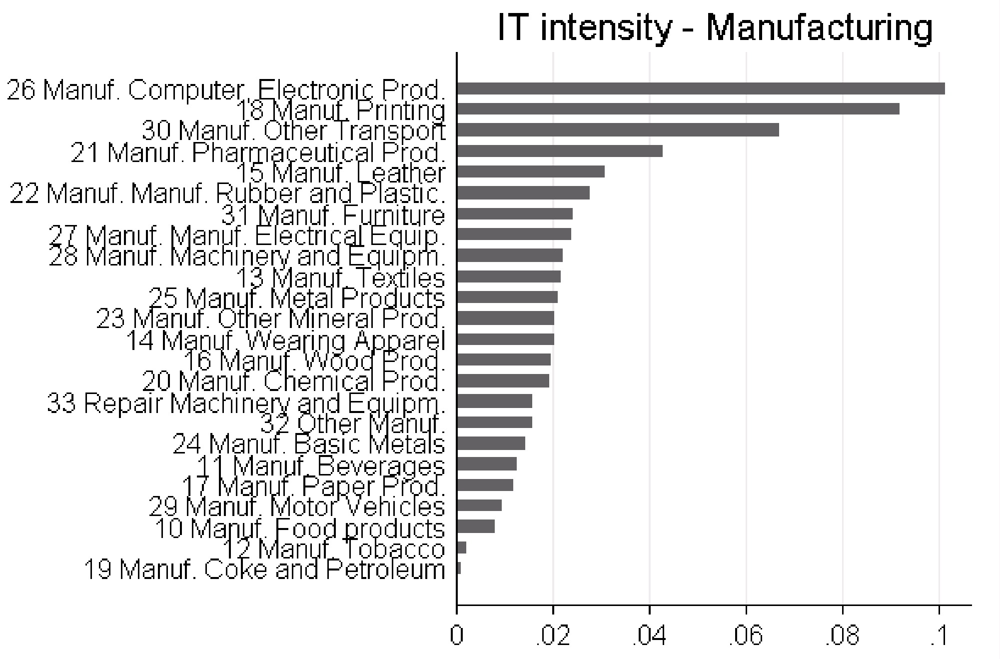
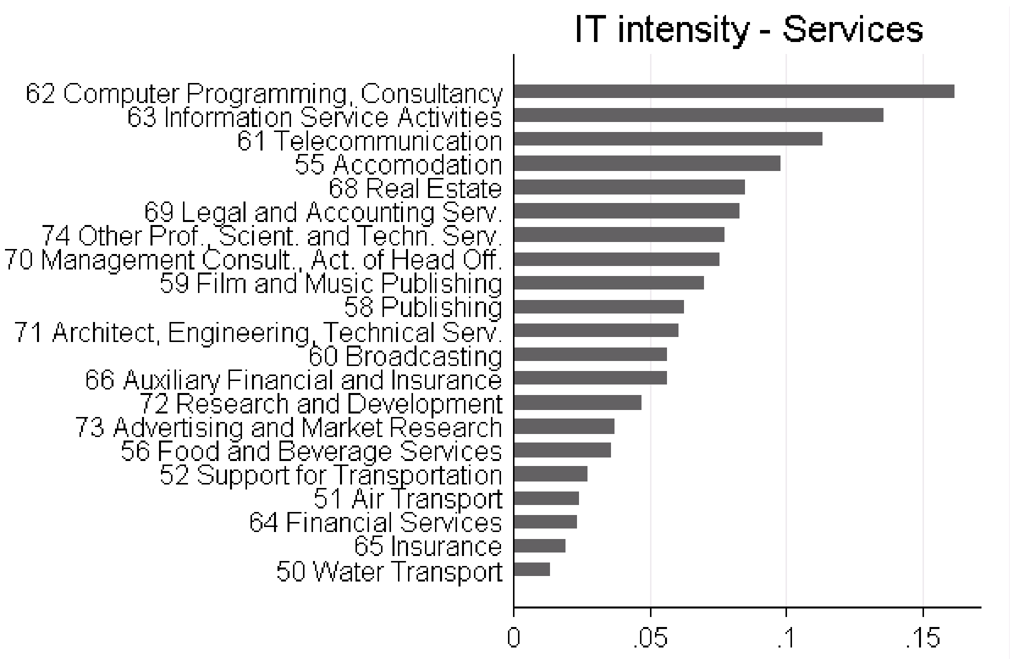


Figure A2b: Distribution of IT intensity in Services



A 2. Construction capital stocks

We construct a real IT capital stock and a real non IT capital stock using the Perpetual Inventory Method (PIM). This method allows us to optimally exploit our unique data on IT purchases and total investments from the VAT transactions dataset. The formula of the PIM is the following:

$$K_{it}^{(N)IT} = K_{it-1}^{(N)IT} * \left(1 - \delta^{(N)IT}\right) + I_{it}^{(N)IT} \tag{1}$$

