Knowledge-based Capital and Productivity Divergence

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Abstract

This paper seeks to determine whether the growing use of Knowledge-Based Capital (KBC) in production drives the divergence of productivity growth between a group of top performing "frontier" firms and the rest of the economy. We use administrative datasets from Germany that record firm-level production variables and investments in four categories of KBC: software, research and development, intellectual property products and organisational capital. We recover firm-specific productivities and elasticities of KBC by implementing a control function estimation procedure, based on a model that allows for non-linearities in the relationship between KBC and productivity. We find that KBC has a positive effect on firm productivity, which increases with KBC and output size, but not with firm-level productivity. We relate these micro findings to industry-level patterns of productivity dynamics. We find that industries with higher average stocks of KBC, a higher marginal effect of KBC on firm productivity, and more marked increasing returns to scale, are those industries where large firms disproportionally improve their productivity compared to other firms, suggesting that KBC is associated with productivity divergence along the size dimension.

Keywords: Knowledge-Based Capital, Productivity, Firm performance
JEL codes: D24, L25, O14, O30

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1 Introduction

Firms in advanced economies are increasingly investing in Knowledge-Based Capital (KBC), which encompasses assets such as Research & Development (R&D) and patents, software, designs, brands and trademarks, and organisational practices. Yearly investments in these assets have reached up to 10% of GDP in countries such as Sweden, the United Kingdom and the United States (Corrado et al., 2016). Furthermore, the positive contribution of these investments to productivity growth has been widely documented.[1] Yet, these investments have not been able to reverse the slowdown of aggregate productivity growth witnessed in these countries. Indeed, across the OECD, the average yearly growth rate of labour productivity declined from 2.3% for the period 1995-2004 to 1.1% for the period 2005-2015 (Syverson, 2017).

In the present paper, we look at the distribution across firms of both KBC and productivity growth to shed light on this puzzle. On the one hand, in any industry, KBC investment is confined to a subset of firms, suggesting that many firms do not have the incentives or ability to exploit this source of growth. On the other hand, the distribution of productivity growth itself is also highly skewed, with some firms sustaining high growth rates that contrast with the general pattern of deceleration (Andrews et al., 2016). By focusing on how the contribution of KBC to productivity varies across firms, we aim to ascertain the role of KBC in productivity divergence. We expect the non-rival property of the knowledge embedded in KBC to generate increasing returns to scale, and thus for the relationship between KBC and productivity to increase with firm size.

The analysis uses extensive firm-level data for Germany for the period 2003-2014, covering 47 detailed industries in the manufacturing sector, as well as knowledge-intensive and other services. The data contain firm expenditures on four KBC assets: software, R&D, organizational capital and Intellectual Property Products (IPP), such as patents, licenses or trademarks. The analysis is split into two stages. The first stage is a firm-level analysis of the effect of KBC on productivity, which allows us to recover firm-specific productivities and elasticities of KBC. We make use of the control function approach of Doraszelski and Jaumandreu (2013) and Ackerberg et al. (2015) to model the role of KBC as directly affecting the evolution of productivity, rather than as an input of production. We specifically allow for this relationship to be non-linear. The estimations are

[1] Early evidence of the importance of KBC for productivity growth is provided by single-country growth accounting exercises, which suggest that, over the period 1995 to 2005, between 20% and 35% of labour productivity growth can be attributed to KBC deepening. See for example Corrado et al. (2009) for the United States, Marrano et al. (2009) for the United Kingdom, Fukao et al. (2009) for Japan and van Ark et al. (2009) for a panel of European countries. Improvements in the measurement of KBC has permitted analyses highlighting that the accumulation of KBC can explain a large share of cross-country and cross-industry differences in labour productivity growth, and that this effect is accentuated by investments in ICT (Roth and Thum, 2013; Niebel et al., 2017; Chen et al., 2016).

carried out separately for each detailed industry. In the second stage, these results are aggregated at the industry level. We compare the evolution of productivity in "frontier" firms, defined as the top 5% of firms in terms of output size or productivity, with the performance of the rest of firms in each industry. We explore whether industries where productivity diverged between the frontier and the rest are also those industries where KBC is more important.

The results from the first stage show that the elasticity of KBC on firm-level productivity is positive across all industries, albeit small in many manufacturing industries. We find consistent evidence of the presence of increasing returns to the size of a firm's stock of KBC, and of a minimum size of this stock below which the effect on productivity is negative. The firm-specific effect of KBC also increases with output size in all but four of the 47 industries: it is 2.4 times higher in the top 20% largest firms than in the bottom 20% smallest firms in the manufacturing sector, and 2.7 times higher in the services sector. By contrast, we find that the firm's level of productivity diminishes the effect of KBC on productivity in 36 of the 47 industries.

In the second part of the analysis, we find that firms on the output frontier are able to grow at a faster rate than the industry average in industries where the average size of KBC, its average elasticity, and the returns to scale are higher. However, we find no such evidence when the frontier is defined along the productivity dimension. Hence, our results imply that the use of KBC does not disproportionally boost productivity on the upper tail of the productivity distribution, as suggested by Andrews et al. (2016). However, the effect of KBC is heterogeneous across firms, and seems to especially benefit large firms.

The structure of the paper is the following: Section 2 discusses the two main strands of literature that motivate our analysis. Section 3 describes the dataset and the measurement of KBC variables. Section 4 presents our structural model of production and the associated estimation strategy used to recover firm-level productivity and KBC elasticity. The results in Section 5 are organised according to the two stages of analysis. We first discuss the results of the structural estimation, focusing on the effect of KBC on firm-level productivity, and some robustness estimations. We then report the industry dynamics of productivity growth, on and off the frontier, and analyse its relationship to KBC. Finally, Section 6 presents our concluding remarks.

2 Related Literature

Our analysis is related to two strands of literature. First, we contribute to the growing micro-level evidence on the role of KBC for productivity, highlighting the importance of firm heterogeneity.

Second, we contribute to the discussion on aggregate productivity dynamics and focus on a potential driver of productivity divergence.

The present analysis is embedded in the line of research that has emerged from the seminal work of Corrado et al. (2005, 2009). The authors acknowledge, contrary to prevailing accounting practices, that a number of expenditures on intangible assets have long-lasting effects on firm performance and should be considered investments, similarly to machinery and buildings. Furthermore, they propose a methodological framework to classify and measure these expenditures. They identify the following three broad categories of knowledge-based assets: computerized information, which covers all information susceptible to be digitalised, innovative property, which is the knowledge, scientific or otherwise, to develop new products, and economic competencies, which is the knowledge embedded in the employees and organisational structures of firms. They suggest that investments in KBC in the United States have increased steadily from around 5% of GDP in the 1950s to around 12% of GDP in 2000, overtaking investment in physical capital in the late 1990s (Corrado et al., 2009). The extension of this methodological framework to most developed economies highlights the broad relevance of this pattern. Over the period 2000-2013, investments in KBC grew at an average annual rate of 2.6% in the United States, and 2.0% in European countries, faster than the growth of investment in physical capital (Corrado et al., 2016).

The individual elements of this broad bundle of KBC and their effect on firm performance have been widely examined.[2] However, analyses encompassing the whole set of knowledge-assets have long been hampered by data availability. Recent efforts to address this issue have resulted in a growing number of studies confirming the overall positive influence of KBC on firm productivity and decomposing the individual contributions of different assets (Crass and Peters, 2014; Bontempi and Mairesse, 2015; Chappell and Jaffe, 2018). Futhermore, KBC investments show strong complementarities between different assets (Bresnahan et al., 2002; Crass and Peters, 2014), and contribute to raising aggregate productivity through spillovers across firms (Marrocu et al., 2011). Haskel and Westlake (2018) argue that the presence of spillovers and complementarities, along with increasing returns resulting from the non-rival nature of the knowledge embedded in these assets, places certain firms at an important advantage to reap the benefits of KBC investments. Indeed, firms need specific human capital, mostly found in large firms, to articulate successfully the variety of investments and to protect the property rights on their intellectual assets. On the contrary, smaller firms have fewer incentives to invest in KBC because they are less able to reap the benefits

[2] For a review of the relationship between productivity and R&D see Ugur et al. (2016), for ICT see Cardona et al. (2013), and for organisational capital see Bloom et al. (2017).

of their investments, while being able to free-ride on those of others.

We make a number of contributions to this literature. First, our research question goes beyond the average effects reported above, and explores whether large firms do observe higher returns on their KBC assets. Second, by estimating a structural model, similar to that of Doraszelski and Jaumandreu (2013) for R&D, we control for the inherent endogeneity involved in estimating productivity. Finally, the extensive coverage of our dataset allows us to account for different production functions across industries and for heterogeneity within industries.

Our analysis is also relevant to the debate around aggregate productivity dynamics. A lot of attention has been devoted to understanding the reasons behind the observed decline of productivity growth across advanced economies.[3] Our analysis does not address this issue head on, but instead seeks to understand how it is compatible with the simultaneous increasing importance of the productivity enhancing factor that is KBC. We follow the insights of Andrews et al. (2015, 2016) and disaggregate productivity growth between a group of top performers and the rest.

Foster et al. (2018) and Haskel and Westlake (2018) have put forward the hypothesis that, in addition to being a driver of average productivity growth, KBC can also be a driver of productivity divergence, accentuating differences between firms. We bring this hypothesis to our detailed micro-level data on investments in KBC, and provide first evidence of the relationship between the effect of KBC on productivity within firms and resulting productivity dynamics at the industry level.

3 Data

The present analysis uses the firm-level datasets collected by the German Statistical Office[4] and used as a source for the construction of the official System of National Accounts (SNA) aggregated data. To ensure the largest possible coverage of the German economy, we combine the AFiD Panel of Manufacturing Firms with the AFiD Panel of Service Firms. Both these datasets consist of multiple sub-datasets, merged through unique firm identifiers. They are described in further detail in Appendix A.

The dataset contains around 1.5 million observations, across 50 detailed industries, in Manufac-

[3] The arguments put forward have emphasised a possible slowdown of technical progress (Gordon, 2012, 2013, 2015), the inability of national accounts to correctly measure the digital economy and its new business models, (Byrne et al., 2016; Syverson, 2017), the strengthening of network effects and the weakening of competitive pressure, or regulatory barriers that have weakened business dynamism and led to a growing number of zombie firms.

[4] Due to Germany's federal structure, its system of statistical offices comprises 16 state-level *Statistical Offices*, and an overarching *German Federal Statistical Office*. The division of responsibility is such that the Federal Office sets common guidelines and the state-level offices are responsible for data collection and processing, and retain ownership of the data. For simplicity we use the term *Statistical Office* without distinguishing between Federal and State level. See www.forschungsdatenzentrum.de for details.

turing, Transport and Warehousing, Information and Communication services, Business services, and Administrative activities.[5] Appendix Table A.1 provides the full list of industries included in the analysis. Appendix Tables A.2, A.3 and A.4 provide a detailed breakdown of the number of observations by year and industry.[6] Complete coverage is available for the period 2009-2014 in the Manufacturing sector, and for the period 2003-2013 for the Services sectors.

We observe firm-level records of standard production variables such as gross value-added, number of employees, payroll, material and energy expenses, and investments in physical capital.[7] To capture the broad bundle of KBC assets, we obtain data on 4 asset categories: software, intellectual property products, research and development, and organisational capital. The last of these variables is constructed from external information on firms' occupational structure obtained from the linked employer-employee dataset (LIAB) of the *Institute for Employment Research (IAB)*.

3.1 Investment in Knowledge-Based assets

The main source of information relating to investment in KBC are the AFiD Panels. Firms are asked to report their "Investments in intangible assets", which captures all expenditures on intangible assets as defined in the SNA. It is split between "Investments in concesssions, patents, licenses, trademarks, etc." and "Investments in software". The first category measures investments in the IPP that firms can report on their balance sheets following the German accounting rules. Investments in software only refer to external purchases of software and databases.[8] This information on software and IPP investments is only collected from 2009 in the manufacturing sector, whereas it is available from 2003 in the services sector.

To capture firms' investments in economic competencies, we follow the widely-used occupation-based method of Corrado et al. (2009, 2005) (as in Niebel et al., 2017; Corrado et al., 2016; Miyagawa and Hisa, 2013; OECD, 2013; Le Mouel and Squicciarini, 2015). This approach relies on the assumption that managers devote 20% of their time to activities that improve the organisational structure of the company over the long run. Hence, 20% of managerial compensation should be

[5] The industry information is presented under the classification *WZ 2008*, the German equivalent of *ISIC Rev. 4*, which came into force in 2008. For the period 2003-2007, the industry information is provided under the classification *WZ 2003*, equivalent to *ISIC Rev. 3.1*, and was converted to the *WZ 2008* using a conversion table.

[6] After data cleaning, the dataset contains a total of 916,673 firm-year observations. We drop observations which lack data on the variables of interest, and drop the following industries from the econometric analysis due to insufficient observations: the mining industry (B05 to B09), the manufacturing of tobacco products (C12), and the manufacturing of refined petroleum products (C19). The real estate industry (L68) is also dropped from the analysis due to missing information on R&D expenditure. Finally, we impute values for value-added and labour for years where we observe unusual growth rates of more than 3000%.

[7] The latter is measured as purchases, sales, new rentals and own-production of machines, tools, and buildings.

[8] Information on software developed in-house is only available from 2012 and is therefore not included in the analysis.

considered long-lasting investments and be capitalised. We obtain the share of managerial wages in firms' total wagebill from the LIAB database, and apply it to the wagebill information present in the AFiD Panel. Firm-specific investment in organisational capital is obtained as 20% of this estimated managerial compensation. The detail of the methodology is provided in Appendix Section A.3.[9]

Finally, investment in innovative property is measured by expenditure on R&D, obtained from the cost structure survey element of the AFiD Panel of Manufacturing firms. All expenses incurred in the R&D process, including investments in capital and intermediary inputs, are covered. This information is not available for firms in the services sectors and we estimate the labour costs of R&D activities in these sectors from the occupational information of the LIAB data in a similar fashion to investment in organisational capital, given that personnel expenditures represent around 60% of total R&D costs in Germany (see OECD Research and Development statistics). We note that the interpretation of the results relating to R&D will therefore differ between the manufacturing and services sectors, but by estimating the model at the 2-digit industry level, we ensure that these different measures of R&D are not pooled into the same estimation.

3.2 Constructing stocks of Knowledge-Based Capital

Following the intuition of Corrado et al. (2005, 2009), we account for the fact that expenditures on knowledge-based assets benefit firms over multiple years and have a cumulative effect. We assume that total KBC stocks, rather than yearly investment flows, improve firm productivity. We apply the perpetual inventory method (PIM) of the OECD and estimate capital stocks for the four KBC assets, as well as tangible capital, from

$$K_{it} = (1 - \delta)K_{it-1} + I_{it} \tag{1}$$

where K_{it} is the current stock of a given asset, I_{it} is current deflated investment in that asset, K_{it-1} is lagged capital stock and δ is the depreciation rate, by asset type, industry and year.

We make the following assumptions regarding deflators, depreciation rates and initial capital stocks. The price deflators for value-added, material expenditure, and investments in tangible capital, software, R&D and other IPP, are taken from the official series provided by the statistical office by 2-digit industry and year. The investment in organisational capital is deflated using the

[9] Our estimates of firm-level organisational capital represent a lower bound compared to other methodologies present in the literature. For example, Corrado et al. (2009) also include purchases of management consulting services in their measure of investment in organisational capital. Alternatively, other authors, (e.g. Eisfeldt and Papanikolaou, 2013; Lev et al., 2009; Chen and Inklaar, 2015) use Sales, General and Administrative (SG&A) expenses. However, our dataset does not contain information on either type of expenditures.

Consumer Price Index. Depreciations rates for R&D, software, IPP and organisational capital are obtained from the OECD (2013). The depreciation rate for tangible capital by 2-digit industry are published as part of the national accounts. Finally, initial capital stocks for the KBC assets are obtained from the steady state assumption: in steady state, the stock of an asset is equal to the ratio of investment over the depreciation rate. Hence, we divide a firm's minimum reported value of investment by the depreciation rate of the year the firm enters the dataset. For physical capital, we adopt a more robust approach, and take the average between two values of initial capital stock. The first value is obtained from the steady state assumption, and the second is the product of the industry capital-labour ratio (provided by the statistical office) with the firm's total labour.

3.3 Descriptive statistics

Table 1 reports the mean and standard deviation of the production variables and the total stock of KBC by 2 digit industry. Our main analysis uses the sum of the four assets as the main variable of interest to acknowledge the fact that the optimal bundle of assets might differ across industries and firms. Descriptive statistics of the four components of the total KBC stock are reported in Appendix Table A.5. The average firm in the manufacturing industry is larger in terms of value-added, labour, and physical capital than the average firm in the service industry. Looking at the distribution of KBC across industries shows large heterogeneity in the importance of this asset. In particular, we find that the bulk of KBC is concentrated in a few industries. The car manufacturing industry stands out as having the highest average stock of KBC of all the industries in our analysis, at €134 million, followed by the pharmaceutical industry where the average stock of KBC is €82million. The service industries with the largest average stock of KBC are Broadcasting and Telecommunications industries, with an average stock of €18 and €14 million respectively. In half of the service industries, the average stock of KBC is less €1 million. In addition, the standard deviation of the stock of KBC suggests large heterogeneity also within industries.

