The contribution of skilled and unskilled workers to capital productivity: the case of Belgian firms[*]

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Abstract

We decompose capital productivity growth into four factors: (i) efficiency change, (ii) technological change, (iii) skilled labor–capital accumulation, and (iv) unskilled labor–capital accumulation. This decomposition recognizes the particular relationships between capital, skills, efficiency, and technological change. We rely on a non-parametric approach to estimate the decomposition dimensions. We use our new approach to study the capital productivity changes of Belgian firms in two sectors, manufacturing and service, from 2006–2013 using a tailored firm-level database. Our results highlight the role of skills and sectors in capital productivity change, while technological change is the main driver. Next, skills and technology improvement together can only explain capital productivity growth. Finally, our approach allows having a new look at two related topics: the skilled-biased technological change (SBTC) and the capital-skill complementarity (CSC) hypotheses. We provide support for the first and partially for the second.

Keywords: capital productivity; skills; technological change; SBTC; CSC.

JEL codes: O30; D24; O47.

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1 Introduction

Capital productivity growth has been identified as a key driver of economic growth, competition, and economic development (Mankiw et al.,1992; McKinsey, 1996). Understanding its role and impact has received particular attention in the empirical macroeconomic literature.[1] In this paper, we study the relationships between capital productivity, skills, (in)efficiency, and technological change from a new angle. We suggest decomposing capital productivity change into four parts: efficiency change (change in the movements toward or away from the best practices), technological change (change in the best practices), skilled labor–capital accumulation, and unskilled labor–capital accumulation (changes in the labor–capital ratios). Such a new decomposition recognizes the potential inefficiency in the production process, the role of technological change, and the particular relationships between skills, capital, and technology. While the first two factors have been included in previous empirical works based on a growth decomposition approach, the two latter represent our distinguished feature.[2] Moreover, by including skilled and unskilled labor separately in our capital productivity change decomposition, we follow two research streams in empirical macroeconomics: the capital-skill complementarity (CSC) and skilled-biased technological change (SBTC) hypotheses.

The capital-skill complementarity (CSC) hypothesis states that capital and skilled labor are more complementary inputs than capital and unskilled labor. This means that we observe an increase in the skilled labor demand when the capital price falls. Hence, if the total labor supply is constant, the wage premium rises. Starting with the pioneering work of Griliches (1969), which confirms the CSC using US manufacturing data, the CSC has received particular attention in the economic literature. An important contribution is due to Krusell et al. (2000) who provide a theoretical framework and an empirical procedure to test the CSC hypothesis. In short, they define an aggregate production function that combines two types of capital (equipment and structures) and two skilled labor groups (skilled and unskilled). Therefore, the CSC hypothesis is verified by estimating the elasticity of substitution between

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[1]See, for example, Kendrick (1956), Bator (1957), Börsch-Supan and Romer (1998), Baily et al. (1990), Choi and Kim (2005), Ahmed (2009), Mohun (2009), Li and Liu (2011), Roth and Thum (2013), Weber and Yang (2014), Arzu (2020), and Caunedo et al. (2021).

[2]See, for example, Kumar and Russell (2002), Henderson and Russell (2005), Badunenko and Romero-Avila (2013), Filippetti and Peyrache (2015), Walheer (2016, 2018, 2021), and Chambers and Pieralli (2020).

capital and the two types of labor. Most of the empirical studies support the CSC hypothesis but not all.[3] Other researchers take the CSC for granted and analyze its effects on economic growth, labor markets, wages, and income inequality.[4]

Moreover, skills may have a particular connection with technological change. The skilled-biased technological change (SBTC) hypothesis says that technological progress is biased towards skilled workers leading to an increase in the relative demand for the skilled workers and thus to an increase in their wage premium. The SBTC concept emphasizes the role of technology in shaping the demand for skilled workers (Carbonero et al., 2023). That means that technological progress may have distributional effects on workers with different levels of skills and education. Most of the empirical works support the SBTC.[5] To be fair, most of the evidence is focused on the US economy.[6] Therefore, it is better to analyze SBTC in terms of differences in time, country, and sector.

In this paper, we decompose capital productivity into four factors: (*i*) efficiency change, (*ii*) technological change, (*iii*) skilled labor–capital accumulation, and (*iv*) unskilled labor–capital accumulation. We recognize the potential different relationships between skilled and unskilled labor and capital by including these two types of labor separately in the production process. This has two main consequences for our empirical exercise. First, this means that skilled and unskilled workers may impact the production process, including technological change, differently (SBTC spirit).