In which $K_{it}^{(N)IT}$ refers to the real (non-)IT capital stock of firm i in year t, $\delta^{(N)IT}$ refers to the depreciation rate for (non-)IT capital and $I_{it}^{(N)IT}$ refers to real (non-)IT investments. We rely on data of the EU KLEMS initiative to turn the nominal values that we can retrieve from our dataset into real values.[17] To this end, the EU KLEMS dataset provides gross fixed capital formation deflators separately for IT investments and non-IT investments at the 2 two-digit level for the entire period of our sample. Also, the EU KLEMS data contains information on depreciation rates for both IT and non-IT capital. The yearly depreciation rate for IT capital is fixed to 31.5 percent. This is consistent with IT capital depreciation rates in other research. The average of the depreciation rate for transport equipment, other machinery equipment, dwellings, other buildings and structures is always close to 8 percent, which we take as fixed depreciation rate for non-IT capital.

The first step in applying the PIM is to calculate the initial IT and non-IT capital stocks since IT capital is part of total fixed assets, but not reported separately. To separate IT capital from non-IT capital in the first year a firm is active in the sample, we rely on a firm's IT investment intensity, i.e. the ratio of nominal IT purchases to total nominal investments. Since capital is by definition an accumulation of investments, we assume and believe this ratio to be representative for the percentage of IT capital in the total capital stock. More specifically, we calculate a firm's IT investment intensity for the first four years the firm is active in the sample and take the average of these observations in order to be robust to outlier investments. We limit ourselves to the first four years because for a longer period this intensity measure could be less informative about the initial IT capital stock. Moreover firms can change their business model over time, i.e. becoming more or less IT focused. This is also consistent with the finding that it takes some years before intangible stocks reach steady state in most industries (Knott et al., 2003). The formula for the construction of the initial capital stock is then the following:

$$K_{i0}^{IT} = \frac{\left[\frac{purch_{i0}^{IT}}{inv_{i0}^{IT}} + \frac{purch_{i1}^{IT}}{inv_{i1}^{IT}} + \frac{purch_{i2}^{IT}}{inv_{i2}^{IT}} + \frac{purch_{i3}^{IT}}{inv_{i3}^{IT}}\right]}{4} * TFA_{i0}$$

$$K_{i0}^{NIT} = TFA_{i0} - K_{i0}^{IT}$$

In which the *i* and *t* subscripts refer to firm and year. P$urch^{IT}$ refers to IT expenditures, inv^{IT} to IT investments and TFA to tangible fixed assets from the annual account. Our results are robust to taking a longer or shorter period to determine the average IT investment intensity. For robustness purposes, we also constructed an initial capital stock based on the method proposed by Hall and

[17] More specifically, we rely on the capital input file from the Netherlands in the December 2016 update. There is no capital input file for Belgium so we assume that the prices for IT in the Netherlands are close to those of Belgium.

Mairesse (1995) and used in earlier work on IT capital by Hempell (2002). They build the initial capital stock by supposing that investments in IT capital grow at a constant rate and that IT capital has a constant depreciation rate. Under these assumptions, the initial capital stock can be obtained from:

$$K_{i0}^{IT} = \frac{purch_{i0}^{IT}}{g_i + \delta}$$

$$K_{i0}^{NIT} = TFA_{i0} - K_{i0}^{IT}$$

With g_i the average firm growth rate of IT investments and δ the depreciation rate of IT capital. Both ways of building the initial capital stock give similar results.

Next to the initial capital stocks, the PIM requires real IT and real non-IT investments. Again, we rely on the yearly IT purchases and nominal investments from the VAT transactions dataset. Nominal IT investments are equal to the IT purchases. To obtain nominal non-IT investments, we subtract the nominal IT investments from the nominal total investments. To obtain real investment measures, we deflate our nominal investment measures with the aforementioned EU KLEMS gross fixed capital formation deflators.