Table 1: Descriptive statistics by 2-digit industry

	VA	Labour†	Capital	Materials	KBC	N		VA	Labour†	Capital	Materials	KBC	N
C10	9.8	210	24.11	34.26	1.37	10337	H51	18.23	120	31.88	43.39	6.37	2047
	(24.42)	(0.37)	(66.17)	(111.69)	(5.98)			(78.45)	(0.49)	(132.52)	(212.48)	(30.04)	
C11	18.86	180	44.23	20.6	1.58	1377	H52	6.24	90	53.14	10.92	1.86	44767
	(48.12)	(0.68)	(132.52)	(68.9)	(6.35)			(58.81)	(0.77)	(1490.75)	(69.46)	(31.21)	
C13	6.18	120	15.45	9.93	1.15	2064	H53	10.68	330	10.53	11.48	0.59	11962
	(12.95)	(0.15)	(27.42)	(21.58)	(4.19)			(266.07)	(5.64)	(203.71)	(191.65)	(14.49)	
C14	8.67	140	13.23	11.07	1.17	1103	J58	7.62	110	4.1	7.17	1.33	15556
	(25.04)	(0.27)	(28.85)	(27.06)	(4.02)			(34.69)	(0.65)	(21.04)	(37.92)	(9.25)	
C15	5.36	110	10.18	9.5	0.78	495	J59	2.13	30	3.05	2.74	0.55	9078
	(6.97)	(0.11)	(12.39)	(18.48)	(2.21)			(16.1)	(0.08)	(13.88)	(12.07)	(7.77)	
C16	6.04	110	15.17	16.27	0.59	2204	J60	31.6	170	21.08	37.04	18.35	1185
	(10.11)	(0.16)	(43.98)	(34.14)	(1.67)			(148.27)	(0.67)	(86.88)	(140.37)	(144.66)	
C17	15.27	220	44.43	33.17	1.56	2431	J61	41.91	280	182.43	68.9	14.18	6180
	(28.26)	(0.36)	(91.76)	(65.55)	(3.94)			(444.33)	(3.66)	(1953.66)	(634.1)	(150.61)	
C18	8.24	140	15.9	10.07	1	1869	J62	4.47	50	3.01	5.06	1.47	62871
	(15.76)	(0.21)	(28.71)	(24.86)	(8.49)			(47.23)	(0.31)	(50.91)	(76.87)	(18.38)	
C20	36.29	330	108.27	61.22	23.25	4524	J63	2.84	50	4.33	2.91	1.23	16901
	(190.8)	(1.44)	(489.75)	(262.37)	(207.24)			(19.49)	(0.44)	(52.37)	(26.96)	(10.65)	
C21	80.88	560	200.4	48.69	82.76	986	L69	1.3	20	0.8	0.5	0.46	118817
	(325.41)	(1.55)	(639.62)	(115)	(477.68)			(15.08)	(0.14)	(6.45)	(7.22)	(17.83)	
C22	15.27	230	27.18	21.07	4.34	4998	M70	3.5	30	5.19	5.14	5.28	51093
	(43.4)	(0.53)	(74.69)	(53.74)	(29.68)			(22.59)	(0.15)	(52.56)	(147.42)	(30.77)	
C23	12.91	190	30.58	14.85	2.52	4002	M71	1.81	20	0.94	1.53	1.92	89018
	(26.37)	(0.3)	(57.63)	(28.56)	(10.08)			(11.3)	(0.12)	(7.6)	(15.04)	(12.39)	
C24	24.76	320	61.2	88.77	3.46	3466	M72	4.3	70	20.07	3.25	0.37	10354
	(83.32)	(0.94)	(219.76)	(366.88)	(24.79)			(35.24)	(0.6)	(181.94)	(20.76)	(2.75)	
C25	10	150	15.13	11.66	2.15	11552	M73	1.64	40	0.87	2.38	1.29	38105
	(19.9)	(0.26)	(31.65)	(28.22)	(11.62)			(8.31)	(0.24)	(12.47)	(11.55)	(5.71)	
C26	25.34	260	45.03	25.54	23.51	4012	M74	0.83	10	0.91	0.96	0.43	26542
	(87.56)	(0.78)	(233.38)	(99.42)	(144.15)			(10.46)	(0.09)	(10.08)	(18.25)	(12.05)	
C27	28.28	360	35.32	32.36	24.24	5592	M75	0.3	10	0.3	0.22	0.01	16666
	(343.78)	(3.6)	(284.81)	(277.16)	(430.89)			(0.52)	(0.01)	(0.59)	(0.51)	(0.1)	
C28	23.16	300	33.97	31.39	15.48	12535	N77	4.01	20	35.44	3.27	0.72	28031
	(122.74)	(1.51)	(237.08)	(149.14)	(275.98)			(37.7)	(0.1)	(239.93)	(31.4)	(8.58)	
C29	118.82	1150	210.42	287.03	134.52	3189	N78	5.85	230	4.27	1.54	0.46	23531
	(960.72)	(8.24)	(1680.3)	(2369.22)	(1294.41)			(33.67)	(1.34)	(374.77)	(48.48)	(13.78)	
C30	44.47	520	74.86	75.38	56	1082	N79	2.09	20	1.54	6.95	0.49	20888
	(174.67)	(1.78)	(363.4)	(336.35)	(455.78)			(29.71)	(0.13)	(26.47)	(99.95)	(6.99)	
C31	8.6	160	12.96	12.9	2.56	2046	N80	3.08	130	2.58	0.88	0.27	9784
	(22.01)	(0.27)	(36.7)	(34.52)	(19.18)			(8.06)	(0.3)	(33.82)	(2.74)	(1.17)	
C32	12.17	170	19.66	8.78	6.08	3292	N81	1.38	90	4.07	0.62	0.13	72869
	(37.43)	(0.39)	(79.28)	(33.01)	(29.12)			(5.94)	(0.38)	(89.77)	(3.74)	(0.7)	
C33	11.87	180	7.86	12.45	3.55	3547	N82	2.73	70	4.06	3.48	1.01	33597
	(50.41)	(0.61)	(28.52)	(73.92)	(36.12)			(14.07)	(0.34)	(40.79)	(21.1)	(7.73)	
H49	2	40	9.23	3.09	0.64	109499	S95	0.48	10	0.24	0.56	0.25	13514
	(28)	(0.39)	(129.6)	(54.15)	(16.49)			(2.35)	(0.04)	(1.3)	(2.98)	(2.66)	
H50	3.5	20	21.7	12.3	0.49	10628							
	(26.88)	(0.11)	(161.51)	(184.12)	(5.99)								

Standard deviation in parentheses; Monetary values in million €: †: head-count number of employees

4 Methodology

The present analysis is centred around the behaviour of firm-level productivity, both in its relationship to KBC within the firm and in its aggregate evolution. As first emphasised by Marschak and Andrews Jr. (1944), recovering productivity from production data is hampered by an inherent endogeneity problem, as firms have information on their productivity level when they make production decisions. From the econometric perspective, this unobserved factor, which is positively correlated with inputs, especially flexible inputs, and output, will introduce bias in the estimations.

To address this issue, we implement the control function approach pioneered by Olley and Pakes (1996) and further developed by Levinsohn and Petrin (2003) and Ackerberg et al. (2015). We specify a structural model of production, where the different inputs of production have different adjustments costs. In particular, we model intermediary inputs to have no adjustments costs, which implies that firms decide upon this expenditure after having observed productivity. The variation in this input can thus be used to control for variation in productivity. Furthermore, we acknowledge the impact of the firm's total stock of KBC on productivity in the model by including it in the law of motion of productivity.

Below, we present the details of our theoretical model and the estimation strategy used to recover firm-level productivity.

4.1 Model of production

Our model consists of two functions: a production function, as spelled out in Equation (2), which dictates how firms transform inputs into output; and the law of motion of productivity, spelled out in Equation (3), which dictates how productivity evolves through time.

Firstly, we assume that firms produce according to a value-added production function of the form

$$y_{it} = f(l_{it}, k_{it}; \boldsymbol{\beta}) + \underbrace{\varepsilon_{it}}_{\omega_{it}+\nu_{it}} \tag{2}$$

where y_{it} is value-added, defined as sales s_{it} minus intermediary inputs m_{it}, l_{it} is labour input and k_{it} is the stock of physical capital, and all variables are in logs. We allow for two different types of unobservables to affect the production function, subsumed in the error term ε_{it}. Firstly, ω_{it} is the firm's productivity, which we are interested in recovering. Secondly, ν_{it} is a mean-zero i.i.d shock, which picks up measurement error or shocks to production, and is unanticipated by firms when they make their production decisions.

Secondly, we follow the literature and assume the evolution of productivity ω_{it} to be governed by a first-order Markov process (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2007; De Loecker and Warzynski, 2012; Doraszelski and Jaumandreu, 2013; Ackerberg et al., 2015):

$$\omega_{it} = E[\omega_{it} \mid \omega_{it-1}, c_{it-1}] + \xi_{it} = g(\omega_{it-1}, c_{it-1}) + \xi_{it} \tag{3}$$

Realised productivity in period t is composed of expected productivity $g(\cdot)$ and a random shock ξ_{it}. Expected productivity has both exogenous and endogenous elements. The former reflects the decay of the previous period's productivity, and the latter takes into account the effect of the firm's decision to invest in KBC. In particular, we model today's productivity as dependent on last period's total stock of KBC, c_{it-1}, which is the sum of R&D capital, software, intellectual property products, and organisational capital.[10] Finally, the productivity shock ξ_{it} is unanticipated but observed by firms when they make their production decisions in period t.

4.2 Estimation of the production function

We follow the identification strategy of Ackerberg et al. (2015), whereby firms choose the level of intermediary inputs that will maximise static, or short-run, profits. The identification of the model is thus determined by the specification of the demand for intermediary inputs m_{it}. As the most flexible input of production, the demand for m_{it} depends on the firm's state variables, which are labour, physical capital and KBC, all decided in the previous period and entering into operation in the current period given the adjustment costs, the realised productivity of period t, and the firm-specific average wage (used as a proxy for all input prices).[11] The intermediate input demand function can thus be expressed as follows

$$m_{it} = h_t(\omega_{it}, l_{it}, k_{it}, c_{it}, \mathrm{w}_{it}) \tag{4}$$

We further assume that productivity is the only unobservable that enters the demand for intermediary inputs and does so monotonically. The function $h(\cdot)$ can thus be inverted to obtain an

[10] We choose to aggregate the different assets into a single capital stock to acknowledge that the optimal composition of innovative expenditures might differ across firms and industries. In Appendix Section C, we relax this assumption and identify the effects of the four individual assets separately.

[11] See De Loecker and Warzynski (2012) for an extended discussion of the relevant variables to include in the demand for intermediary inputs, such as firm-specific input prices.

expression for ω_{it} as a function of observables[12]

$$\omega_{it} = h_t^{-1}(m_{it}, l_{it}, k_{it}, c_{it}, \mathrm{w}_{it}) \tag{5}$$

Productivity ω_{it} is recovered using a two-step estimation procedure. The first stage allows us to net out the effect of the shock to production ν_{it} by controlling for productivity with the proxy function $h_t^{-1}(\cdot)$. The second stage allows us to identify the unbiased production coefficients $\boldsymbol{\beta}$, and to recover productivity.

Estimation of the first stage In the first stage, we substitute ω_{it} in the production function (2) by its expression in (5). We add further controls in the production function measuring the legal status of the firm, its geographical location, and time fixed effects, collected in the vector of control variables $\mathbf{X}_{it}$. Our first stage estimation equation becomes

$$\begin{aligned} y_{it} &= f(l_{it}, k_{it}; \boldsymbol{\beta}) + h_t^{-1}(m_{it}, l_{it}, k_{it}, c_{it}, \mathrm{w}_{it}) + \mathbf{X}_{it}\gamma + \varepsilon_{it} \\ &= \varphi_t(m_{it}, l_{it}, k_{it}, c_{it}, \mathrm{w}_{it}) + \mathbf{X}_{it}\gamma + \varepsilon_{it} \end{aligned} \tag{6}$$

We do not impose a functional form assumption on $h_t^{-1}(\cdot)$, and because the labour and capital inputs enter both the production function $f(\cdot)$ and the function $h_t^{-1}(\cdot)$, we cannot consistently estimate the production coefficients $\boldsymbol{\beta}$ in this first stage.[13] We therefore estimate the generic function $\varphi_{it}(.)$ with a second-degree polynomial approximation, and predict $\hat{\varphi}_{it}$. It follows from equations (5) and (6) that ω_{it} can be predicted, up to the still unknown production coefficients, as:

$$\tilde{\omega}_{it} = \hat{\varphi}_{it}(m_{it}, l_{it}, k_{it}, c_{it}, \mathrm{w}_{it}) - f(l_{it}, k_{it}; \boldsymbol{\beta}) \tag{7}$$

Estimation of the second stage Equation (7) is used to recover the production coefficients $\boldsymbol{\beta}$ in the second stage of the estimation. We substitute unobserved productivity in Equation (3) with its expression in Equation (7) to get

$$\begin{aligned} \tilde{\omega}_{it} &= g(\tilde{\omega}_{it-1}, c_{it-1}) + u_{it} \\ \hat{\varphi}_{it}(\cdot) - f(l_{it}, k_{it}; \boldsymbol{\beta}) &= g(\hat{\varphi}_{it-1}(\cdot) - f(l_{it-1}, k_{it-1}; \boldsymbol{\beta}), c_{it-1}) + u_{it} \end{aligned} \tag{8}$$

[12] See Levinsohn and Petrin (2003) for the proof of invertability.
[13] For an extensive discussion on this issue see Ackerberg et al. (2015).

where u_{it} is the error term of this expression. It includes the unanticipated shock to productivity ξ_{it} and an i.i.d. error that captures measurement error resulting from the fact that we use the predicted values of $\hat{\varphi}_{it}$. While observed by firms in t, this error term is uncorrelated with past productivity and the past stock of KBC, and is used to build a GMM estimator to obtain the production coefficients $\boldsymbol{\beta}$.

Our moment condition is

$$\begin{aligned} &E[u_{it} \mid I_{it-1}] = 0 \\ &E[\tilde{\omega}_{it} - g(\tilde{\omega}_{it-1}, c_{it-1}) \mid I_{it-1}] = 0 \end{aligned} \tag{9}$$

The timing assumptions of our model are used to choose a vector of instruments $\boldsymbol{Z_{it}}$ that satisfies

$$E[u_{it}\boldsymbol{Z_{it}}] = 0 \tag{10}$$

It contains the contemporaneous values of the labour and capital inputs,[14] as well as of KBC. The use of current physical capital stock stems from the assumption, widespread in the literature, that investment conducted in t is decided upon in $t-1$ after ξ_{it-1} has been observed. Current capital stock is theretofore uncorrelated with the productivity shock in t. If labour has high adjustments costs, as it does in countries with rigid employment protection legislation (EPL), its value in t will also be uncorrelated with the productivity shock ξ_{it}.[15] Finally, we extend the assumption found in the literature concerning the relationship between R&D and productivity to hold for all KBC assets (Aw et al., 2011; Doraszelski and Jaumandreu, 2013; Kancs and Siliverstovs, 2016). If a firm decides to invest in R&D and conducts the investment in year t, the effect on productivity will only be witnessed in $t+1$. Consequently, c_{it-1} is uncorrelated with ξ_{it}. We impose the same assumption on the other KBC assets.

Functional form assumptions For our econometric analysis, we need to make functional form assumptions for both $f(\cdot)$ and $g(\cdot)$. Our preferred specification assumes a translog specification for both, such that

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_{ll} l_{it}^2 + \beta_k k_{it} + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \nu_{it} \\ \omega_{it} &= \beta_\omega \omega_{it-1} + \beta_{\omega^2} \omega_{it-1}^2 + \beta_c c_{it-1} + \beta_{c^2} c_{it-1}^2 + \beta_{c\omega} c_{it-1} \omega_{it-1} + \xi_{it} \end{aligned} \tag{11}$$

[14] We include squared and interaction terms as required by our functional form assumptions, discussed in the following paragraph.

[15] Ackerberg et al. (2015) discuss the conditions under which labour can be considered a fixed input, and argue that this is the case in countries with stringent EPL. See (OECD, 2015, p.64) for evidence for Germany.

This functional form assumption offers more flexibility than the commonly used alternative Cobb-Douglas assumption, by allowing the marginal effects of the independent variables on the dependent variable to be firm- and time-specific. The output elasticity of any input Ψ for a translog production function with N inputs, which measures the percentage change in output resulting from a percentage change in that input, is derived as follows[16]

$$\theta_{\psi it} = \frac{\partial Y_{it}/Y_{it}}{\partial \Psi_{it}/\Psi_{it}} = \beta_{\psi} + 2\beta_{\psi^2}\psi_{it} + \sum_{n\neq\psi}^{N} \beta_{\psi n} n_{it} \tag{13}$$

Consequently, the marginal effect of past KBC and past productivity on current productivity are calculated according to

$$\theta_{c_{it-1}} = \frac{\partial \omega_{it}}{\partial c_{it-1}} = \beta_c + 2\beta_{c^2} c_{it-1} + \beta_{c\omega}\omega_{it-1} \tag{14a}$$

$$\theta_{\omega_{it-1}} = \frac{\partial \omega_{it}}{\partial \omega_{it-1}} = \beta_\omega + 2\beta_{\omega^2}\omega_{it-1} + \beta_{c\omega} c_{it-1} \tag{14b}$$

In the remainder of the paper, we focus on the law of motion of productivity. The discussion around the production function $f(\cdot)$ is reported in Appendix Section B, where we present the estimated production coefficients $\boldsymbol{\beta}$ and the calculated output elasticities of labour and capital, θ_l and θ_k, and test an alternative functional form assumption for $f(\cdot)$.