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[3]Supporting studies include Fallon and Layard (1975), Bergstrom and Panas (1992), Goldin and Katz (1998), Ruiz-Arranz (2003), Duffy et al. (2004), Gilboa and Justman (2005), He and Liu (2008), Slavik and Yazici (2014), Goel (2017), Alvarez-Cuadrado et al. (2018), Domeij and Ljungqvist (2019), Ohanian et al. (2021), Castex et al. (2022), and Gechert et al. (2022). The CSC hypothesis has not been confirmed by Duffy et al. (2004), Papageorgiou and Chmelarova (2005), and Henderson (2009).

[4]Stokey (1996), Krusell et al. (2000), Lindquist (2004, 2005), Caselli and Coleman (2002), Polgreen and Silos (2008), Maliar and Maliar (2011), Parro (2013), Correa et al. (2019), Chen (2020), Perez-Laborda and Perez- Sebastian (2020), Ohanian et al. (2021), Hutter and Weber (2021), Lindner et al. (2022), Maliar et al. (2022), Taniguchi and Yamada (2022), and Caunedo et al. (2023).

[5]Refer, for example, to Bound and Johnson (1992), Berman et al. (1994), Berman et al. (1998), Goldin and Katz (2008), Balleer and van Rens (2013), Pi and Zhang (2018), Perez-Laborda and Perez-Sebastian (2020), and Hutter and Weber (2023).

[6]The increase in the wage gap in the US can be attributed to the SBTC in the 1960–1990 (Baltagi and Rich, 2005). More recently, Mallick and Sousa (2017) found that technology has become more favourable to skilled labour since the 1980s. In other developed economies, that have the same advanced technology as the US (such as France, Korea, and Japan), the increase in the wage gap was not wide (Wood, 1998; Acemoglu, 2002). For developing countries, such an effect is not clear. See for Chile (Pavcnik, 2003); Colombia (Attanasio et al., 2004); India (Berman et al., 2005); and Malaysia (Marouani and Nilsson, 2016).

Second, we end up with two different factors in our capital productivity decomposition, one for each labor type (CSC spirit). An interesting side effect of our modeling is that it provides new ways to look at the CSC and SBTC hypotheses.

Another distinguished feature of our paper is that we use a non-parametric approach to estimate the decomposition dimensions. A main advantage of the non-parametric approach is that it avoids making a functional assumption for the production process, which is not insidious. Even when convincing arguments are found to support a specific functional form, a weakness of the parametric approach is the important number of parameters. This is particularly true in a context with two types of labor, (in)efficiency, and technological change. Also, empirical evidence has shown that the production process may be too complex to be captured by methods focusing on the first (or second) moment, making econometric regressions not applicable.

Finally, our last contribution is to rely on firm-level data. We rely on an exclusive and complete database of the whole Belgian firms for the period 2006–2013. It contains output, capital, and labour provided directly by the firms every year. Also, a distinction between skilled and unskilled workers is made, and it distinguishes two sectors: manufacturing and service. We may indeed expect that the impacts of technological change, (in)efficiency, and skills differ across sectors (Fallon and Layard, 1975; Duffy et al., 2004; Chen, 2020; Perez-Laborda and Perez-Sebastian, 2020; Taniguchi and Yamada, 2022). Also, as evidenced by Acemoglu and Guerrieri (2008), Valentinyi and Herrendorf (2008), Alvarez-Cuadrado et al. (2018), and more recently by Chen (2020), capital intensities as well as labor shares may change differently across sectors and over time. All in all, this represents a unique opportunity to study and decompose capital productivity at the firm level.

Our empirical study highlights several important stylized facts about capital productivity change at the firm level. First, the shapes of the distributions of capital productivity heavily depend on skills and sectors. Second, technological change is the main factor affecting the capital productivity change. Third, skilled labor– and unskilled labor–capital accumulations also have a positive role, yet less important. Fourth, we find strong positive and significant associations between skilled labor accumulations and technological improvements in both sectors, supporting the SBTC hypothesis. Finally, we have evidence that the skilled labour-capital accumulation is stronger than the unskilled labour-capital accumulation only for the service sector, supporting the CSC hypothesis for that sector.

The rest of the paper unfolds as follows. Section 2 presents our database and our empirical context. In Section 3, we describe our theoretical decomposition, and in Section 4, our estimation method. Section 5 presents our results and their implications. The final section concludes our paper.

2 Data and empirical context

Belgium is a small economy of more than 11.5 million people, located in north-western Europe. In 2021, its GDP was EUR 502.3 billion and represented 3.5% and 4.1% of the GDP of the European Union (EU27) and the Euro area, respectively. Despite its relatively small size, the Belgian economy remains a very open economy with an openness rate of 86.3%.[7]

We rely on an exclusive and complete database of Belgian firms from the Belgian Ministry of Economy (SPF Economie - Direction générale Statistique - Statistics Belgium). It contains detailed information provided directly by the firms on a yearly basis. Output and capital data are available and the distinction between skilled and unskilled workers is made. By taking all the data publicly available, we end with the period 2006–2013. Even though our analysis period is short (8 years), we have complete information for each company over the entire study period. This enabled us to calculate all the variables used in this study accurately. Moreover, the major advantage of our database is that it does not come from a survey but from administrative data gathered on the entire population of firms in Belgium. Given the administrative procedures involved, this database is the best and the most recent publicly available at the moment.