There are observations for which reported nominal IT purchases are larger than reported nominal total investments. For such observations, we set nominal non-IT investments equal to zero. Given the novelty of our data, we did several checks on how this could potentially affect our analysis to guarantee that our estimates are not biased. Reporting higher IT purchases than investments can occur for several reasons:

1) *Firms make mistakes in filling in the VAT declarations.* We checked the accounting regulations with accountants and auditors. They ensured that each purchase of IT equipment should be registered as an investment. Nevertheless, they admit that firms sometimes make mistakes against this rules. Such mistakes could be seen as idiosyncratic errors and are not problematic for our analyses.
2) *Firms make mistakes on purpose in filling in the VAT declarations.* Although IT equipment should be registered as an investment, it is interesting for firms to cheat on this and to report IT purchases as intermediate inputs when profits are high. This way, profits are lower and taxes are minimized. Since our productivity measures are TFPR measures, they contain demand shocks, and hence partly reflect profitability. If this mechanism would be at play, IT investments and hence the IT capital stock would be underestimated for firms with high value added. This would result in a downward bias of the correlation between value added and IT capital and hence an underestimation of the output elasticity of IT capital. The output elasticity on IT capital would then be a lower bound estimate of the true output elasticity.
3) *IT purchases are IT consumables, like cartridges and printing paper, rather than IT equipment.* Such expenditures are reported in the VAT declaration as material costs instead of investments. The legal guideline on small IT consumables that cost less than 1000euro, is to report these as material inputs. However, each purchase from an IT producer larger than 250euro is included in our IT purchases variable. Since not all IT purchases are IT investments, our IT investments measure is probably overestimated. As a rough robustness check, we assumed 25% of IT purchases to be IT consumables rather than IT equipment, and this did not affect our estimates.

4) *IT expenditures are effectively intermediate inputs instead of IT investments.* Some industries can have a production process in which IT expenditures serve as inputs. This could for example explain why IT expenditures are higher than investments for 70% of observations in NACE 2680 (Manufacture of magnetic and optical media). Leaving out a set of industries, based on the ratio of observations for which IT expenditures exceed investments, does not alter our findings. We also tried to exploit the time dimension in our data to investigate whether IT expenditures end up in materials rather than in investments. More specifically, we estimated the following model:

$$\Delta m_{it} = \beta_0 + \beta_1 \Delta inv_{it}^{NIT} + \beta_2 \Delta sales_{it} + \beta_3 k_{it} + \beta_4 l_{it} + \beta_{5-510} \Delta purch_{it}^{IT} * Ind_{4digit} + \varepsilon_{it}$$

This model allows to investigate for which four digit industries changes in IT expenditures are correlated with changes in material expenditures. The model includes changes in gross output and changes in non-IT investments to control for increases in material expenditures that originate from increasing demand or non IT investments. Labor and capital are included to control for material expenditures growth because of firm size. The purpose of this model is not to causally infer which industries have a production process in which IT products are used as intermediate input. However, this simple model can help to check whether there is systematically more correlation between IT expenditures and IT investments in some industries. The results indicate that changes in material expenditures are mostly explained by changes in gross output. The coefficient of IT expenditures growth is neither higher nor more often significant for those industries in which there is a high percentage of observations that report higher IT expenditures than investments. These results support that IT expenditures are not systematically reported as material input.

As final robustness check for the aforementioned potential issues, we did our analyses again after dropping all observations for which IT purchases were larger than reported investments.

Table A 2.1 (NACE 1-82)

Value Added Production Function	OLS		ACF	
	All observations	Reduced sample	All observations	Reduced sample
Labor	0.6868***	0.6604***	0.6189***	0.5903***
	(0.0015)	(0.0015)	(0.0035)	(0.0041)
Non IT Capital	0.1621***	0.2144***	0.2257***	0.3189***
	(0.0012)	(0.0014)	(0.0048)	(0.0075)
IT Capital	0.1026***	0.0756***	0.1032***	0.0683***
	(0.0009)	(0.0010)	(0.0028)	(0.0012)
# obs	973386	729923	897119	620572
Industry & Year FE	YES	YES	YES	YES

*** is significant at 1% level. Standard errors are clustered at the firm level.

Dropping observations for which IT expenditures are larger than reported investments lowers the IT capital coefficient and increases the non IT capital coefficient. This is hardly surprising since the highly IT intensive firms are not included anymore and the production function reflects the importance of IT capital in the production process. The qualitative findings regarding returns from IT capital hold.

Appendix B: Robustness checks

All empirical research comes with assumptions and choices on the most appropriate model. To minimize the impact from potential researcher degrees of freedom, this section shows results for alternative data generating processes and alternative modelling assumptions on the capital stocks.

B.1 Alternative Data Generating Processes

In the paper, the same data generating process as in Olley and Pakes (1996) is assumed: firms choose how much IT investments they make in year *t* and these investments become part of the productive capital stock in year *t+1*. This way, there is no simultaneity between current productivity and IT capital, i.e. IT capital is chosen before current productivity was observed by the firm, and since current productivity is controlled for by the control function approach, the identification of the IT capital coefficient is unbiased.