5 Results

5.1 Effect of KBC on firm-level productivity

5.1.1 Main estimation results

The results relating to the relationship between a firm's stock of knowledge assets and its productivity, obtained from the estimation of the law of motion of productivity, are reported in Tables 2 and 3.[17] In the first two columns, we report the mean industry values of θ_c and θ_ω, calculated from Equations (14a) and (14b), along with the standard error of these means in parentheses. θ_c is the elasticity of KBC, describing the percentage change of productivity from increasing a firm's

[16] In our baseline specification, the output elasticities of labour and capital are calculated as follows

$$\theta_{lit} = \frac{\partial y_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it} \tag{12a}$$

$$\theta_{kit} = \frac{\partial y_{it}}{\partial k_{it}} = \beta_k + 2\beta_{kk} k_{it} + \beta_{lk} l_{it} \tag{12b}$$

[17] Throughout, we report results for the manufacturing and services sectors separately, given their different production structures and the different way in which R&D expenditures are measured.

stock of KBC by 1%. θ_ω gives the persistence of the productivity process.

The average effect of KBC on productivity is positive across all sectors of the economy, but the magnitude of the effect differs between the manufacturing and services sectors. In the manufacturing sector, the effect of KBC ranges from a low of 0.001-0.003 in industries with very small average stocks of KBC, to a high of 0.01-0.012 in industries with high stocks of KBC. For example, in industry C29 (*Manufacturing of motor vehicles*), where the average stock of KBC is the highest, at €134 million, increasing a firm's stock of KBC by 1% is associated with 0.011% higher productivity. On the other end of the spectrum, in industry C16 (*Manufacturing of wood products*), which has the lowest average stock of KBC at €500,000, increasing a firm's stock of KBC by 1% is associated with 0.001% higher productivity.

We observe a similar pattern in the services sector, where the magnitude of the effect of KBC on productivity ranges between 0.002 to 0.1. The lowest effect of KBC is found in industry H50 (*Water transport*), where the average stock of KBC stands at €500,000, and the highest effect of KBC is in M70 and M71 (*Management consulting, Architectural and engineering activities*), where the average stock of KBC stands at €5.3 and €1.9 million, respectively.

More generally, the correlation between θ_c and the average stock of KBC is 0.56 in the manufacturing sector and 0.57 in the services sector. In other words, we observe the highest stocks of KBC in industries where its effect on productivity is the highest. Furthermore, we find a strong negative correlation between θ_c and θ_ω, of -0.51 in the manufacturing sector and -0.69 in the services sectors. This implies that productivity displays less persistence in industries where the effect of KBC on productivity is higher.

To understand the non-linearities in the relationship between KBC and productivity, we report the coefficients and standard errors obtained from estimating the law of motion of productivity in the remaining columns of Tables 2 and 3. Of particular interest are the coefficients on the squared term of KBC, β_{c^2}, and on the interaction term between productivity and KBC, $\beta_{c\omega}$. The former tells us whether there are increasing returns to the size of the KBC stock, and the latter whether the effect of KBC on productivity is augmented in more productive firms.

The evidence strongly supports the presence of increasing returns to the size of KBC, as the coefficient β_{c^2} is significantly positive across manufacturing and services sectors, with only four exceptions. Figure 1 offers a visualisation of the increasing returns to KBC stock, by plotting the average θ_c by quintile of KBC stock, with an additional group for the top 5%. The average θ_c increases across the distribution of KBC, and in most industries, it is even higher for the top 5% than for other firms in the top quintile. The only exceptions to this pattern are the four sectors

Table 2: Marginal effect of KBC on productivity and full estimates of law of motion of productivity, by 2-digit industry in Manufacturing

	Average		Point estimates of the law of motion of productivity						
Industry	θ_c	θ_ω	β_ω	β_{ω^2}	β_c	β_{c^2}	$\beta_{c\omega}$	Constant	N
C10	.006	.93	-.231	.041***	.049***	.001***	-.004***	9.29***	9482
	(.00004)	(.0003)	(.16)	(.01)	(.01)	(0)	(0)	(1.16)	
C11	.005	.916	-.244	.092***	.073***	.001***	-.011***	4.216***	1297
	(.00014)	(.0019)	(.16)	(.01)	(.02)	(0)	(0)	(.6)	
C13	.005	.92	1.533***	-.036***	-.024	.001**	.002	-1.893**	1929
	(.00006)	(.0005)	(.18)	(.01)	(.02)	(0)	(0)	(.77)	
C14	.003	.969	.399	.019**	.073***	0	-.004***	4.673**	1053
	(.00008)	(.0007)	(.25)	(.01)	(.03)	(0)	(0)	(1.91)	
C15	.007	.945	1.397***	.012	-.032	.002**	-.001	3.312	469
	(.00035)	(.0005)	(.47)	(.01)	(.06)	(0)	(0)	(4.55)	
C16	.001	.92	1.769***	-.024*	.011	0	-.001	-6.042	1994
	(.00003)	(.0003)	(.48)	(.01)	(.03)	(0)	(0)	(4.2)	
C17	.006	.921	.794***	.012	.027	.002**	-.005	.968	2257
	(.00005)	(.0002)	(.18)	(.01)	(.04)	(0)	(.01)	(.67)	
C18	.009	.908	1.186***	-.017	.015	.002***	-.003	-.481	1635
	(.00014)	(.0005)	(.22)	(.02)	(.01)	(0)	(0)	(.75)	
C20	.01	.931	.884***	.015**	.048***	.002***	-.01***	.17	4222
	(.00005)	(.0003)	(.07)	(.01)	(.01)	(0)	(0)	(.2)	
C21	.013	.869	1.836***	.084***	-.087**	.002***	-.016**	2.099***	913
	(.00017)	(.0016)	(.26)	(.02)	(.04)	(0)	(.01)	(.78)	
C22	.006	.907	.82***	.012	.005	.001***	-.002	.553***	4573
	(.00004)	(.0001)	(.07)	(.01)	(.01)	(0)	(0)	(.14)	
C23	.007	.935	.991***	-.003	-.005	.001***	0	.305	3763
	(.00005)	(0)	(.14)	(.01)	(.01)	(0)	(0)	(.52)	
C24	.004	.855	.757***	.008	.024**	.001***	-.003**	1.457	3275
	(.00004)	(.0002)	(.27)	(.02)	(.01)	(0)	(0)	(1.09)	
C25	.005	.883	1.318***	-.025***	-.021***	.001***	.002**	-.808	10430
	(.00003)	(.0001)	(.16)	(.01)	(.01)	(0)	(0)	(.7)	
C26	.012	.901	.585***	.05***	.048***	.002***	-.013***	.872***	3664
	(.00007)	(.0005)	(.1)	(.01)	(.01)	(0)	(0)	(.23)	
C27	.008	.904	1.132***	-.008	.048***	.001***	-.006***	-.515	5063
	(.00003)	(.0003)	(.13)	(.01)	(.02)	(0)	(0)	(.58)	
C28	.009	.865	1.103***	-.018**	-.043***	.001***	.005***	.371	11500
	(.00003)	(.0001)	(.13)	(.01)	(.01)	(0)	(0)	(.51)	
C29	.011	.873	-.65	.037***	.164***	.001***	-.008***	18.37***	2974
	(.00008)	(.0005)	(.45)	(.01)	(.05)	(0)	(0)	(4.7)	
C30	.007	.914	.898***	.006	.006	.001***	-.003	.323	1000
	(.00011)	(.0003)	(.21)	(.03)	(.01)	(0)	(0)	(.44)	
C31	.023	.858	1.568	-.016	-.053	-.005***	.006	-5.035	1875
	(.00015)	(.0001)	(1.73)	(.04)	(.27)	(0)	(.01)	(19.96)	
C32	.006	.919	-.094	.031***	.033	.001***	-.002	9.687***	3042
	(.00008)	(.0004)	(.32)	(.01)	(.02)	(0)	(0)	(2.6)	
C33	.006	.907	1.035***	-.009	.01	.001***	-.003**	.069	3171
	(.00009)	(.0003)	(.06)	(.01)	(.01)	(0)	(0)	(.17)	

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 3: Marginal effect of KBC on productivity and full estimates of law of motion of productivity, by 2-digit industry in Services

	Average		Point estimates of the law of motion of productivity						
Industry	θ_c	θ_ω	β_ω	β_{ω^2}	β_c	β_{c^2}	$\beta_{c\omega}$	Constant	N
H49	.006	.846	1.956***	-.051***	-.064***	.001***	.006***	-4.358***	75957
	(.00002)	(.0002)	(.05)	(0)	(0)	(0)	(0)	(.28)	
H50	.002	.922	3.024***	-.064***	-.047**	.001	.003**	-15.82***	7454
	(.00005)	(.0012)	(.1)	(0)	(.02)	(0)	(0)	(.83)	
H51	.025	.772	4.526***	-.054***	.22***	.006***	-.007***	-57.4***	1482
	(.00077)	(.0036)	(.18)	(0)	(.08)	(0)	(0)	(3.08)	
H52	.019	.839	1.075***	-.007**	.031***	.003***	-.003***	.354	32179
	(.00006)	(.0001)	(.08)	(0)	(.01)	(0)	(0)	(.55)	
H53	.011	.875	.831***	0	-.034***	.001*	.007***	.853***	7820
	(.00012)	(.0005)	(.01)	(0)	(0)	(0)	(0)	(.04)	
J58	.014	.905	1.286***	-.024***	-.013**	.002***	0	-.77***	10931
	(.00009)	(.0003)	(.04)	(0)	(.01)	(0)	(0)	(.14)	
J59	.022	.888	1.245***	-.016***	-.051***	.003***	.004**	-.663	5869
	(.00017)	(.0003)	(.12)	(.01)	(.02)	(0)	(0)	(.71)	
J60	.022	.907	1.109***	-.002	.142	.003***	-.004	-1.165	838
	(.00035)	(.0007)	(.36)	(.01)	(.14)	(0)	(0)	(6.25)	
J61	.018	.857	.435	.011	.033	.002***	-.002	6.547**	4212
	(.0001)	(.0002)	(.31)	(.01)	(.04)	(0)	(0)	(2.89)	
J62	.016	.84	1.591***	-.035***	.064***	-.002***	-.002*	-2.695***	43097
	(.00002)	(.0002)	(.06)	(0)	(.01)	(0)	(0)	(.31)	
J63	.02	.866	1.532***	-.047***	-.068***	.004***	.006***	-1.262***	10904
	(.00015)	(.0006)	(.05)	(0)	(.01)	(0)	(0)	(.18)	
M69	.004	.872	1.228***	-.024***	-.004	0***	.001***	-.361***	81249
	(.00001)	(.0001)	(.03)	(0)	(0)	(0)	(0)	(.11)	
M70	.098	.739	.302***	.024***	.152***	.015***	-.018***	5.077***	32538
	(.00018)	(.0002)	(.05)	(0)	(.01)	(0)	(0)	(.3)	
M71	.129	.675	-.875***	.127***	.569***	.059***	-.105***	8.032***	59139
	(.00015)	(.0003)	(.05)	(0)	(.02)	(0)	(0)	(.19)	
M72	.026	.927	-.101	.054***	.249***	.028***	-.04***	6.129***	7208
	(.00009)	(.0003)	(.13)	(.01)	(.06)	(0)	(.01)	(.44)	
M73	.043	.82	.545***	.015***	.005	.007***	-.003***	3.037***	26002
	(.00018)	(.0001)	(.05)	(0)	(.01)	(0)	(0)	(.23)	
M74	.01	.855	.773***	.011***	.021***	.002***	-.004***	.816***	17242
	(.00006)	(.0001)	(.04)	(0)	(0)	(0)	(0)	(.09)	
M75	.003	.847	2.471***	-.095***	-.08***	-.001	.01***	-5.622***	11214
	(.00003)	(.0005)	(.19)	(.01)	(.02)	(0)	(0)	(.82)	
N77	.01	.89	.918***	-.001	-.002	.001***	0	2.015*	18494
	(.00006)	(0)	(.12)	(0)	(.01)	(0)	(0)	(1.22)	
N78	.047	.698	.953***	-.01**	.028***	.01***	-.008***	1.182***	16880
	(.00033)	(.0003)	(.07)	(0)	(.01)	(0)	(0)	(.33)	
N79	.048	.814	1.677***	-.041***	-.013	.01***	-.002	-2.679***	14240
	(.00025)	(.0005)	(.08)	(0)	(.01)	(0)	(0)	(.36)	
N80	.102	.748	.512***	.017***	.028	.017***	-.01***	2.961***	6746
	(.00055)	(.0003)	(.09)	(.01)	(.02)	(0)	(0)	(.34)	
N81	.012	.841	.708***	.015***	-.006***	.005***	-.002***	1.047***	48348
	(.00011)	(.0001)	(.02)	(0)	(0)	(0)	(0)	(.06)	
N82	.025	.875	.678***	.021***	.037***	.005***	-.009***	1.163***	22407
	(.00013)	(.0002)	(.03)	(0)	(0)	(0)	(0)	(.09)	
S95	.008	.833	.451***	.082***	.022***	.004***	-.015***	.898***	8586
	(.00023)	(.001)	(.04)	(.01)	(0)	(0)	(0)	(.06)	

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

with a negative β_{c^2}. Futhermore, we observe that the elasticity of KBC stock is negative in the bottom quintile in 11 of the 22 manufacturing sectors and 12 of the 24 services sectors, implying that there is a minimum scale for KBC to be effective.

The evidence concerning the relationship between the effect of KBC and a firm's level of productivity is more mixed. For KBC to be a driving force of productivity divergence between the top performers and the rest of firms, we would expect to find positive values for the coefficient $\beta_{c\omega}$. However, we find a significantly positive coefficient in only two manufacturing industries and only seven service industries. In the majority of industries, this coefficient is significantly negative. This mixed picture is reflected in Figure 2, where the average θ_c is plotted by quintiles of productivity. The elasticity of KBC increases with productivity quintiles in only 8 Manufacturing industries. In services, however, there is evidence of increasing returns to productivity in all but four sectors. The fact that we observe higher θ_c in higher quintiles of productivity, even in industries with a negative $\beta_{c\omega}$, implies that the increasing returns to the stock outweigh the decreasing returns to the level of productivity.

Finally, we plot the average θ_c by quintiles of value-added in Figure 3, to understand how the elasticity of KBC varies with firm size. This picture is very similar to Figure 1, as we find increasing returns to output size in all but 6 of the 47 sectors. Given that output size is not a variable in the law of motion of productivity, this pattern needs to be driven by the correlation of KBC stock with firm size. The effect of KBC on productivity is negative in only 3 industries, suggesting that there is no minimum size of operation required to reap positive benefits from KBC.

When it comes to the effect of KBC, it seems that size is a more important dimension than productivity. We thus expect that any relationship between an industry's KBC and productivity divergence to be more pronounced along the size dimension than the productivity dimension.