B.1.1 IT investments become productive immediately

Identification problems arise when IT investments become productive immediately. In the main body of the paper, we follow the standard assumption of the productivity literature that it takes one period to install capital. Investments I_t that are observed in the law of motion for capital, $K_t = K_{t-1} * (1-\delta) + I_t$, are decided upon in $t-1$ but only installed and paid in year t. Under the alternative data generating process that IT investments become productive in the same year as they are ordered, I_t is decided upon, installed and paid in year t. This conveys an identification problem since the decision on I_t is now correlated with ξ_{it} in equation (9), i.e. the decision on how much IT capital to employ in the production process in year t is correlated with the productivity shock the firm observes in year t. This discussion is similar to the arguments that Bond and Söderbom (2005) and ACF (2015) raise about the choice of labor. To solve for this potential simultaneity bias, the same way forward as with the labor variable can be applied, i.e. instrument IT capital with its lagged value. Table B.1.1 shows the results from this modeling approach with the ACF estimator.

Table B.1.1 (NACE 1-82)

Value Added Production Function	ACF (1)	ACF (2)
Labor	0.6189***	0.6036***
	(0.0035)	(0.0023)
Non IT Capital	0.2257***	0.0853***
	(0.0048)	(0.0015)
IT Capital	0.1032***	0.0961***
	(0.0028)	(0.0091)
# obs	897119	757213
Industry & Year FE	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level.

Model (1) is the baseline model, in model (2) we instrument IT capital with its lagged value. The results show that the IT capital coefficient does not change significantly, which indicates that our findings are robust to the situation in which IT investments do not take a full period to become productive.

B.1.2 Learning from IT investments

In the results that are presented in the main body of the paper, we abstract from learning from IT investments. Equation (9) explicitly states $\omega_{it} = \omega_{it-1} + \xi_{it}$, so productivity is modeled as if it evolves according to an exogenous process. However, when firms invest in IT in year $t-1$, this may affect their productivity in year t. Doraszelski & Jaumandreu (2013) and De Loecker (2013) show the importance of controlling for learning from R&D and learning from export. We follow their idea for IT and allow in our model that firms improve their performance (productivity) by doing IT investments. We can achieve this by modifying the ACF estimation procedure. In the second stage of the estimation procedure, we explicitly allow the evolution of productivity to depend on previous IT investments: $\omega_{it} = \omega_{it-1} + \mathrm{Inv}_{t-1}^{\mathrm{IT}} + \xi_{it}$. Table B.1.2 shows the results from modeling IT investments experience in the law of motion in three different ways.

Table B.1.2 (NACE 1-82)

Value Added Production Function	ACF (1)	ACF (2)	ACF (3)	ACF (4)
Labor	0.6189***	0.6208***	0.6098***	0.5857***
	(0.0035)	(0.0034)	(0.0039)	(0.0046)
Non IT Capital	0.2257***	0.2236***	0.2462***	0.2235***
	(0.0048)	(0.0046)	(0.0062)	(0.0059)
IT Capital	0.1032***	0.1038***	0.0974***	0.0846***
	(0.0028)	(0.0033)	(0.0033)	(0.0185)
# obs	897119	897119	724129	546746
Industry & Year FE	YES	YES	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level.

Model (1) is the baseline model without allowing for learning from IT investments. Model (2) includes a dummy in the law of motion of productivity that indicates whether or not a firm invested in IT in year $t-1$. Model (3) includes IT investment intensity, defined as the ratio of IT investments to total investments, in year $t-1$ and model (4) includes lagged IT investments directly in the law of motion of productivity. Under learning from past IT investments, we expect the IT capital coefficient to be biased upwards since too much variation in output (controlling for the other production inputs) will be attributed to variation in IT capital when the learning mechanism is not modeled. Indeed, we see that the IT capital coefficient is lower when allowing for learning from past IT investments experience. However, the difference is not significant and our findings remain unchanged.

B.2 Alternative ways to construct IT capital

B.2.1: Including communication goods in IT capital

In the data section we show that communication goods are only a small part of the ICT investments of a firm. Table B.2.1 shows the results when including communication goods such that we obtain an ICT capital stock.

Table B.2.1: Results Private Sector ICT capital (NACE 1-82)

Value Added Production Function	OLS		ACF		CWDL	
	IT	ICT	IT	ICT	IT	ICT
Labor	0.6868***	0.6842***	0.6189***	0.6148***	0.4942***	0.4890***
	(0.0015)	(0.0014)	(0.0035)	(0.0034)	(0.0063)	(0.0061)
Non IT Capital	0.1621***	0.1623***	0.2257***	0.2250***	0.3150***	0.2764***
	(0.0012)	(0.0012)	(0.0048)	(0.0046)	(0.0657)	(0.0674)
IT Capital	0.1026***	0.1051***	0.1032***	0.1103***	0.1497***	0.1711***
	(0.0009)	(0.0009)	(0.0028)	(0.0030)	(0.0364)	(0.0357)
# obs	973386	1006277	897119	925455	319549	337470
Industry & Year FE	YES	YES	YES	YES	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

The output elasticity of ICT capital is not significantly different from the output elasticity of IT capital and all our findings can be generalized for ICT capital.

B.2.2: Calculating initial capital stocks from more aggregated IT intensity measures

Instead of using firm level IT intensity measures, this robustness check shows the results when the initial IT capital stock is derived from more aggregated IT intensity measures. For the OLS and ACF estimator we present the baseline model in (1), and in specification (2) and (3) we apply the same methodology as specified in appendix A but respectively at the two- and four-digit level instead of at the firm level.

Table B.2.2 Alternative initial capital stocks (NACE 1-82)

Value Added	OLS			ACF		
Production Function	(1)	(2)	(3)	(1)	(2)	(3)
Labor	0.6868***	0.7008***	0.6992***	0.6189***	0.6170***	0.6181***
	(0.0015)	(0.0013)	(0.0013)	(0.0035)	(0.0030)	(0.0029)
Non IT Capital	0.1621***	0.1430***	0.1438***	0.2257***	0.2203***	0.2226***
	(0.0012)	(0.0011)	(0.0011)	(0.0048)	(0.0043)	(0.0046)
IT Capital	0.1026***	0.1038***	0.1012***	0.1032***	0.1059***	0.1032***
	(0.0009)	(0.0009)	(0.0009)	(0.0028)	(0.0019)	(0.0017)
# obs	973386	1221649	1246008	897119	1077110	1095678
Industry & Year FE	YES	YES	YES	YES	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level.

This robustness check shows that our results are robust to reducing cross sectional heterogeneity by calculating the initial capital stocks from more aggregate IT intensity measures.

B.2.3: IT capital calculated from IT intensity instead of the PIM approach

The results in the main body of the paper and in other robustness checks applies the PIM method to obtain either IT capital, non-IT capital or both. The PIM approach is standard in the productivity literature. However, as discussed in appendix A, there is some noise on the IT investments variable. We argued in appendix A that there is no pattern in this noise. However, noise in the investment variables could be exacerbated by the PIM approach. Therefore, the following robustness check does not make use of the PIM method. Instead, IT capital is obtained by multiplying a firm's average IT intensity with its total fixed assets.[18] Non-IT capital is obtained by subtracting IT capital from total fixed assets. The results from this approach are shown in model (2) of table B.2.3 and compared with the results of baseline model (1).

Table B.2.3 IT capital calculated from IT intensity (NACE 1-82)

Value Added	OLS		ACF	
Production Function	(1)	(2)	(1)	(2)
Labor	0.6868***	0.7475***	0.6189***	0.7074***
	(0.0015)	(0.0013)	(0.0035)	(0.0019)
Non IT Capital	0.1621***	0.1205***	0.2257***	0.0867***
	(0.0012)	(0.0011)	(0.0048)	(0.0016)
IT Capital	0.1026***	0.0588***	0.1032***	0.0679***
	(0.0009)	(0.0010)	(0.0028)	(0.0022)
# obs	973386	1140273	897119	1052043
Industry & Year FE	YES	YES	YES	YES

Note: *** is significant at 1% level. Standard errors are clustered at the firm level.

Both the IT and non IT capital coefficients are significantly lower in model (2), which is unsurprising given that this approach ignores a large part of cross sectional and time series variation. Therefore we interpret these coefficient estimates as an absolute lower bound.

B.2.4: Only IT capital with PIM approach

IT capital calculated with the PIM method based on IT investments from the VAT data (see appendix A). Non IT capital calculated by subtracting IT capital from the reported book value of tangible fixed assets from the annual accounts data.

Table B.2.4 IT capital with PIM and non IT capital equal to the difference with book value of capital (NACE 1-82)

Value Added Production Function	OLS		ACF		CWDL	
	(1)	(2)	(1)	(2)	(1)	(2)
Labor	0.6868***	0.6961***	0.6189***	0.6585***	0.4942***	0.4671***
	(0.0015)	(0.0013)	(0.0035)	(0.0034)	(0.0063)	(0.0057)
Non IT Capital	0.1621***	0.1570***	0.2257***	0.1246***	0.3150***	0.1537***
	(0.0012)	(0.0010)	(0.0048)	(0.0027)	(0.0657)	(0.0242)
IT Capital	0.1026***	0.0804***	0.1032***	0.1087***	0.1497***	0.1872***
	(0.0009)	(0.0008)	(0.0028)	(0.0034)	(0.0364)	(0.0389)
# obs	973386	943011	897119	842178	319549	312238
Industry & Year FE	YES	YES	YES	YES	YES	YES

Note: *** is significant at 1% level. * is significant at 10% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

This the same approach is followed by Brynjolfsson & Hitt (1996) and shows similar results as in our main specification.