Figure 1: Marginal effect of KBC by quintiles of KBC and industry

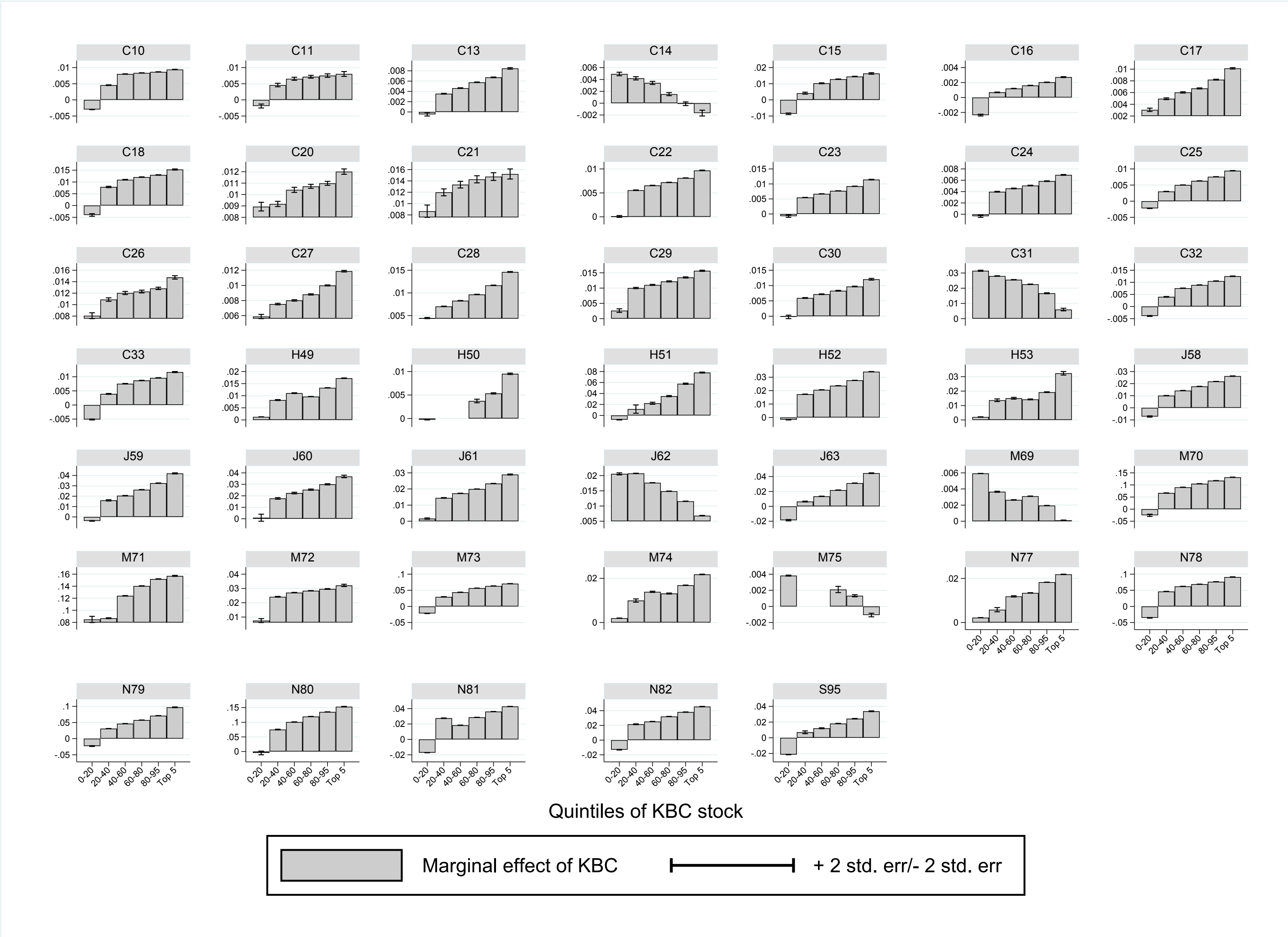


Figure 2: Marginal effect of KBC by quintiles of productivity and industry

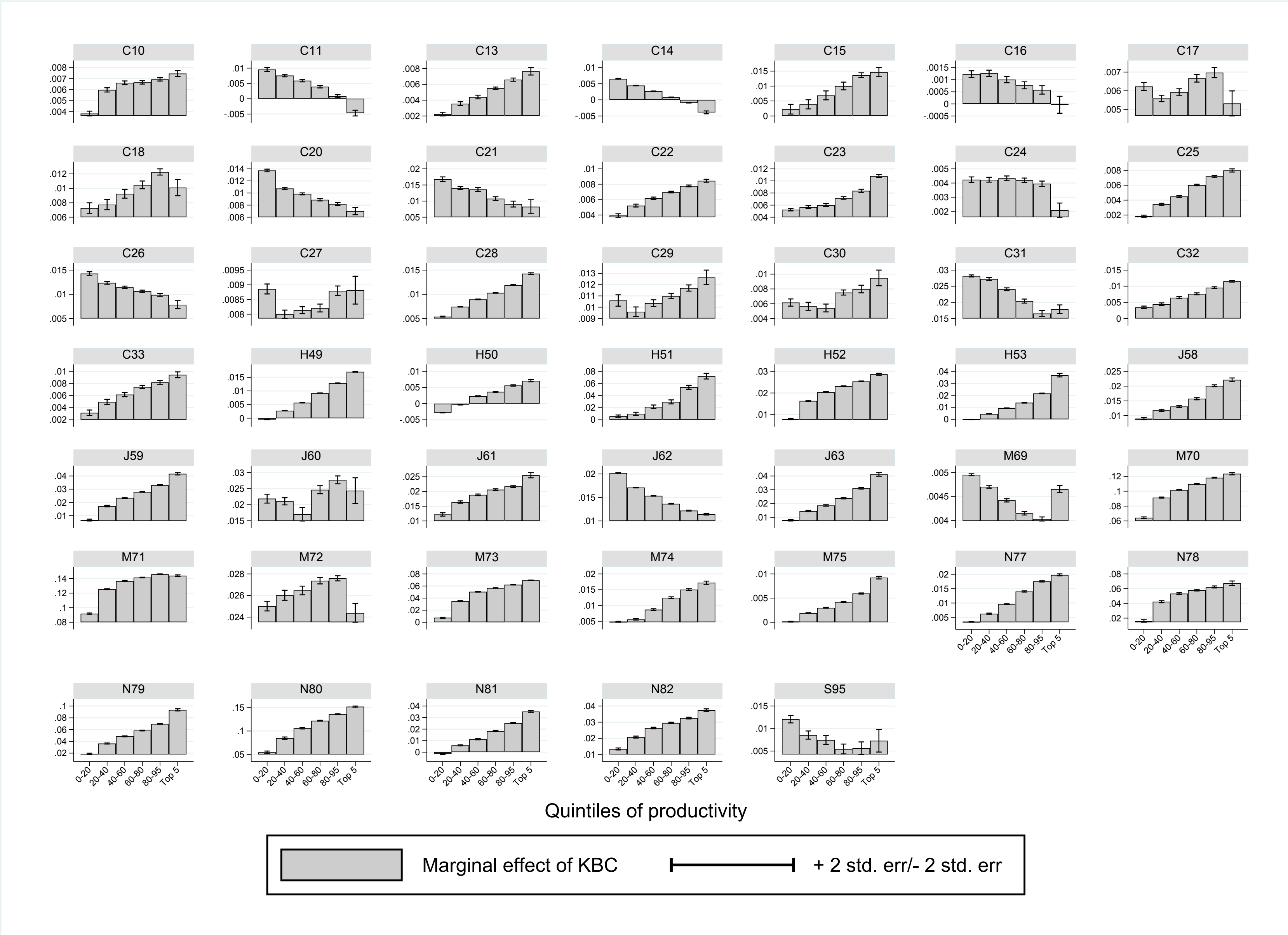
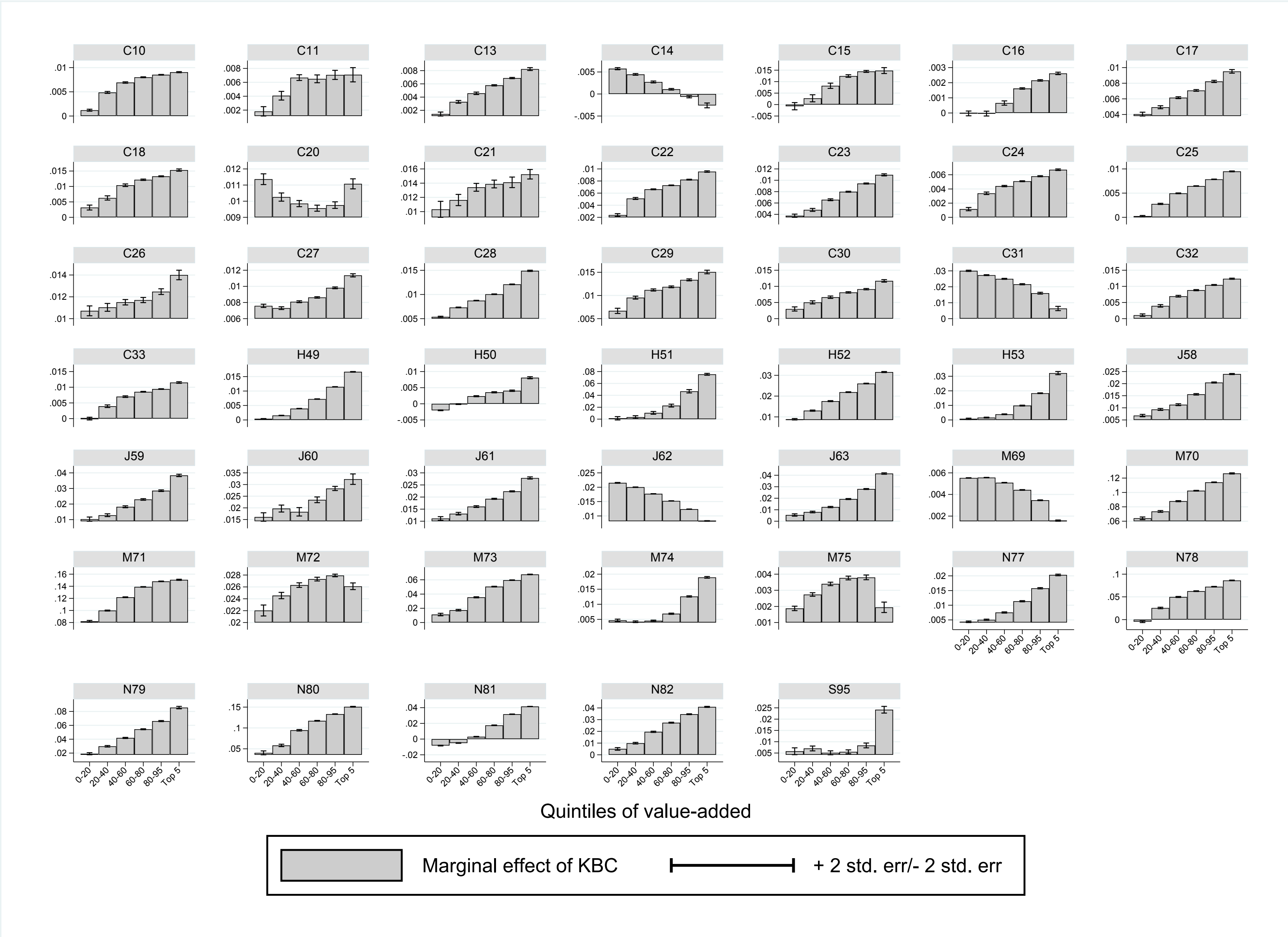


Figure 3: Marginal effect of KBC by quintiles of value-added and industry



5.1.2 Robustness estimations of the law of motion of productivity

In the present subsection, we report additional estimations of the law of motion of productivity, to assess the sensitivity of the results to two assumptions. We present the main point estimates of the sensitivity analyses in Tables 4 and 5, and report the full estimation results in Appendix Section C.

The first robustness check relates to the inclusion of our constructed measure of organisational capital. In the first column of Tables 4 and 5, we report the average θ_c obtained from a model that excludes our constructed measure of organisational capital. We confirm the positive impact of KBC (here the sum of R&D, software and IPP) on productivity, but find an average effect that is lower in magnitude when organisational capital is excluded. The only manufacturing sector which sees a large change in θ_c is C31 (*Manufacturing of Furniture*), which was an outlier in Table 2. In the services sector, the magnitude of θ_c drops noticeably in sectors N78, N79 and N80 (*Temporary employment agencies, Tavel agencies and Security and investigation activities*). In Section 5.2, where we report industry results, we use the results excluding organisational capital for these four industries where we find particularly sensitive estimates.

The second robustness check relaxes the functional form assumption of $g(\cdot)$. The fourth and fifth columns of Tables 4 and 5 report the point estimates of past KBC and past productivity from a linear estimation of the law of motion. In the manufacturing sector, the results do not seem sensitive to the functional form assumption, and the direction of the effect is preserved in all industries (with the excdption of C16 where the effect is now zero). In the services sector, in contrast, we find important differences in six sectors: N78, N79 and N80, where we find that the results are also sensitive to the inclusion of organisational capital, along with M70 and M73 (*Management consulting, Advertising and market research*) where we find a smaller effect of KBC and M72 (*Scientific R&D*) where we find a much larger effect of KBC, from 0.026 to 0.098. We therefore exclude industry M72 from the analysis of Section 5.2.

Table 4: Results of robustness estimations of the law of motion of productivity, by 2-digit industry

	Translog Law of motion KBC without OC			Linear Law of motion Sum of 4 KBC		
Industry	θ_{cnoOC}	β_c^2	$\beta_{c\omega}$	β_c	β_ω	N
C10	.002 (.0001)	0***	-.003***	.003***	.937***	9482
C11	.003 (.0001)	0	-.003**	.003***	.928***	1297
C13	.001 (0)	0	.004**	0	.935***	1929
C14	.001 (.0002)	0	-.002	.004***	.972***	1053
C15	.003 (.0003)	.001	-.002	.002	.949***	469
C16	0 (0)	0	0	-.001	.929***	1994
C17	.001 (0)	0	-.003**	.004***	.923***	2257
C18	.002 (.0003)	.001***	-.008***	.003***	.913***	1635
C20	.003 (.0001)	0***	-.003***	.006***	.939***	4222
C21	.006 (.0004)	.001***	-.012***	.009***	.884***	913
C22	.002 (.0001)	0***	-.002**	.003***	.908***	4573
C23	.003 (.0001)	.001***	.001	.001	.942***	3763
C24	.001 (0)	0	-.001	.001*	.861***	3275
C25	.002 (0)	0**	.003***	.001***	.888***	10430
C26	.004 (.0001)	.001***	-.009***	.007***	.91***	3664
C27	.004 (.0001)	0***	-.004***	.005***	.922***	5063
C28	.004 (0)	0***	.003***	.005***	.87***	11500
C29	.004 (.0002)	.001***	-.008***	.006***	.879***	2974
C30	.004 (.0003)	.001***	-.002	.002**	.921***	1000
C31	.003 (.0001)	.001***	.002	.021***	.856***	1875
C32	.003 (.0001)	.001***	-.001	.002***	.929***	3042
C33	.002 (.0001)	0**	0	.002***	.91***	3171

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 5: Results of robustness estimations of the law of motion of productivity, by 2-digit industry

	Translog Law of motion KBC without OC			Linear Law of motion Sum of 4 KBC		
Industry	θ_{cnoOC}	β_c^2	$\beta_{c\omega}$	β_c	β_ω	N
H49	.004 (0)	0***	.004***	.007***	.846***	75957
H50	.003 (.0001)	0	.002*	.005***	.902***	7454
H51	.030 (.0013)	.005***	-.007***	.022***	.758***	1482
H52	.006 (0)	0*	0	.01***	.849***	32179
H53	.010 (.0001)	-.001	.005***	.007***	.911***	7820
J58	.002 (.0002)	.001***	-.003***	.004***	.927***	10931
J59	.006 (0)	0	.003***	.012***	.904***	5869
J60	.013 (.0014)	.003***	-.004**	.011***	.917***	838
J61	.004 (.0003)	.001***	-.003**	.011***	.861***	4212
J62	0 (0)	0***	-.001	.017***	.841***	43097
J63	.008 (.0003)	.002***	.003***	.006***	.882***	10904
M69	.004 (0)	-.001***	.001***	.004***	.867***	81249
M70	.103 (.0005)	.016***	-.018***	.025***	.855***	32538
M71	.120 (.0002)	.059***	-.106***	.098***	.707***	59139
M72	.007 (0)	.028***	-.041***	.098***	.767***	7208
M73	.037 (.0003)	.006***	-.007***	.012***	.875***	26002
M74	.008 (.0001)	.001***	-.005***	.01***	.858***	17242
M75	.004 (.0001)	-.001	.01***	.003***	.826***	11214
N77	.010 (.0001)	.001***	0	.01***	.892***	18494
N78	.003 (.0002)	.002***	0	.01***	.735***	16880
N79	.008 (0)	0	.006***	.016***	.852***	14240
N80	.004 (0)	0	0	.018***	.853***	6746
N81	.004 (0)	0**	0	.004***	.856***	48348
N82	.006 (.0001)	.001***	-.003***	.008***	.902***	22407
S95	.003 (.0002)	.001***	-.013***	.001***	.848***	8586

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses.

5.2 Productivity dynamics at the industry level

In the present section, we discuss the relationship between KBC and productivity dynamics at the industry level. We follow the framework of Andrews et al. (2015, 2016), and single out a group of frontier firms. We are interested in whether firms in this group have achieved higher productivity growth compared to the rest of firms in the industry, and how any productivity divergence between the frontier and the rest is related to KBC.

Andrews et al. (2015, 2016) define a group of "frontier" firms as the top 5% most productive firms in each industry and year, and a group of "laggard" firms as the other 95%. Similarly, we define the productivity frontier as the top 5% most productive firms by industry-year, and furthermore define an output frontier, as the top 5% largest firms (in terms of value-added) by industry-year. The firms in the group of the other 95% are representative of the industry as a whole, and we therefore refer to this group as the industry average (rather than laggard firms).

We discuss the relative productivity, size, capital-labour ratio and KBC stocks of frontier firms in comparison to the industry average in Appendix Section D. Frontier firms are more productive, larger, have higher capital-labour ratios and larger KBC stocks on both the productivity and the output frontier. Additionally, we find more persistence on the output frontier than on the productivity frontier.

5.2.1 Productivity growth and divergence

Table 6 presents the cumulative growth of total factor productivity over the period 2009 and 2013 in the frontier group, the group of the other 95% of firms, and the percentage point difference between the two groups, for each 2-digit industry. The first three columns present the results for the productivity frontier, while the last three columns present the results for the output frontier.

The first and fourth columns of Table 6 suggest that there has been strong TFP growth in most industries over the period 2009-2013, and that the average in the group of 95% of firms is not sensitive to the definition of the frontier, and hence can be considered representative of the whole industry. TFP growth has declined in only two manufacturing industries and four services industries, while it has exceeded a cumulative growth of 10% over five years in 4 manufacturing industries, including the high-tech industries C26 and C29 (i.e. *Manufacturing of computer, eletronic and optical products and of motor vehicles*), and 6 service industries.

The third and sixth columns of Table 6 report the size of the productivity divergence between the frontier and the industry average, which appears highly sensitive to the definition of the frontier.

This is especially the case in the manufacturing sector, where we find evidence of convergence on the productivity frontier, whereas we find evidence of divergence on the output frontier.

More specifically, on the productivity frontier, TFP growth has been of the same rate or slower than the industry average in the majority of manufacturing industries. Industries C15, C18 and C21 (*Manufacturing of Leather products, Printing, and Pharmaceuticals*) stand out, as TFP growth on the productivity frontier was more than 10 percentage points slower than the industry average. TFP growth on the productivity frontier exceeded the average growth by more than 5 percentage points in only four manufacturing industries: C11, C14, C20, and C29 (*Manufacturing of Beverages, Wearing apparel, Chemicals, and Motor vehicles*). On the output frontier, on the other hand, the evidence for divergence appears more convincing. We find that TFP growth was at least 5 percentage points higher than the average in six manufacturing industries (C18, C21, C26, C28, C29 and C31 (*Printing, Pharmaceuticals, Manufacturing of computers, electronic and optical products, of Machinery, of Motor vehicles, and of Furniture*)) and that it was slower than the average by more than 2 percentage points in only 5 sectors (C14, C15, C16, C32 and C33 (*Manufacturing of Wearing apparel, of Leather products, of Wood products, Other manufacturing, and Repare activities*)). The findings relating to the productivity frontier echo those of Andrews et al. (2016), who report small, if any divergence in TFP growth between frontier and laggards firms in manufacturing after 2009. However, we do find that the largest manufacturing firms were able to capitalise on their good position to further accelerate their productivity growth compared to the industry average.

In the services sector, the extent of productivity divergence seems less sensitive to the definition of the frontier, as productivity seems to have diverged on both the productivity and output frontiers. On the productivity frontier, TFP growth exceeded the industry average by between 2 and 10 percentage points in the majority of industries, reaching 16 percentage points in M73 (*Advertising and market research*), 21 percentage points in H51 (*Air transport*) and 40 percentage points in J60 (*Broadcasting activities*). The transport sector (H49 to H53, excluding H51), M72 (*Scientific R&D*) and N80 (*Security activities*) are the only industries to have witnessed productivity convergence. This is in line with the findings of Andrews et al. (2016), who find strong evidence of productivity divergence in the services sector. On the output frontier, we find the same evidence of productivity divergence, in all but four sectors.

Table 6: Cumulative growth of productivity over the period 2009-2013, by frontier and industry

	TFP Frontier			Output frontier		
	Other	Top		Other	Top	
Industry	95%	5%	Diff.	95%	5%	Diff.
10	2	4.3	2.3	2.1	2.1	0
11	1.2	12.1	10.9	1.8	2	.1
13	7.5	6.1	-1.3	6.8	7.7	1
14	-.1	6	6.1	.9	-5.8	-6.7
15	11.9	-16.6	-28.5	11.2	-3	-14.2
16	6.7	1.5	-5.2	6.4	3.9	-2.5
17	2.9	2.1	-.8	3.1	3.3	.3
18	-6.9	-18.7	-11.7	-7.7	-3.1	4.6
20	3.2	9.3	6.1	3.8	4	.1
21	7.3	-5.9	-13.1	6.4	11.9	5.5
22	5.8	2.6	-3.2	5.5	5	-.6
23	9.6	7.8	-1.9	9.6	8.1	-1.5
24	10.3	8.4	-1.8	10.2	8.7	-1.5
25	7.2	7.1	-.1	7.1	7.7	.6
26	11.8	8.4	-3.5	11.3	16.6	5.3
27	3.3	3.9	.7	3.1	4.7	1.6
28	7.8	6.4	-1.4	7.3	12.3	5.1
29	14.7	20	5.3	15	26.4	11.4
30	-2	-9.1	-7.2	-2	-3.2	-1.2
31	-.2	-2	-1.8	-.8	5.5	6.3
32	5.4	2	-3.4	5.5	2.8	-2.7
33	1.6	5.2	3.5	2.2	-7.5	-9.7
49	4.7	4.1	-.6	4.9	1.1	-3.8
50	-2.4	-31.3	-28.9	-5.4	-5.6	-.2
51	1.4	22.7	21.2	.4	17.5	17.1
52	11	2.6	-8.5	10.8	6.5	-4.3
53	4.5	-14.2	-18.7	4.1	-12.7	-16.8
58	5.4	9.6	4.2	5.4	7.1	1.7
59	16.1	26.4	10.3	16.6	20.5	3.9
60	18	58.4	40.4	16.9	62.2	45.3
61	-8.7	-1.5	7.2	-9.3	-.5	8.8
62	1.2	5.4	4.2	1.5	-3.5	-4.9
63	5.9	12.4	6.5	6.7	8.8	2
69	2.7	2.2	-.5	2.7	1.8	-.9
70	1.6	3.5	1.9	1.7	-.9	-2.5
71	.8	5.1	4.4	.6	2.6	2.1
72	-2.6	-7.5	-4.9	-2.3	-2.7	-.4
73	-1.3	14.4	15.7	-1.5	9.6	11.1
74	3.1	8.7	5.6	2.7	6.8	4.2
75	3.4	4.2	.8	3.2	1.1	-2.1
77	21.6	29.7	8.1	22.4	9.2	-13.2
78	11.7	20.3	8.6	12.1	14.3	2.2
79	-2.9	-1.9	1	-3.3	-4.3	-1
80	19.7	10	-9.7	19.7	11.5	-8.2
81	-.4	4.7	5.1	-.8	7.7	8.5
82	7.1	9.7	2.6	7	6.1	-.9
95	3.5	7.2	3.7	3.8	4.9	1.1

5.2.2 Relationship between productivity divergence and KBC at the industry level

We explore here whether the reported variation in the divergence of productivity growth is related to the variation in the importance of KBC across industries. Table 7 presents correlation coefficients between, on the one hand, the reported percentage point differences in TFP growth between the frontier and the industry average, and, on the other, various measures of the importance of KBC at the industry level. These are the average stock of KBC (as reported in Table 1), the average θ_c, reflecting the effect of KBC on productivity, β_{c^2}, the coefficient on the squared stock of KBC, capturing the increasing returns to KBC stock, and $\beta_{c\omega}$, the coefficient on the interaction of KBC with productivity, capturing the extent to which past productivity accentuates the effect of KBC on productivity, and finally, the difference between θ_c on the frontier and θ_c at the median, as an alternative measure of increasing returns to scale. For each frontier (productivity and output), we look at productivity divergence over the period 2009-2013 for both manufacturing and services. To understand the sensitivity of the results to the time period under consideration, we additionally report results where productivity divergence is calculated over the period 2003-2013, for which we only have data for the services sector.

Looking at the first three columns of Table 7 suggests a weak and negative relationship between productivity divergence and the KBC variables, on the productivity frontier. In the manufacturing sector, all the correlation coefficients are negative and insignificant. For services, we observe a positive correlation between the productivity gap calculated over the period 2009-2013 and all the KBC variables, except $\beta_{c\omega}$. The correlation is also significant for the average effect of KBC on productivity, θ_c, and for the coefficient measuring increasing returns to KBC stock, β_{c^2}. However, these correlations do not seem to be robust to changing the time period, as seen in the third column. Appendix Figure E.1 provides an illustration of the correlation between productivity divergence and the KBC variables for the productivity frontier. In contrast, the last three columns of Table 7 suggest that productivity divergence on the output frontier is strongly related to the importance of KBC. We find a positive correlation between productivity divergence and all the KBC variables, except $\beta_{c\omega}$, in both manufacturing and services, and for the latter, for both time periods, and these correlations are significant at the 5% level for the period 2009-2013. This is illustrated in Appendix Figure E.2.

Put together, these results suggest that larger firms are in a better position to exploit KBC as a source of TFP growth compared to other firms in the industry. Indeed, we find that these large firms were able to achieve stronger productivity gains compared to the industry average precisely in industries where the average size of the KBC stock is higher, where this stock has a stronger effect on TFP, and where this effect is further accentuated by the size of the stock and the size of the firm. However, being a productive firm does not appear to be in itself a sufficient condition to achieve disproportionally higher TFP growth from using KBC.

Table 7: Correlation between productivity gap and KBC variables

Frontier definition:	Productivity			Output		
Time period	2009-2013		2003-2013	2009-2013		2003-2013
Industry	Manuf.	Serv.	Serv.	Manuf.	Serv.	Serv.
KBC stock	-0.141	0.347	-0.0308	0.597**	0.152	0.295
θc	-0.237	0.539**	-0.0218	0.558**	0.483**	0.325
βc^2	-0.289	0.478**	0.0684	0.500**	0.597**	0.300
$\beta c\omega$	-0.0674	-0.338	-0.336	-0.189	-0.381*	0.0124
$\theta_{cTOP5} - \theta_{cMEDIAN}$	-0.286	0.341	-0.348	0.264	0.524**	0.166

* p<0.1, ** p<0.05

6 Conclusion and discussion

In this paper, we shed light on the heterogeneous effect of KBC on productivity, both at the firm level and at the industry level. At the micro level, we estimate a model of production where a firm's stock of KBC directly influences the level of productivity and is allowed to vary with the size of the stock and the past productivity level of the firm. Our average results are in line with existing micro-level evidence on the positive effect of KBC on productivity. We bring additional evidence of increasing returns to scale to a firm's stock of KBC, and even find that below a certain size of KBC stock, firms observe a negative effect on their productivity. More surprisingly, we do not find that the effect of KBC increases noticeably with firm productivity. These results imply that large firms, rather than more productive firms, are in a better position to reap the benefits of investing in KBC.

These results are echoed in the second part of our analysis, where we look at productivity growth at the industry level. We focus on the phenomenon of productivity divergence, as described by Andrews et al. (2015, 2016), because we expect the increasing returns observed in the micro-level analysis to translate into heterogeneous productivity growth at the industry level. Indeed, we find that in most industries, larger firms grew at a faster rate than the industry average, and that this divergence is accentuated in those industries where firms have larger stocks of KBC, these assets have a larger effect on productivity and where increasing returns are stronger. In accordance with the results of the firm-level analysis, we do not find any relationship between the variation in productivity divergence on the productivity frontier and various measure of KBC importance.

KBC investments appear to be an uneven source of growth, whose rewards accrue to a fraction of firms in the economy. Our data does not allow us to explore other relevant characteristics of these firms, but we hypothesise that two additional dimensions play an important role.

Firstly, the ability to finance KBC investments is itself biased towards larger firms. As argued by Haskel and Westlake (2018), investments in KBC tend to be sunk for firms, as these assets cannot be easily sold on or used as collateral. This stems both from under-developed markets for the exchange of knowledge assets and from the firm-specific nature of many of these investments. Hence, only firms with the deepest pockets are able to afford these expenditures in the first place, which results in large heterogeneity in observed KBC investment patterns, even within industries (Arrighetti et al., 2014).

Secondly, we expect the important KBC players to be the large multinational enterprises that play prominent roles in global value chains, given that large investments in KBC are a necessary condition for effective participation in global markets (Chen et al., 2017). Additionally, the findings of Aw et al. (2008, 2011) highlight a potential feedback mechanism whereby participation in exporting allows firms to leverage their investments over larger markets and thereby increase the returns to their innovative investments.

Finally, two policy implications emerge. Firstly, if KBC improves the performance of firms that are already in a strong position on their market, and if this is further accentuated by financing constraints and participation in global value-chains, we would expect these effects to dampen competition. Secondly, our results raise the question of whether certain policy interventions, for example through knowledge diffusion, might allow more firms to reap the benefits of KBC and thus have incentives to invest.

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A Description of the datasets

The three main datasets used in the present analysis are the *AFiD Panel of Manufacturing Firms*, the *AFiD Panel of Service Firms* and the *Linked Employer-Employee Data of the IAB* (LIAB). All the data are representative at the 2-digit industry and the size class levels. The AFiD Panels are of very high quality because they serve as the basis for the construction of the National Accounts. Firms are legally required to deliver the requested data, and the Statistical Office ensures that the non-response rate is as low as possible (around 2% in recent years). The Statistical Office is also responsible for performing quality checks and checking for implausibilities.

The AFiD Panel of Manufacturing Firms consists of the following three surveys, which are merged together using unique firm identifiers:

- the annual report for manufacturing, mining and quarrying companies (JBU)
- the investment survey of manufacturing, mining and quarrying companies (IEU)
- the cost structure survey in manufacturing, mining and quarrying (KSE)

The AFiD Panel of Service Firms consists of individual surveys for the following sectors: transport and warehousing (H), information and communication (J), provision of professional, scientific and technical services (M), provision of other economic services (N), other services (S95).

We provide a brief description of the coverage and list of variables for each of the sub-datasets, and refer interested readers to Schiersch and Schmidt-Ehmcke (2011); Richter and Schiersch (2017); Fritsch et al. (2004); Koch (2007); Heining et al. (2014) for detailed descriptions of the Investment Survey, the Cost Structure survey, the annual reports and the LIAB dataset.

A.1 AFiD-Panel of Manufacturing Firms

A.1.1 Annual report for manufacturing, mining and quarrying companies

Coverage The annual report is a census of all manufacturing and quarrying firms with more than 20 employees. In some industries, such as the food industry or the mining sector, the threshold has been lowered to 10 employees. The dataset contains a total of around 61,000 indivudal firms, with approximately 22,000 that are observed for the entire sample period of 2003 to 2014, and around 4,800 that are observed only once. The remaining 34,400 are observed between two and eleven years.

List of variables The analysis uses the following variables from the annual report: number of active persons; payroll; turnover.

A.1.2 Investment survey of manufacturing, mining and quarrying companies

Coverage The investment survey is also a census of all manufacturing and quarrying firms with more than 20 employees and a reduced threshold of 10 employees in a few industries.

List of variables The analysis uses the following variables from the investment survey: investments in concessions, patents, licenses, trademarks, etc.; investments in software; purchased and self-constructed property, plant and equipment; value of newly leased new property, plant and equipment; sales of property, plant and equipment. Note that the variables investment in software and investment in concessions, patents, licenses, trademarks, etc. were only included in the investment survey starting in 2009.

A.1.3 Cost structure survey in manufacturing, mining and quarrying

Coverage The cost structure survey includes both the full census of firms with at least 500 employees, and a sample for firms below that threshold. Smaller firms are sampled from the full population of manufacturing, mining and quarrying firms recorded in the business register, using a stratification strategy that ensures representativeness at the industry and size class levels. Note that the survey is not representative at the level of federal states. To limit the response burden of firms, a new sample is drawn every four years. However, in industries with few firms, even small firms are part of the sample almost every year. The total number of firms in the cost structure survey covers around 45 % of all firms in the mining and manufacturing industry.

List of variables The analysis uses the following variables from the cost structure survey: legal form; federal state; industry code; total number of employees; total number of active persons; number of active persons in R&D; total turnover; gross production value; gross value added; consumption of raw materials and supplies; gross payroll (without employer contributions); employer payroll taxes; expenditure on R&D; weighting factors; correction factors.

A.2 AFiD-Panel of Service Firms

Coverage The AFiD Panel of Service Firms is a sample of firms, drawn from the population of firms subject to VAT, with at least €17,500 of annual turnover, to be representative at the industry, federal state and size class levels. The number of firms included in the sample represent around 15% of total firms in the relevant services sectors. To minimize the administrative burden on firms, new samples were drawn in 2003, 2008, 20011 and 2014. As a result, only 2 percent of the firms in the services dataset are present for the entire sample period of 2003 to 2013. Around 10 percent of the firms are constantly in the surveys between 2003 to 2007 and just about 5 percent of all firms are constantly observed in the period 2008 to 2013.

List of variables The analysis uses the following variables from the AFiD Panel of Services Firms: legal form; federal state; industry code; number if employees; number of all active persons; turnover; gross wages and salaries; consumption of raw materials and supplies; weighting factors; investment in property, plant and equipment; investments in concessions, patents, licenses, trademarks, etc.; investment in software.

A.3 Linked Employer-Employee Data of the IAB

Two important asset categories are unavailable in the AFiD Panels (organisational capital for all firms, and R&D for firms in services sectors), and are thus estimated using occupational information from a third source, the Linked Employer-Employee Data for the IAB (LIAB). To overcome the legal prohibition on the merger of these two datasets at the firm level, we adopt a two-step methodology inspired from the model of Crepon et al. (1998) (commonly referred to as the CDM model, see Griffith et al., 2016; Hall et al., 2009; Hall, 2011; Baumann and Kritikos, 2016).

The intuition of the approach is as follows. In a first step, the authors estimate the likelihood of a company to engage in R&D activities. In a second step, all companies above a certain likelihood threshold are attributed an estimated R&D intensity (i.e. R&D expenditure relative to employment), which replaces observed values of R&D intensity. The procedure implies that certain firms that report zero R&D expenditures are nevertheless given a positive value for R&D. Crepon et al. (1998) use this procedure for two reasons. Firstly, it solves the selection problem with respect to the R&D choice. Secondly, it addresses the well-known problem of under-reporting of R&D activities and investment in surveys.

In a first step, we thus estimate the likelihood of firms to be engaged in investment in either organisational capital or R&D. We do so by estimating probit models at the 2-digit industry level, where the explanatory variables are chosen to be available in both the LIAB and the AFiD Panels. The dependent variable is, in the case of organisational capital, a dummy for observing at least one manager with an employee relationship to the firm.[18] In the case of R&D, the dependent variable of the probit model is a dummy for engaging in R&D activities, included in the LIAB dataset. We apply the estimated coefficients of the probit estimations to predict the likelihood of firms in the AFiD Panels to invest in the two assets. The calculations are calibrated to match the share of firms engaged in investment at the 1 digit industry level in the two datasets.

For each firm that we predict to participate in OC and R&D investment, we then calculate the compensation paid to managerial and R&D occupations. We identify the relevant occupations from the *KldB 2010*, the German pendant to *ISCO 2008*, and observe their monthly wages in the LIAB data. We calculate the share of managerial and R&D wages in total wagebill for each firm. To transfer this information to the AFiD Panels, we construct tables by 2 digit industry, geographical region and biennium, where each cell reports the average wage share of the relevant occupations. These tables are applied to the AFiD table to calculate the firm-specific compensation of managers and R&D workers by multiplying these shares with the firm wagebill.

Finally, the estimated compensations are considered investment in the relevant asset and capitalised as described in Section 3.2. Note that only 20% of managerial compensation is considered investment (following Corrado et al., 2009), whereas 100% of R&D worker compensation is considered investment.