[18] The average IT intensity of a firm over the entire sample period is used since contemporaneous IT intensity could still be subject to outliers in IT investments.

B.2.5: IT capital stock on PIM and non IT capital stock based on book value

The PIM method is applied to obtain the non-IT capital stock of a firm. While this approach is most common in the literature, there are papers that use the book value of reported tangible fixed assets and deflate this with a gross fixed capital formation deflator. Therefore, we show a robustness check following this approach, with the IT capital stock calculated with the PIM method as described in appendix A.

Table B.2.5 IT capital calculated from PIM and non IT capital from book value (NACE 1-82)

Value Added Production Function	OLS		ACF		CWDL	
	(1)	(2)	(1)	(2)	(1)	(2)
Labor	0.6868***	0.7076***	0.6189***	0.6684***	0.4942***	0.5003***
	(0.0015)	(0.0013)	(0.0035)	(0.0033)	(0.0063)	(0.0048)
Non IT Capital	0.1621***	0.1660***	0.2257***	0.1456***	0.3150***	0.1690***
	(0.0012)	(0.0010)	(0.0048)	(0.0028)	(0.0657)	(0.0189)
IT Capital	0.1026***	0.0684***	0.1032***	0.0908***	0.1497***	0.0556*
	(0.0009)	(0.0008)	(0.0028)	(0.0029)	(0.0364)	(0.0292)
# obs	973386	1026577	897119	945749	319549	454394
Industry & Year FE	YES	YES	YES	YES	YES	YES

Note: *** is significant at 1% level. * is significant at 10% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

Since the non-IT capital stock now also contains IT capital, both the coefficients for non-IT capital and IT capital should to be lower. This is exactly what this robustness check shows.

B.2.6: Non depreciating IT capital

An argument often made when estimating the returns from IT capital is that IT investments only contribute to output with a lagged effect. A survey on managers suggested it takes up to five years before IT investments pay off (Brynjolfsson, 1993). Another study of Brynjolfsson (1994) found that it took two to three years before organizational impacts of IT are felt. In our main specification, we apply an annual geometric depreciation rate of 32.5%. Although it is common in the literature to do so, this approach may induce a discrepancy between capital productivity and capital wealth (Harper, 1982).[19] In this study, we are interested the productive IT capital rather than the market value of IT capital. Under lagged returns from IT capital, the true current productive IT capital stock is underestimated which then would potentially result in a biased estimate of the IT output elasticity. The table below shows the estimates for non-depreciating IT capital, which is the most extreme solution to cope with the argument that the productive IT capital stock does not depreciate as fast as its market value.

Table B.2.6 Non depreciating IT capital (NACE 1-82)

Value Added Production Function	OLS		ACF		CWDL	
	(1)	(2)	(1)	(2)	(1)	(2)
Labor	0.6868***	0.6912***	0.6189***	0.6018***	0.4942***	0.4931***
	(0.0015)	(0.0015)	(0.0035)	(0.0040)	(0.0063)	(0.0063)
Non IT Capital	0.1621***	0.1613***	0.2257***	0.2104***	0.3150***	0.1999***
	(0.0012)	(0.0012)	(0.0048)	(0.0047)	(0.0657)	(0.0620)
IT Capital	0.1026***	0.0928***	0.1032***	0.1531***	0.1497***	0.4627***
	(0.0009)	(0.0009)	(0.0028)	(0.0039)	(0.0364)	(0.0437)
# obs	973386	973386	897119	897119	319549	319549
Industry & Year FE	YES	YES	YES	YES	YES	YES

Note: *** is significant at 1% level. * is significant at 10% level. Standard errors are clustered at the firm level. The number of observations for the CWDL estimation is substantially lower because it requires the first and second lag of investments in IT capital and non IT capital while these are not required for the other estimators.

Since IT capital is now assumed not to depreciate over time, the importance of IT capital in the production process is now likely to be overestimated, which is what the results suggest.

[19] The assumption of geometric depreciation avoids the distinction between productive capital and capital wealth. Productive capital reflects the efficiency of capital, which is in theory the marginal rate of technical substitution between old capital and new capital. Capital wealth reflects the market value of capital, which is obtained by depreciating the capital stock to account for changes in the real prices of the assets. Assuming that the efficiency of IT capital declines geometrically over time by the IT capital depreciation rate is not consistent with the finding of lagged returns from IT capital.