A.4 Additional descriptive tables

In Table A.1 we present the list of industries included in the analysis, along with the industry codes and description, according to the German classification of industries *WZ 2008*. In Table A.2 we report the number of observations of the raw dataset for each 1-digit industry and year. In Tables A.3 and A.4, we report the number of observations of the raw dataset for each 2-digit industry and year, in the manufacturing and services sectors respectively.

Finally, in Table A.5 we provide additional descriptive statistics: we report the mean and standard deviation for the stock of each KBC asset individually. We observe large heterogeneity between industries in the breakdown of the KBC bundle into its four elements. For example, the average R&D stock in the car production sector is around €127 million, while it is €0.5 million or less in a number of other manufacturing industries. The broadcasting and telecommunications industries stand out as having the stocks of software and IPP at multiple millions of euros, whereas the rest of the services sectors do not have stocks of these assets that exceed one million euro. The

[18] Many firms do not hire professional managers and are instead managed by their owners. The presence of an owner manager is included as one of the explanatory variables in the probit model.

distribution of organisational capital across industries is the most homogenous of the four assets, ranging from a low of €10,000 in the legal and accounting services to a high of €3.7 million in the car manufacturing industry. Finally, the large standard errors of these variables suggest large heterogeneity also within industries.

Table A.1: 2 digit industry classification

	(WZ 2008)	Industry code	Description
Manufacturing		C10	Food Products
		C11	Beverages
		C13	Textiles
		C14	Wearing apparel
		C15	Leather and related products
		C16	Wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
		C17	Paper and paper products
		C18	Printing and reproduction of recorded media
		C20	Chemicals and chemical products
		C21	Basic pharmaceutical products and pharmaceutical preparations
		C22	Rubber and plastics products
		C23	Other non-metallic mineral products
		C24	Basic metals
		C25	Fabricated metal products, except machinery and equipment
		C26	Computer, electronic and optical products
		C27	Electrical equipment
		C28	Machinery and equipment n.e.c.
		C29	Motor vehicles, trailers and semi-trailers
		C30	Other transport equipment
		C31	Furniture
		C32	Other manufacturing
		C33	Repair and installation of machinery and equipment
Transport	& Logistics	H49	Land transport and transport via pipelines
		H50	Water transport
		H51	Air transport
		H52	Warehousing and support activities for transportation
		H53	Postal and courier activities
Information	Communications	J58	Publishing activities
		J59	Motion picture, video and television programme production, sound recording and music publishing activities
		J60	Programming and broadcasting activities
		J61	Telecommunications
		J62	Computer programming, consultancy and related activities
		J63	Information service activities
Professional, scientific	& technical activities	M69	Legal and accounting activities
		M70	Activities of head offices; management consultancy activities
		M71	Architectural and engineering activities; technical testing and analysis
		M72	Scientific research and development
		M73	Advertising and market research
		M74	Other professional, scientific and technical activities
		M75	Veterinary activities
Administrative &	support activities	N77	Rental and leasing activities
		N78	Employment activities
		N79	Travel agency, tour operator, reservation service and related activities
		N80	Security and investigation activities
		N81	Services to buildings and landscape activities
		N82	Office administrative, office support and other business support activities
		S95	Repair of computers and personal and household goods

Table A.2: Number of observations per 1-digit industry and year

Year	Mining	Manufacturing	Transportation	Communication	Real estate	Professional services	Administrative services	Total
2003	-	-	19,084	10,975	22,174	32,271	17,011	102,066
2004	-	-	19,688	11,688	23,411	33,924	17,003	106,251
2005	-	-	2,056	12,602	25,081	36,426	1,729	78,418
2006	-	-	20,958	13,394	25,571	38,288	17,442	116,170
2007	-	-	21,848	14,026	25,428	40,629	17,985	120,416
2008	-	-	20,251	15,311	15,106	48,345	26,968	129,867
2009	558	37,448	21,466	16,298	16,893	51,587	28,363	176,386
2010	564	36,868	21,869	16,985	18,091	53,831	29,345	181,299
2011	559	36,926	21,413	16,668	18,673	59,996	3,027	159,925
2012	554	38,618	22,022	17,304	19,103	62,574	32,279	195,191
2013	534	38,317	22,731	18,245	19,725	64,593	33,809	200,781
2014	522	38,030	-	-	-	-	-	38,552

The sum in the Total category exceeds the sum of the other columns because it includes observations in 2-digit industry S95.

Table A.3: Number of observations per 2-digit Industry and year (Ind. B05-C33)

	2009	2010	2011	2012	2013	2014
B05	6	6	5	6	5	5
B06	5	5	5	5	5	5
B08	535	539	533	526	533	496
B09	12	14	16	17	16	16
C10	4.761	4.789	4.838	4.981	4.838	4.846
C11	514	504	495	497	495	484
C12	21	21	22	22	22	22
C13	706	673	666	681	666	660
C14	329	301	280	298	280	263
C15	140	132	131	130	131	119
C16	1.190	1.135	1.130	1.163	1.130	1.122
C17	816	801	796	813	796	785
C18	1.500	1.430	1.384	1.373	1.384	1.259
C19	42	44	47	50	47	49
C20	1.185	1.187	1.189	1.261	1.189	1.253
C21	242	246	250	277	250	271
C22	2.747	2.693	2.709	2.826	2.709	2.829
C23	1.623	1.584	1.591	1.629	1.591	1.599
C24	932	913	924	978	924	921
C25	6.762	6.653	6.626	7.029	6.626	7.123
C26	1.600	1.586	1.608	1.741	1.608	1.702
C27	1.910	1.867	1.882	2.011	1.882	1.977
C28	5.296	5.186	5.219	5.487	5.219	5.413
C29	1.078	1.056	1.040	1.056	1.040	1.037
C30	244	251	252	278	252	271
C31	974	969	963	995	963	960
C32	1.428	1.431	1.440	1.482	1.440	1.489
C33	1.408	1.416	1.444	1.561	1.444	1.576

Table A.4: Number of observations per 2-digit Industry and year (Ind. H49-S95)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
H49	10.354	10.781	11.127	11.380	11.694	12.603	13.126	13.261	14.111	14.306	14.111	-
H50	1.435	1.487	1.647	1.702	1.804	1.497	1.692	1.662	1.506	1.498	1.506	-
H51	310	323	328	326	351	276	291	296	266	280	266	-
H52	5.294	5.354	5.617	5.690	5.969	4.668	4.828	4.941	4.129	4.170	4.129	-
H53	1.431	1.490	1.605	1.688	1.825	1.207	1.529	1.709	1.401	1.768	1.401	-
J58	1.409	1.379	1.314	1.289	1.273	3.370	2.573	2.605	2.393	2.417	2.393	-
J59	12	12	13	13	14	2.193	2.338	2.412	2.331	2.445	2.331	-
J60	0	0	0	0	0	292	337	286	221	228	221	-
J61	728	697	714	742	736	861	907	928	888	944	888	-
J62	7.164	7.483	8.006	8.546	8.999	7.241	7.993	8.704	8.434	9.034	8.434	-
J63	2.374	2.786	3.238	3.523	3.685	2.205	2.150	2.050	2.401	2.236	2.401	-
L68	19.602	20.901	22.538	23.100	22.968	15.106	16.893	18.091	18.673	19.103	18.673	-
M69	9.185	9.849	10.689	11.279	11.852	13.603	14.706	15.297	17.018	18.016	17.018	-
M70	6.924	7.435	8.342	8.915	9.674	6.747	7.312	7.614	8.415	8.571	8.415	-
M71	8.141	8.444	8.921	9.377	9.885	12.273	12.842	13.363	15.042	15.348	15.042	-
M72	1.391	1.428	1.490	1.537	1.648	1.142	1.192	1.273	1.256	1.299	1.256	-
M73	4.263	4.367	4.594	4.734	5.015	4.788	5.185	5.496	5.591	5.994	5.591	-
M74	2.298	2.338	2.332	2.408	2.510	6.911	7.192	7.531	9.054	9.563	9.054	-
M75	0	0	0	0	0	2.884	3.158	3.257	3.620	3.783	3.620	-
N77	6.090	5.936	5.877	5.739	5.768	4.834	4.918	4.927	3.993	4.089	3.993	-
N78	1.625	1.644	1.686	1.773	1.878	2.564	2.777	2.896	3.158	3.356	3.158	-
N79	2.286	2.310	2.409	2.477	2.562	2.298	2.440	2.576	2.681	2.877	2.681	-
N80	1.119	1.053	1.031	1.018	999	1.388	1.482	1.567	1.034	1.207	1.034	-
N81	3.426	3.635	3.853	4.018	4.216	9.591	10.422	11.027	12.645	13.621	12.645	-
N82	1.996	2.009	2.064	2.082	2.243	6.295	6.324	6.352	6.759	7.129	6.759	-
S95	551	537	524	517	500	3.887	3.773	3.746	2.663	2.737	2.663	-
Other	3.875	3.732	3.655	3.370	3.408	195	8	3	0	3	0	-
Total	103.283	107.410	113.614	117.243	121.476	130.919	176.394	181.302	187.168	195.195	187.168	38.552

Table A.5: Descriptive statistics by 2-digit industry

	R&D	Software	IPP	OC	N		R&D	Software	IPP	OC	N
C10	0.5	0.07	0.13	0.67	10337	H51	5.75	0.09	0.11	0.42	2047
	(3,72)	(0,39)	(2,47)	(1,82)			(27,91)	(0,69)	(1,46)	(2,17)	
C11	0.08	0.1	0.46	0.94	1377	H52	1.49	0.08	0.08	0.21	44767
	(0,62)	(0,34)	(3,3)	(4,47)			(28,49)	(1,42)	(1,29)	(2,17)	
C13	0.65	0.05	0.04	0.41	2064	H53	0.02	0.1	0.05	0.42	11962
	(3,71)	(0,16)	(0,28)	(0,78)			(0,2)	(2,75)	(1,35)	(11,51)	
C14	0.43	0.18	0.12	0.45	1103	J58	0.57	0.11	0.35	0.29	15556
	(1,98)	(1,39)	(0,93)	(1,24)			(4,48)	(0,67)	(6,59)	(1,62)	
C15	0.42	0.04	0.03	0.3	495	J59	0.08	0.02	0.37	0.07	9078
	(1,76)	(0,1)	(0,19)	(0,49)			(0,87)	(0,41)	(7,66)	(0,3)	
C16	0.2	0.04	0.04	0.31	2204	J60	1.38	0.55	15.45	0.97	1185
	(1,21)	(0,17)	(0,44)	(0,59)			(13,66)	(3,36)	(143,54)	(4,21)	
C17	0.68	0.11	0.06	0.72	2431	J61	0.16	4.2	8.9	0.93	6180
	(2,73)	(0,45)	(0,41)	(1,36)			(1,07)	(47,27)	(113,41)	(8,42)	
C18	0.48	0.08	0.03	0.4	1869	J62	0.64	0.31	0.26	0.26	62871
	(7,85)	(0,28)	(0,22)	(0,85)			(11,79)	(5,25)	(7,8)	(2,3)	
C20	20.2	0.38	1.28	1.39	4524	J63	0.68	0.16	0.24	0.14	16901
	(180,71)	(3,45)	(19,17)	(7,9)			(7,67)	(1,6)	(5,22)	(1,16)	
C21	74.4	0.76	5.08	2.52	986	L69	0.43	0.01	0.02	0.01	118817
	(441,55)	(2,83)	(33,26)	(8,34)			(17,69)	(0,11)	(0,2)	(0,16)	
C22	3.56	0.11	0.1	0.57	4998	M70	4.77	0.09	0.2	0.23	51093
	(27,64)	(0,72)	(0,9)	(1,69)			(28,29)	(0,81)	(4,07)	(1,53)	
C23	1.57	0.08	0.05	0.83	4002	M71	1.74	0.02	0.02	0.14	89018
	(8,55)	(0,47)	(0,33)	(1,75)			(11,14)	(0,17)	(0,63)	(1,1)	
C24	2.45	0.14	0.19	0.69	3466	M72	0	0.08	0.12	0.17	10354
	(22,29)	(0,56)	(2,47)	(2,23)			(0)	(0,79)	(1,9)	(1,2)	
C25	1.41	0.07	0.07	0.6	11552	M73	1.13	0.02	0.06	0.09	38105
	(10,12)	(0,29)	(0,78)	(1,51)			(3,9)	(0,2)	(3,34)	(0,38)	
C26	21.61	0.35	0.34	1.22	4012	M74	0.35	0.01	0.01	0.05	26542
	(138,85)	(2,7)	(2,77)	(5,54)			(10,81)	(0,22)	(0,25)	(1,3)	
C27	22.71	0.23	0.2	1.09	5592	M75	0	0	0	0	16666
	(415,59)	(1,39)	(1,68)	(14,58)			(0,08)	(0)	(0,03)	(0,03)	
C28	14.01	0.24	0.3	0.93	12535	N77	0.49	0.04	0.14	0.05	28031
	(263,1)	(2,16)	(5,63)	(6,24)			(4,33)	(1,04)	(6,76)	(0,35)	
C29	127.29	0.97	2.55	3.7	3189	N78	0.15	0.05	0.08	0.18	23531
	(1242,65)	(8,76)	(30,85)	(30,42)			(5,86)	(3,89)	(7,15)	(1,52)	
C30	53.4	0.33	0.47	1.8	1082	N79	0.31	0.03	0.09	0.05	20888
	(449,18)	(1,04)	(3,01)	(7,39)			(4,9)	(0,39)	(2,87)	(0,47)	
C31	1.94	0.09	0.03	0.5	2046	N80	0.03	0.01	0.02	0.22	9784
	(17,89)	(0,47)	(0,16)	(1,11)			(0,8)	(0,04)	(0,18)	(0,6)	
C32	4.95	0.17	0.19	0.78	3292	N81	0.01	0	0.01	0.11	72869
	(25,46)	(1,03)	(1,46)	(2,51)			(0,21)	(0,04)	(0,21)	(0,55)	
C33	2.57	0.05	0.05	0.88	3547	N82	0.7	0.08	0.07	0.16	33597
	(34,08)	(0,35)	(0,77)	(3,77)			(6,41)	(1,68)	(0,97)	(0,85)	
H49	0.53	0.01	0.03	0.07	109499	S95	0.21	0	0	0.03	13514
	(15,13)	(0,21)	(1,76)	(0,91)			(2,54)	(0,05)	(0,04)	(0,28)	
H50	0.35	0.02	0.09	0.04	10628						
	(4,83)	(0,17)	(2,34)	(0,43)							

Standard errors in parentheses; Monetary values in million €

B Production function results

In Tables B.1, B.2 and B.3 we report the results from the different GMM estimations of the production function $f(\cdot)$. The first 5 lines report the coefficients and standard errors from the baseline model, where $f(\cdot)$ is assumed to be a translog function. The following two lines report the output elasticities of labour and capital, calculated from Equations (12a) and (12b). The final two lines report the coefficients and standard errors of the robustness estimation, where $f(\cdot)$ is assumed to be a Cobb-Douglas function. These last coefficients can be directly interpreted as output elasticities, and can therefore be compared to the output elasticities reported in the two preceding lines. This comparison suggests that the average output elasticities of labour and capital obtained with the translog assumption are very close to the output elasticities estimated in a Cobb-Douglas model, and implies that our results are not sensitive to the functional form assumption in the production function $f(\cdot)$.

Table B.1: Production function coefficients obtained from ACF procedure by 2-digit industry

Industry	C10	C11	C13	C14	C15	C16	C17	C18	C20	C21	C22	C23	C24	C25	C26	C27
β_L	2.09***	.76***	1.24**	.39	6.02***	2.6***	1.21*	-.45	.53	-3.04***	.15	1.08***	1.59***	.92***	-.61	1.34***
	(.154)	(.204)	(.391)	(1.299)	(.428)	(.27)	(.472)	(.525)	(2.192)	(.7)	(3.18)	(.147)	(.075)	(.076)	(.454)	(.366)
β_{LL}	.19***	.12***	-.01	-.04	.35	.14*	.01	.04	.09	-.58***	.09	.03	.13***	.07	-.17**	.12***
	(.02)	(.03)	(.047)	(.033)	(.217)	(.067)	(.083)	(.088)	(.098)	(.063)	(.401)	(.052)	(.016)	(.037)	(.062)	(.021)
β_K	-1.12***	.21	.02	-.51*	2.3*	-1.54**	.01	.72	.54	2.78***	.88	.13	-.07	.08	1.18	-.04
	(.109)	(.5)	(.173)	(.221)	(1.143)	(.474)	(.149)	(.416)	(2.663)	(.77)	(2.503)	(.22)	(.241)	(.238)	(1.027)	(.567)
β_{KK}	.14***	.03	.02	.03	-.02	.16***	.03*	-.04	-.01	-.26***	-.04	.02	.05**	.02	-.11	.04
	(.009)	(.03)	(.01)	(.029)	(.097)	(.03)	(.016)	(.04)	(.198)	(.045)	(.255)	(.013)	(.016)	(.012)	(.064)	(.042)
β_{LK}	-.16***	-.05***	-.03	.04	-.43***	-.15***	-.04	.05	-.02	.39***	0	-.04***	-.09***	-.04**	.14***	-.07**
	(.008)	(.006)	(.021)	(.082)	(.063)	(.01)	(.048)	(.052)	(.152)	(.052)	(.32)	(.009)	(.01)	(.012)	(.013)	(.024)
Output elasticity																
θ_l	.386	.542	.786	.749	.760	.800	.594	.569	.521	.845	.595	.535	.682	.671	.875	.745
θ_k	.440	.471	.189	.042	.138	.291	.384	.260	.339	.206	.274	.326	.321	.264	.081	.177
Cobb-Douglas model																
β_L	.4***	.56***	.78***	.76***	.78***	.77***	.58***	.61***	.54***	.68***	.62***	.53***	.68***	.68***	.82***	.78***
	(.025)	(.08)	(.057)	(.084)	(.119)	(.07)	(.056)	(.058)	(.043)	(.099)	(.035)	(.058)	(.037)	(.024)	(.039)	(.029)
β_K	.43***	.47***	.18**	.02	.32	.28***	.39***	.27***	.34***	.35**	.28***	.32***	.32***	.26***	.14**	.16***
	(.029)	(.064)	(.07)	(.371)	(.235)	(.04)	(.034)	(.046)	(.042)	(.113)	(.028)	(.039)	(.026)	(.015)	(.045)	(.029)
N	9482	1297	1929	1053	469	1994	2257	1635	4222	913	4573	3763	3275	10430	3664	5063

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. First panel: results of baseline model with translog assumption in production function and in law of motion of productivity. Second panel: average output elasticity of labour and capital from baseline mode. Third panel: results of robustness model with Cobb-Douglas assumption in production function and translog assumption in law of motion of productivity.