Appendix C: Extensions

C.1. Firm size heterogeneity: Random Coefficients production function

We split our sample in bins to investigate the heterogeneity in the return from IT capital for small and large firms. Although dividing the sample into bins of different firm sizes is intuitively appealing, from an econometric perspective this can be argued to be a rather arbitrary approach. Therefore we augment our analyses with a random coefficients model in which we estimate firm specific output elasticities (Swamy, 1970). The random coefficient model fully recognizes firm heterogeneity and exploits the panel data to obtain a firm specific output elasticity for IT capital on top of an output elasticity that represents an average effect for the entire sample. Alcácer et al. (2013) illustrate the potential of random coefficient models in strategic management research and Kasahara, Schrimpf and Suzuki (2017) show how random coefficient production functions can prove to be usefulness in the industrial organization literature by allowing for production functions that are heterogeneous across firms beyond Hicks-neutral technology. We follow Knott (2008) in how to specify the random coefficient model:

$$y_{it} = (\beta_0 + \beta_{0,i}) + (\beta_l + \beta_{l,i})l_{it} + (\beta_{IT} + \beta_{IT,i})k_{it}^{IT} + (\beta_{NIT} + \beta_{NIT,i})k_{it}^{NIT} + \epsilon_{it}$$

In which the coefficients with index i refer to the firm specific output elasticities and the coefficients without this index to the average output elasticity.[20]

Table B.6 (NACE 1-82)

Value Added Production Function	Fixed coefficient	Firm specific coefficient		
		P10	P90	Std. Dev.
Labor	0.5670*** (0.0014)	-0.1984	0.1901	0.1751
Non IT Capital	0.1111*** (0.0010)	-0.0018	0.0017	0.0017
IT Capital	0.0615*** (0.0007)	-0.0026	0.0026	0.0025
# obs	1062259			
Industry & Year FE	YES	YES	YES	YES

10% *** is significant at 1% level. Standard errors are clustered at the firm level.

The fixed coefficients of the production inputs should be compared with the OLS estimates shown in section 4.1. The average effect of the input factors are lower than the OLS estimates. The random coefficient model also provides firm specific coefficients. These are of particular interest in investigating firm size heterogeneity in the output elasticities. Although the focus of this paper is on IT capital, it is interesting to see that there is large firm level heterogeneity on the labor coefficient. The magnitude of firm level capital coefficients is much smaller. Figure C.1.1-C.1.3 below show these firm specific output elasticities of IT capital as a function of firm size. Scatter plot C.1.1 illustrates that the output elasticity of IT capital increases with firm size. This is also apparent from figures C.1.2-C.1.3 which show the mean and the median of the firm specific IT capital output elasticities for the same bins as we used for the split sample estimations. Both the simple split sample analysis and the more elaborate random coefficient estimation support the finding that returns from IT increase with firm size.

[20] Note that, just as with OLS, we ignore potential endogeneity issues in this specification. Kasahara et al. (2017) propose a way forward on this by extending the Gandhi, Navarro, Rivers (2013) framework. As the random coefficient model only serves as robustness check, we retain from these more advanced approaches.