Table B.2: Production function coefficients obtained from ACF procedure by 2-digit industry *Continued*

Industry	C28	C29	C30	C31	C32	C33	H49	H50	H51	H52	H53	J58	J59	J60	J61
β_L	1.52***	3.45***	.12	2.01***	1.89	-.28	2.22***	1.61***	3.56***	1.48***	1.27***	.58**	1.39	4.8**	2.99***
	(.065)	(.087)	(5.884)	(.236)	(5.751)	(3.41)	(.137)	(.254)	(.315)	(.111)	(.157)	(.188)	(.811)	(1.557)	(.173)
β_{LL}	.05***	.27***	-.12	.07	.07	-.07	.14***	.12***	.11	.06***	-.07***	-.05*	.08*	.21	.2***
	(.015)	(.007)	(17.456)	(.042)	(1.851)	(.883)	(.012)	(.028)	(.056)	(.011)	(.017)	(.026)	(.038)	(.193)	(.018)
β_K	.04	-2.34***	1.04	-2.22***	-1.19	1.11	-.72***	-1.06	-3.63***	-.68***	.52	.3	-.43	-4.62***	-1.73***
	(.047)	(.087)	(112.021)	(.127)	(2.802)	(.644)	(.17)	(.606)	(.615)	(.104)	(.533)	(.189)	(1.159)	(1.185)	(.155)
β_{KK}	.03***	.25***	-.09	.19***	.12	-.1	.11***	.1*	.29***	.08***	-.01	.01	.06	.43***	.17***
	(.003)	(.004)	(5.469)	(.009)	(.087)	(.118)	(.014)	(.041)	(.037)	(.008)	(.043)	(.017)	(.1)	(.098)	(.011)
β_{LK}	-.06***	-.26***	.09	-.11***	-.1	.1	-.15***	-.09***	-.21***	-.07***	-.05***	0	-.08	-.35**	-.19***
	(.006)	(.004)	(4.974)	(.007)	(.912)	(.502)	(.011)	(.016)	(.03)	(.009)	(.014)	(.018)	(.065)	(.132)	(.012)
Output elasticity															
θ_l	.810	.483	.936	.637	.621	.838	.476	.439	.737	.504	.396	.437	.501	.427	.524
θ_k	.192	.421	.051	.230	.246	.064	.469	.376	.106	.256	.261	.398	.202	.552	.446
Cobb-Douglas model															
β_L	.81***	.4**	.91***	.64***	.61***	.81***	.46***	.52***	.57***	.51***	.36***	.45***	.5***	.28	.37***
	(.02)	(.126)	(.072)	(.059)	(.05)	(.045)	(.009)	(.034)	(.083)	(.012)	(.028)	(.029)	(.034)	(.144)	(.052)
β_K	.19***	.43***	.08	.23***	.25***	.13**	.47***	.24***	.25***	.23***	.31***	.38***	.23***	.58**	.52***
	(.016)	(.091)	(.113)	(.036)	(.052)	(.04)	(.011)	(.041)	(.053)	(.011)	(.043)	(.025)	(.052)	(.194)	(.086)
N	11500	2974	1000	1875	3042	3171	75957	7454	1482	32179	7820	10931	5869	838	4212

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. First panel: results of baseline model with translog assumption in production function and in law of motion of productivity. Second panel: average output elasticity of labour and capital from baseline mode. Third panel: results of robustness model with Cobb-Douglas assumption in production function and translog assumption in law of motion of productivity.

Table B.3: Production function coefficients obtained from ACF procedure by 2-digit industry *Continued*

Industry	J62	M69	M70	M71	M72	M73	M74	M75	N77	N78	N79	N80	N81	N82	S95
β_L	1.53***	1.75***	1.36***	.96***	1.16***	1.22***	.65***	-.17	2.21	.76***	.6***	.77***	.3***	.45***	.32
	(.086)	(.142)	(.049)	(.047)	(.134)	(.105)	(.125)	(.279)	(5.51)	(.055)	(.087)	(.097)	(.052)	(.105)	(.928)
β_{LL}	.15***	.21***	.11***	.03***	.03	-.05***	.09***	.13***	.17	.03**	-.03*	.04*	0	-.03**	.09
	(.011)	(.014)	(.007)	(.007)	(.017)	(.014)	(.022)	(.035)	(.398)	(.01)	(.015)	(.016)	(.007)	(.012)	(.089)
β_K	-.21**	.07	-.46***	-.04	-.18**	-.09	.7***	.19	-1.88	.29***	.11	.17	.8***	.64***	1.21
	(.079)	(.191)	(.055)	(.046)	(.06)	(.113)	(.107)	(.394)	(3.079)	(.045)	(.072)	(.131)	(.044)	(.134)	(1.007)
β_{KK}	.05***	.04*	.05***	.02***	.02**	.03**	-.03**	0	.17	-.01***	0	0	-.04***	-.03**	-.09
	(.008)	(.017)	(.004)	(.004)	(.006)	(.011)	(.01)	(.036)	(.257)	(.004)	(.007)	(.01)	(.004)	(.011)	(.101)
β_{LK}	-.09***	-.12***	-.09***	-.05***	-.05***	-.05***	-.02*	.04	-.15	-.02*	0	-.03***	.01	.01	.02
	(.009)	(.013)	(.004)	(.005)	(.01)	(.011)	(.012)	(.027)	(.403)	(.007)	(.009)	(.01)	(.005)	(.01)	(.093)
Output elasticity															
θ_l	.718	.723	.466	.468	.527	.463	.505	.559	.233	.678	.579	.440	.425	.449	.670
θ_k	.257	.368	.072	.120	-.03	.200	.304	.298	.525	.062	.116	.071	.259	.228	.260
Cobb-Douglas model															
β_L	.73***	.71***	.42***	.46***	.55***	.41***	.53***	.58***	.26***	.67***	.57***	.44***	.45***	.45***	.72***
	(.01)	(.01)	(.01)	(.009)	(.033)	(.017)	(.016)	(.02)	(.023)	(.01)	(.017)	(.024)	(.009)	(.015)	(.028)
β_K	.25***	.39***	.13***	.13***	-.05*	.21***	.29***	.32***	.44***	.06***	.12***	.06	.24***	.2***	.23***
	(.012)	(.01)	(.007)	(.004)	(.021)	(.015)	(.013)	(.017)	(.034)	(.012)	(.013)	(.031)	(.007)	(.016)	(.013)
N	43097	81249	32538	59139	7208	26002	17242	11214	18494	16880	14240	6746	48348	22407	8586

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. First panel: results of baseline model with translog assumption in production function and in law of motion of productivity. Second panel: average output elasticity of labour and capital from baseline mode. Third panel: results of robustness model with Cobb-Douglas assumption in production function and translog assumption in law of motion of productivity.

C Robustness checks for the Law of motion of productivity

Tables C.1, C.2, and C.3 provide the detailed results from the three robustness estimations around the law of motion of productivity, $g(\cdot)$. The first panel reports the point estimates and standard errors from a linear estimation of the law of motion, where the four KBC stocks are summed. The second panel reports the point estimates and standard errors of a linear estimation of the law of motion, where the four KBC stocks enter seperately. The bottom panel reports the coefficients and standard errors from an estimation of the law of motion that includes the squared and interaction terms of past productivity and past stock of KBC. Here, only three KBC stocks (R&D, IPP and software) are summed. The results of the first and third robustness checks are discussed in the main text. We discuss here the results from the second robustness check, which seeks to identify the separate contributions of each of the four KBC elements.

We observe a similar difference between the manufacturing and services sectors as in the main results: the estimated coefficients are an order of magnitude smaller in manufacturing compared to services. In the manufacturing sector, the most important asset in the majority of industries is R&D, where we observe a significantly positive effect ranging between 0.0008 and 0.0018 in 14 of the 22 industries. In contrast, the effect of software is in this range in 6 industries and that of IPP in 5. Finally, organisational capital has a significantly positive effect in 8 industries (of which industry C31, which appears to be an outlier in this respect), and significantly negative in 2.

In the services sectors, we find that all four KBC assets tend to have a positive and significant effect on productivity, and that the two most important assets are software and organisational capital, followed by R&D and finally IPP. We find that software has its strongest effect, with coefficients ranging between 0.008 and 0.01 in H53, J63, N74 and N77 (*Postal activities, IT services, Professional, scientific and technical activities, and Rental activities*). Regarding organisational capital, the two industries with the highest coefficients (0.016 and 0.019) are N79 and N80 (*Travel agencies and Security and investigation activities*), for which the total effect of KBC was shown to be sensitive to including organisational capital. Other industries where OC is important, with an effect around 0.008 are J59, J62, M72 and N78 (*Film and music production, Computer programming, Scientific R&D, and Temporary employment agencies*). Industries J59 and N79, along with industry J60 (*Broadcasting activities*), are the three industies where IPP has the highest effect on productivity, while R&D has its highest impact in industries H51, M70 and M71 (*Air transport, Management consulting and Architectural and engineering activities*), where the last two industries were highlighted as having particularly sensitive estimates of the effect of total KBC stock.

Table C.1: Coefficients from Law of Motion by 2-digit industry

Variables	C10	C11	C13	C14	C15	C16	C17	C18	C20	C21	C22	C23	C24	C25	C26	C27
Linear LoM																
ω_{it-1}	.937***	.928***	.935***	.972***	.949***	.929***	.923***	.913***	.939***	.884***	.908***	.942***	.861***	.888***	.91***	.922***
	(0)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(0)	(.01)	(.01)	(.01)	(.01)	(0)	(.01)	(.01)
c_{it-1}	.003***	.003***	0	.004***	.002	-.001	.004***	.003***	.006***	.009***	.003***	.001	.001*	.001***	.007***	.005***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.042***	2.02***	.436***	.294***	.586***	1.354***	.662***	.672***	.431***	.462***	.494***	.356***	1.151***	1.04***	.934***	.76***
	(.05)	(.24)	(.05)	(.06)	(.15)	(.14)	(.06)	(.07)	(.04)	(.06)	(.03)	(.03)	(.06)	(.04)	(.07)	(.05)
Sep. KBC																
ω_{it-1}	.937***	.928***	.934***	.976***	.933***	.93***	.912***	.924***	.931***	.873***	.913***	.936***	.878***	.89***	.907***	.917***
	(0)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(0)	(.01)	(.01)
r_{it-1}	.001***	.003***	0	0	.002	0	0	.001	.001***	.001**	.001***	.001***	.001*	.001***	.002***	.001***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
s_{it-1}	.001***	0	0	.001	.001	0	.001**	.001	.001*	-.001	0	0	0	.001**	.002***	.002***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
z_{it-1}	.001***	.001	.001	.002**	.002	0	0	.002**	0	.002**	0	0	.001**	0	-.001	-.001*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
o_{it-1}	.001***	0	0	.002**	0	-.001**	.017***	.001	.002**	.001	.001***	-.001**	0	.001***	.002**	.001
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	.958***	1.559***	.368***	-.033***	-.24***	1.282***	.766***	.511***	.56***	.593***	.477***	.518***	1.205***	.994***	.978***	.764***
	(.05)	(.22)	(.04)	(.01)	(.05)	(.14)	(.07)	(.06)	(.04)	(.06)	(.03)	(.04)	(.07)	(.04)	(.07)	(.05)
No OC																
ω_{it-1}	.097	-.486	1.78***	.583***	1.114***	1.132**	.617***	.988***	.83***	2.564***	.816***	.898***	.567**	1.213***	-.115	.925***
	(.11)	(.33)	(.21)	(.2)	(.14)	(.48)	(.18)	(.05)	(.13)	(.28)	(.07)	(.12)	(.28)	(.17)	(.19)	(.15)
ω^2_{it-1}	.046***	.03***	-.049***	.02*	.019	-.004	.022*	-.005	.009	.108***	.016	.002	.018	-.019**	.072***	.002
	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)
c_{it-1}	.025***	.072**	-.037**	.027*	-.011	-.003	.026**	.014***	.026***	-.094***	.007**	-.008	.004	-.024***	.067***	.041***
	(.01)	(.03)	(.01)	(.02)	(.02)	(.03)	(.01)	(0)	(.01)	(.03)	(0)	(.01)	(.01)	(.01)	(.01)	(.01)
c^2_{it-1}	0***	0	0	0	.001	0	0	.001***	0***	.001***	0***	.001***	0	0**	.001***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\omega_{it-1} * c_{it-1}$	-.003***	-.003**	.004**	-.002	-.002	0	-.003**	-.008***	-.003***	-.012***	-.002**	.001	-.001	.003***	-.009***	-.004***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	4.454***	18.37***	-3.002***	2.161**	.152	-.654	1.627**	.046	.821	5.687***	.476***	.558	2.419**	-.336	4.322***	.602
	(.51)	(4.08)	(.92)	(.99)	(.34)	(5.42)	(.64)	(.06)	(.52)	(1.12)	(.12)	(.36)	(1.18)	(.76)	(.71)	(.72)
N	9482	1297	1929	1053	469	1994	2257	1635	4222	913	4573	3763	3275	10430	3664	5063

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. Translog assumption in production function. Robustness models for law of motion. First panel: Linear assumption with aggregated KBC stock. Second panel: linear assumption with four individual KBC stocks. Third panel: Translog assumption with aggregated KBC stock without OC.

Table C.2: Coefficients from Law of Motion by 2-digit industry

Variables	C28	C29	C30	C31	C32	C33	H49	H50	H51	H52	H53	J58	J59	J60	J61
Linear LoM															
ω_{it-1}	.87***	.879***	.921***	.856***	.929***	.91***	.846***	.902***	.758***	.849***	.911***	.927***	.904***	.917***	.861***
	(0)	(.01)	(.01)	(.01)	(.01)	(.01)	(0)	(0)	(.01)	(0)	(0)	(0)	(.01)	(.01)	(.01)
c_{it-1}	.005***	.006***	.002**	.021***	.002***	.002***	.007***	.005***	.022***	.01***	.007***	.004***	.012***	.011***	.011***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.018***	2.594***	.47***	2.931***	1.208***	.162***	1.633***	1.064***	5.306***	2.062***	1.18***	.308***	1.056***	3.189***	2.675***
	(.03)	(.15)	(.08)	(.23)	(.1)	(.01)	(.02)	(.05)	(.29)	(.04)	(.06)	(.01)	(.06)	(.44)	(.14)
Sep. KBC															
ω_{it-1}	.864***	.888***	.904***	.821***	.927***	.904***	.847***	.902***	.777***	.848***	.884***	.927***	.901***	.901***	.878***
	(0)	(.01)	(.01)	(.01)	(.01)	(.01)	(0)	(0)	(.01)	(0)	(0)	(0)	(.01)	(.01)	(.01)
r_{it-1}	.001***	.002***	.001	.001**	.001***	.001***	.002***	.002	.022***	.001***	-.001	.001*	-.001	.003	-.001*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
s_{it-1}	.001*	0	0	0	0	.001	.004***	.003**	.005	.005***	.012***	.001	.005***	-.002	.003***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
z_{it-1}	.001**	0	0	.002***	0	0	.001**	.001	-.002	.002***	.003***	.001**	.005***	.007***	.002***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
o_{it-1}	0	.001	.001	.042***	.001	0	.005***	.001	-.006*	.006***	.002***	.003***	.008***	.002	.006***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.156***	2.297***	.595***	3.832***	1.187***	-.221***	1.487***	.968***	4.073***	2.048***	1.528***	.444***	1.435***	4.523***	2.357***
	(.03)	(.14)	(.09)	(.25)	(.1)	(.02)	(.02)	(.04)	(.24)	(.04)	(.06)	(.02)	(.08)	(.53)	(.14)
No OC															
ω_{it-1}	1.235***	-1.671***	.896***	3.449**	-.05	1.043***	1.924***	3.093***	4.322***	1.365***	.769***	1.03***	1.335***	1.255***	-.002
	(.14)	(.45)	(.25)	(1.49)	(.36)	(.05)	(.05)	(.1)	(.17)	(.08)	(.05)	(.03)	(.12)	(.36)	(.27)
ω_{it-1}^2	-.023***	.063***	.006	-.061*	.032***	-.016***	-.045***	-.065***	-.052***	-.018***	.005*	-.007***	-.016***	-.004	.024***
	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(.01)
c_{it-1}	-.028***	.155***	.005	-.053	.011	-.001	-.046***	-.038*	.229***	.005	-.033***	.01***	-.03**	.149*	.044*
	(.01)	(.03)	(.01)	(.05)	(.02)	(.01)	(.01)	(.02)	(.08)	(.01)	(.01)	(0)	(.01)	(.08)	(.02)
c_{it-1}^2	0***	.001***	.001***	.001***	.001***	0**	0***	0	.005***	0*	-.001	.001***	0	.003***	.001***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\omega_{it-1} * c_{it-1}$	.003***	-.008***	-.002	.002	-.001	0	.004***	.002*	-.007***	0	.005***	-.003***	.003***	-.004**	-.003**
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	-.299	28.58***	.353	-24.53	8.676***	.121	-4.564***	-16.75***	-52.43***	-1.618***	1.691***	.102	-1.52*	-3.565	10.43***
	(.6)	(4.65)	(.52)	(15.87)	(2.72)	(.12)	(.3)	(.85)	(2.79)	(.58)	(.22)	(.09)	(.79)	(6.66)	(2.54)
N	11500	2974	1000	1875	3042	3171	75957	7454	1482	32179	7820	10931	5869	838	4212

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Translog assumption in production function. Robustness models for law of motion. First panel: Linear assumption with aggregated KBC stock. Second panel: linear assumption with four individual KBC stocks. Third panel: Translog assumption with aggregated KBC stock without OC.

Table C.3: Coefficients from Law of Motion by 2-digit industry

Variables	J62	J63	M69	M70	M71	M72	M73	M74	M75	N77	N78	N79	N80	N81	N82	S95
Linear LoM																
ω_{it-1}	.841***	.882***	.867***	.855***	.707***	.767***	.875***	.858***	.826***	.892***	.735***	.852***	.853***	.856***	.902***	.848***
	(0)	(0)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)
c_{it-1}	.017***	.006***	.004***	.025***	.098***	.098***	.012***	.01***	.003***	.01***	.01***	.016***	.018***	.004***	.008***	.001***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.314***	.574***	.732***	1.294***	2.129***	1.976***	1.142***	.711***	1.031***	2.332***	2.37***	1.09***	1.365***	.712***	.602***	.488***
	(.02)	(.02)	(.01)	(.03)	(.02)	(.07)	(.03)	(.02)	(.03)	(.07)	(.04)	(.03)	(.06)	(.01)	(.02)	(.02)
Sep. KBC																
ω_{it-1}	.829***	.859***	.867***	.868***	.719***	.851***	.875***	.868***	.823***	.89***	.737***	.831***	.852***	.856***	.898***	.841***
	(0)	(0)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)
r_{it-1}	.001***	-.001***	-.001***	.015***	.084***		.006***	.001***	-.006*	.005***	.003***	.001	-.002	.001	0	.003***
	(0)	(0)	(0)	(0)	(0)	(.)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
s_{it-1}	.003***	.009***	.004***	.003***	.005***	.006***	.005***	.008***	.003***	.008***	.003***	.007***	.004***	.005***	.006***	.005***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
z_{it-1}	0	.003***	.001***	.002***	.003***	.002***	.002***	.002***	.001	.004***	.001	.005***	.002*	.002***	.002***	.001
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
o_{it-1}	.01***	.006***	.001**	.003***	.002***	.008***	.002***	.004***	0	.001**	.008***	.016***	.019***	.003***	.005***	-.002***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.658***	1.047***	.745***	1.235***	2.136***	2.087***	1.233***	.652***	1.113***	2.266***	2.311***	1.252***	1.384***	.703***	.628***	.641***
	(.03)	(.03)	(.01)	(.03)	(.02)	(.09)	(.03)	(.02)	(.03)	(.07)	(.04)	(.03)	(.06)	(.01)	(.02)	(.02)
No OC																
ω_{it-1}	1.137***	1.452***	1.281***	.346***	-.918***	-.121	.447***	.691***	2.456***	.919***	1.294***	2.358***	.83***	.79***	.736***	.76***
	(.05)	(.04)	(.03)	(.04)	(.05)	(.13)	(.05)	(.04)	(.19)	(.12)	(.06)	(.08)	(.08)	(.03)	(.02)	(.01)
ω^2_{it-1}	-.016***	-.045***	-.026***	.022***	.129***	.056***	.023***	.022***	-.095***	-.001	-.036***	-.087***	.001	.007**	.02***	.085***
	(0)	(0)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)	(0)	(0)	(0)	(.01)	(0)	(0)	(.01)
c_{it-1}	.003	-.035***	-.002	.152***	.589***	.261***	.036***	.029***	-.079***	.004	-.004	-.045***	.004	.004	.017***	.009***
	(0)	(.01)	(0)	(.01)	(.02)	(.06)	(.01)	(0)	(.02)	(.01)	(.01)	(.01)	(.01)	(0)	(0)	(0)
c^2_{it-1}	0***	.002***	-.001***	.016***	.059***	.028***	.006***	.001***	-.001	.001***	.002***	0	0	0**	.001***	.001***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\omega_{it-1} * c_{it-1}$	-.001	.003***	.001***	-.018***	-.106***	-.041***	-.007***	-.005***	.01***	0	0	.006***	0	0	-.003***	-.013***
	(0)	(0)	(0)	(0)	(0)	(.01)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	.112	-.942***	-.583***	4.73***	8.156***	6.192***	3.166***	.909***	-5.512***	2.026	-.085	-5.243***	1.129***	.776***	.761***	.106***
	(.24)	(.15)	(.12)	(.27)	(.19)	(.45)	(.21)	(.08)	(.81)	(1.24)	(.25)	(.35)	(.28)	(.06)	(.05)	(0)
N	43097	10904	81249	32538	59139	7208	26002	17242	11214	18494	16880	14240	6746	48348	22407	8586

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Translog assumption in production function. Robustness models for law of motion. First panel: Linear assumption with aggregated KBC stock. Second panel: linear assumption with four individual KBC stocks. Third panel: Translog assumption with aggregated KBC stock without OC.

D Characteristics of Frontier firms

Table D.1 reports average characteristics of frontier firms in comparison to the industry average, according to both the productivity and the output frontier.

The first 4 columns show that firms on the productivity frontier are more productive (by definition), larger and have higher KBC stocks than the industry average. In the manufacutring sector, frontier firms are 2.4 times more productive, 9 times larger, and have KBC stocks 118 times larger than the average. They are not much more capital intensive than the average, given that their capital-labour ratio is only 1.2 times that of the average firm. In the services sector, firms on the productivity frontier are 6.3 times more productive, 28 times larger and have capital stocks almost 4000 times larger than the average firms, while having a capital-labour ration that is only twice as large.

The sixth to ninth columns of Table D.1 suggest that these ratios are more accentuated on the output frontier. In the manufacturing sector, frontier firms are 1.8 times more productive, 28 times larger, have capital-labour ratios 1.5 times larger and KBC stocks 350 times larger than the average. In the services sector, frontier firms are 4 times more productive, 75 times larger, have capital-labour ratios 2.4 times larger and KBC stocks 5,700 times larger than the average firm.

Finally, comparing the fifth and tenth columns of Table D.1 shows that persistence is higher on the output frontier than on the productivity frontier. In these columns, we report the average ratio of the number of years that a firm is on the frontier (in the period 2009-2013) if it is on the frontier in t, over the number of years that the firm is in the sample (in this same period).[19] Manufacturing firms that are on the productivity frontier in one year stay on the this frontier on average 3.75 years over the 5 year period. However, manufacturing firms on the output frontier stay on average 4.4 years on the that frontier. In services, firms on the productivity frontier stay on average 4 years on the frontier, and firms on the output frontier stay on average 4.3 years on the frontier.

E Correlation of productivity gap with measures of KBC importance

Figures E.1 and E.2 illustrate the details of the correlation coefficients reported in Table 7, for the productivity frontier and the output frontier respectively. In each Figure, the first column of plots shows the correlation between productivity divergence and the KBC stock of the average

[19] We need to report persistence as a share of years in the sample given the important resampling taking place in the years 2008 and 2011 for services and 2012 for manufacturing.

Table D.1: Ratio of average characteristic of frontier firms over average characteristics of other firms, 2009-2013

	Productivity frontier					Output frontier				
		Value			Share of years		Value			Share of years
Industry	ω	Added	K/L	KBC	on Frontier	ω	Added	K/L	KBC	on Frontier
C10	2.46	9.25	1.18	104.11	.83	2.04	22.31	1.65	317.75	.87
C11	2.68	1.46	.48	2.47	.85	1.3	29.51	1.44	56.16	.9
C13	2.04	5.26	1.34	10.65	.73	1.7	12.53	1.43	39.27	.86
C14	4.24	13.16	1.3	108.98	.88	3.16	25.55	1.36	396.84	.94
C15	4.71	8.12	1.53	207.18	.87	3.72	10.94	1.17	179.06	.69
C16	1.74	1.12	.56	.19	.65	1.02	15.25	2.15	110.63	.8
C17	1.67	2.51	1	2.52	.69	1.4	16.1	2.06	22.54	.85
C18	2.08	2.87	.87	7.69	.68	1.46	13.44	1.33	101.47	.85
C20	2.34	9.47	1.69	19.06	.79	1.88	38.04	1.9	90.44	.91
C21	2.7	14.62	.81	120.04	.74	1.95	53.67	1.08	389.48	.91
C22	1.94	8.51	1.3	103.15	.72	1.66	21.46	1.3	294.95	.89
C23	2.33	12.38	1.17	54.01	.83	2.09	19.69	1.29	56.45	.88
C24	1.7	1.49	.89	.5	.59	1.22	30.24	1.45	229.54	.88
C25	1.76	3.71	.92	24.26	.64	1.44	17.25	1.42	474.5	.86
C26	2.16	7.15	1.47	19.93	.71	1.71	28.87	1.93	126.59	.88
C27	1.96	10.77	1.24	30.71	.73	1.72	32.9	1.48	171.13	.91
C28	1.87	7.71	1.06	24.86	.71	1.56	26.7	1.37	159.18	.88
C29	2.57	29.16	1.41	539.52	.85	2.11	72.53	1.39	1070.32	.89
C30	2.3	21.87	1.46	148.48	.74	1.95	71.09	1.25	1501.33	.91
C31	1.83	4.36	1.02	5.77	.63	1.47	17.4	1.44	40.98	.85
C32	2.79	19.68	1.45	922.21	.85	2.42	33.07	2.5	1373.25	.91
C33	2.22	7.26	1.86	140.24	.8	1.79	24.55	1.1	533.52	.91
H49	3.17	6.99	.71	558.71	.77	2.08	29.25	3.25	11780.55	.83
H50	5.96	4.76	.92	2.37	.63	2.19	41.11	1.27	28399.99	.74
H51	7.44	190.31	.55	84831.2	.77	5.06	375.48	.74	81223.02	.89
H52	3.59	14.67	.8	163.06	.82	2.62	38.26	2.73	383.37	.82
H53	13.57	31.91	1.22	5754.2	.85	9.16	40.5	.92	7037.73	.81
J58	4.46	18.71	.88	29.11	.82	2.97	50.39	2.5	83.54	.92
J59	7.44	17.42	.92	141.39	.79	4.41	33.58	.92	128.49	.79
J60	12.99	42.82	3.34	64.59	.79	6.63	405.19	3.27	403.59	.91
J61	4.47	49.44	.67	236.48	.77	3.18	278.13	9.52	1253.82	.91
J62	2.69	4.24	2.17	4.02	.71	1.59	40.53	2.03	44.88	.87
J63	4.35	28.79	4.12	67.63	.78	3.13	55.16	1.36	157.86	.89
M69	2.57	2.38	.81	7.87	.79	1.38	19.03	.96	1602.95	.88
M70	10.15	37.22	1.27	117.61	.88	6.32	47.45	3.45	85.06	.84
M71	6.45	27.13	.79	44.65	.89	5.26	28.37	1.02	33.61	.83
M72	13.99	40.14	1	60.06	.94	8.69	42.31	.82	36.07	.84
M73	6.91	21.18	1.85	204.24	.85	5.13	26.38	2.5	171.19	.82
M74	4.1	12.59	2.78	1453.59	.77	2.44	18.74	2.52	2800.23	.8
M75	2.09	1.86	.79	2.87	.71	1.17	8.66	1.2	88.85	.85
N77	6.47	18.17	1.29	1273.73	.79	3.51	76.12	10.09	3189.37	.88
N78	3.96	9.95	1.94	39.18	.74	2.68	24.5	.56	238.26	.85
N79	5.78	29.96	1.56	262.65	.85	3.99	53.33	1.26	140.57	.8
N80	9.91	41.67	1.79	120.31	.88	8.69	42.29	1.14	115.9	.88
N81	3.64	16.57	2.54	487.29	.8	2.84	30.25	1.46	3131.16	.88
N82	7.52	31.49	7.46	426.23	.84	5.16	45.32	2.36	745.02	.86
S95	3.02	7.69	5.53	26.64	.75	1.88	21.85	1.96	389.98	.83

firm in the industry, taken from the final column of Table 1. The second column of plots shows the correlation between productivity divergence and the average θ_c, the marginal effect of KBC on productivity, taken from the first column of Tables 2 and 3. The third column of plots shows the correlation between productivity divergence and β_{c^2}, taken from the sixth column of Tables 2 and 3. Finally, the fourth column of graphs shows the correlation between productivity divergence and the difference between θ_c in the group of frontier firms and θ_c in the middle quintile. In the first row of each Figure, productivity divergence is calculated for manufacturing industries over the period 2009-2013, in the second row of each Figure, productivity divergence is calculated for service industries over the period 2009-2013, and in the final row of plots of each Figure, productivity divergence is calculated for service industries over the period 2003-2013.

Figure E.1: Relationship between gap in productivity growth on productivity frontier, 2009-2013, in Manufacturing sector

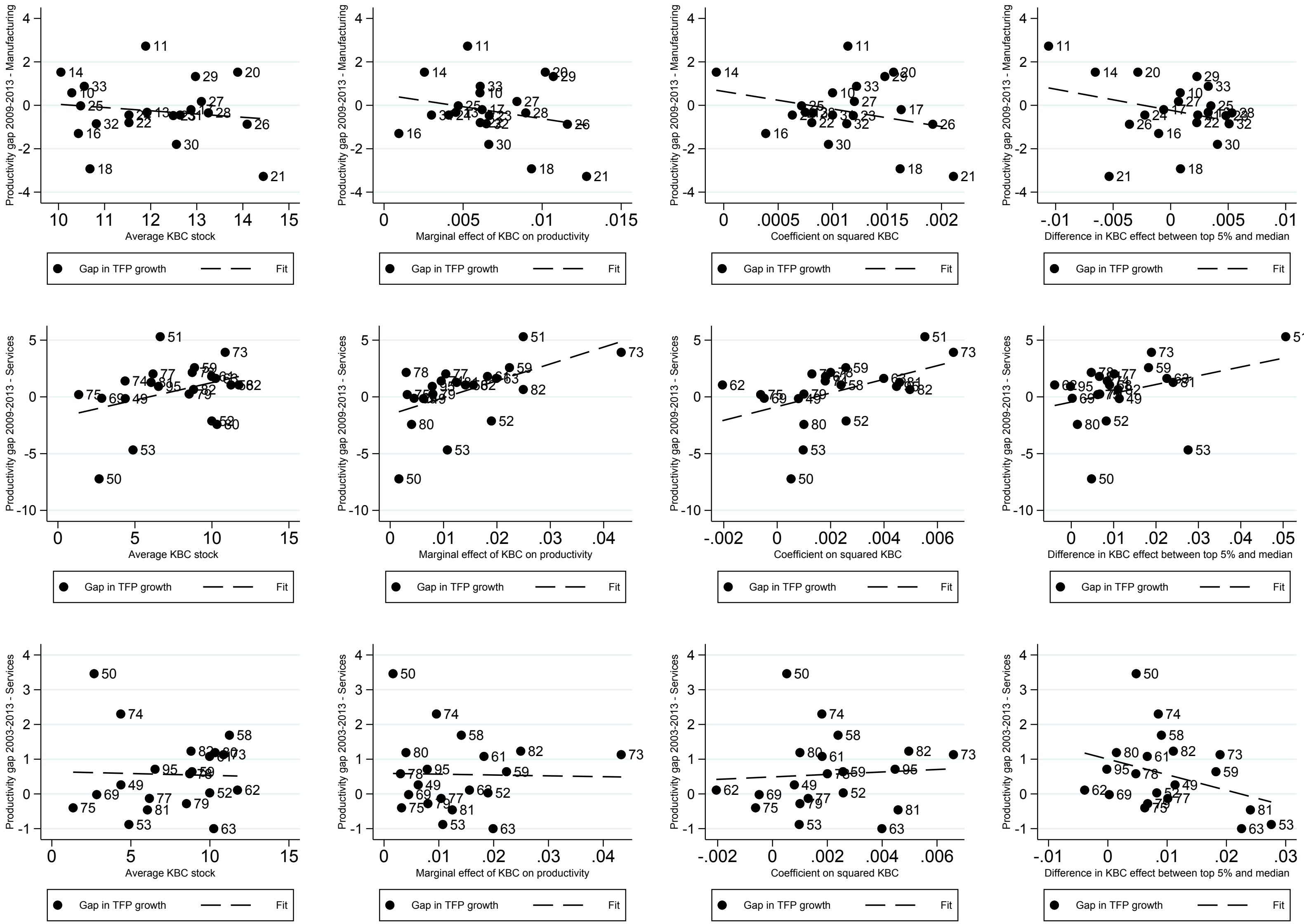

Figure E.2: Relationship between gap in productivity growth on output frontier, 2009-2013, in Manufacturing sector