Figure C.1.1

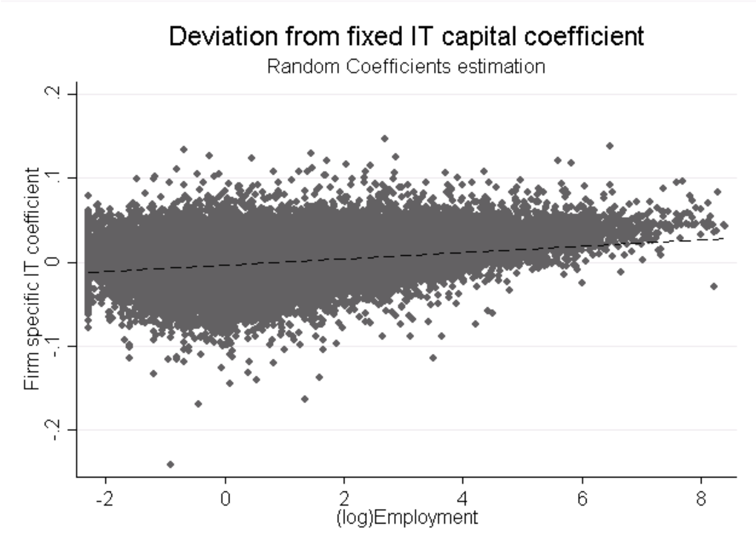


Figure C.1.2

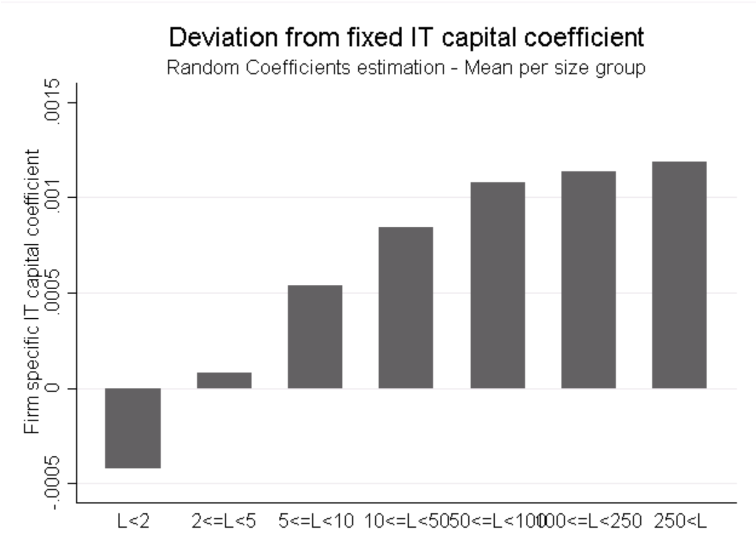
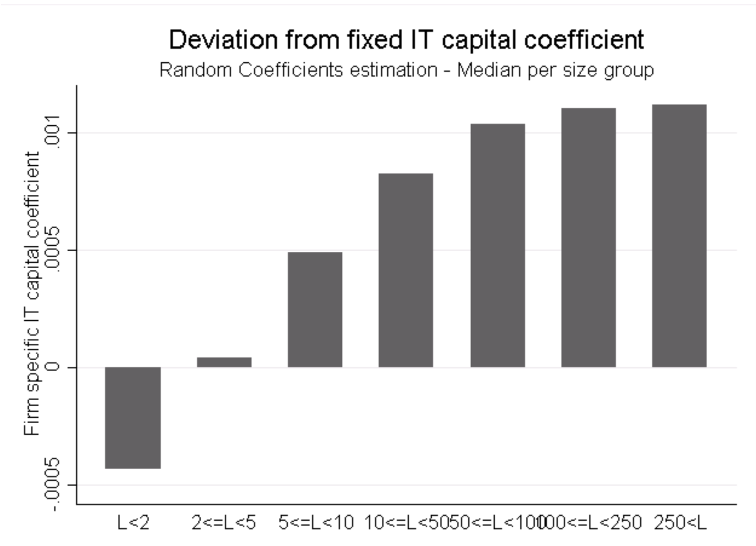


Figure C.1.3



Appendix D: Definitions

To obtain IT investments, we use VAT declarations of firms that are producing IT equipment. Earlier studies used very aggregate (mostly two-digit, sometimes three-digit) definitions of IT producing industries.[21] Data at such aggregate levels comprises more that IT production only. For example, Houseman et al. (2015) and Acemoglu et al. (2014) use data from the NAICS 334 industry, which also includes manufacturing of audio and video equipment; navigational, measuring, electromedical, and control instruments; and magnetic and optical media. The reason they select this industry is because the BEA does not publish more disaggregate data. Having firm level data allows for a more narrow classification of IT producing industries. Firms that are active in the NACE four-digit codes below, are considered to be producing IT equipment.

IT capital

IT goods

Nace-code	Description
2620	Manufacture of computers and peripheral equipment
4651	Wholesale of computers, computer peripheral equipment and software
4741	Retail sale of computers, peripheral units and software in specialized stores
5829	Other software publishing

IT services

Nace-code	Description
6200	Computer programming, consultancy and related activities
6201	Computer programming activities
6202	Computer consultancy activities
6203	Computer facilities management activities
6209	Other information technology and computer service activities
6311	Data processing, hosting and related activities
6312	Web portals

Imports IT goods

Nace-code	Description
2620	Manufacture of computers and peripheral equipment
5829	Other software publishing

Communications capital

Communication goods

Nace-code	Description
2630	Manufacture of communication equipment
4652	Wholesale of electronic and telecommunications equipment and parts
4742	Retail sale of telecommunications equipment in specialized stores

Communication services

Nace-code	Description
6110	Wired telecommunications activities
6120	Wireless telecommunications activities
6130	Satellite telecommunications activities
6190	Other telecommunications activities

Imports communication goods

Nace-code	Description
2630	Manufacture of communication equipment

[21] Examples are Bloom, Draca, Kretschmer, Sadun & Van Reenen (2010), Houseman, Bartik & Sturgeon (2015), Acemoglu, Autor & Dorn (2014), Stiroh (2002) and Van Ark (2002).