We distinguish three types of firms: those that use unskilled workers only, those that rely on skilled workers only, and those using both worker types. That distinction is made for different reasons. First, for a matter of fairness: firms that use both skilled and unskilled workers can not be compared to firms using skilled or unskilled workers only. Also, it has little sense to compare firms using only skilled workers to firms relying on unskilled workers only. It is for the same reason that we distinguish firms in the service and manufacturing sectors. Second, it has been acknowledged in the literature that different firm types (e.g. SME, multinational, family-owned firms,

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[7]All figures in this paragraph are taken from: SPF Economie, P.M.E., classes moyennes et energie, 2023 : Aperçu de l'économie belge: note conjoncturelle, 2023.

state-owned firms, and size) exhibit significant variations in productivity (Wagner, 2012; Huang and Zhang, 2017; Coad et al., 2018; Yasin et al., 2021; Bhakar et al., 2024). In our context, this implies that firms with different workforce compositions may exhibit distinct productivity patterns. The separation allows for more nuanced analysis because certain firms are more skilled or unskilled intensive. Finally, the relationship between skilled and unskilled workers and capital can be different, as also acknowledged in the literature on SBTC and CSC, making an overall comparison less attractive.[8]

To obtain a set of comparable firms, we proceed in three steps. First, we select firms that are part of the manufacturing sector (NACE code: C) and those that are in the service sector (NACE codes: G, H, I, J, K, M, N, and S).[9] Next, we keep only firms with no missing data for the whole period and remove potential outliers and extreme values. Specifically, we remove observations satisfying the following conditions: (1) negative or missing value in any of the input–output variables, and (2) the lower and upper 1-tails of the input–output variables. Indeed, we want to understand the capital productivity changes between an initial and a final period. Closures before the final period imply that we can not measure capital productivity for the final period. Similarly, new establishments mean that we cannot measure capital productivity for the initial period. However, we acknowledge that these data filtering conditions could create selectivity issues that may impact the results, as those firms can be found as important peers when computing the decomposition components. To test how far these selectivity issues could impact our results, we conduct a sensitivity analysis in Section 5.4. For example, we have redone the analysis when including closures and new establishments, controlled for firm characteristics such as firm size, ownership. Results show that our results are stable and have not been polluted by our data filtering conditions. Our final dataset consists of 7,848 firms per year, i.e., 62,784 observations in total. Note that 148 use only unskilled workers, 4,234 use only skilled

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[8]We can connect our firm distinction to theoretical models used in the literature (see e.g. Acemoglu, 2002; Gancia and Zilibotti, 2009; Hutter and Weber, 2021). Such models assume that, in an economy composed of two or more goods and two types of workers (skilled and unskilled), each good is produced exclusively using one type of worker, either skilled or unskilled. This implies that some firms will produce one of the two goods using either skilled or unskilled labor, and others produce both goods by utilizing both types of workers. Hence, firms composed of only skilled/unskilled workers will specialize in the production of goods using only that type of worker. However, firms using both types of workers will produce both goods.

[9]See Table 11 in the Appendix for a list of the NACE codes.

workers, and 3,466 use both worker types. This represents 2%, 54%, and 44% of the total number of firms in our sample, respectively.

Our main variables are output, capital, and two labor types. One limitation of our dataset is that we do not have any information on firms' value added. However, we do have information on sales and purchase inputs. Given that in Belgium, by law, all firms are required to report annual sales worth EUR 250 and more, we have accurate information on sales. Hence, we follow the literature and subtract total purchased inputs from total sales to have the nominal value added. In a sense, this effectively accounts for output quality differences across firms. Higher-quality outputs typically have higher prices. To measure the stock of capital, we also follow what is done in the literature and measure the stock of capital through the (book value of the beginning of the year of) gross fixed assets/property plants and equipment. Finally, we use deflators from Eurostat to transform nominal values into real values.[10]

Skilled and unskilled labor are measured by the number of employees. A second limitation of our dataset is that we do not observe employees' skill levels. Nevertheless, we have the exact number of workers by occupation type by the firm, namely blue and white collar. So, we use this information as a proxy for the skill level of employees by firm. This choice is in line with the existing literature which used the blue-collar and white-collar occupations as proxies for unskilled and skilled labour, respectively (see Bjerk, 2007; Staffolani and Valentini, 2010; Eriş-Dereli and Pinar, 2025). Moreover, as evidenced by Kirkegaard (2004), white collar workers usually are associated with high pay wages and require high skill levels. Hence, we follow these studies and approximate skills with blue/white collar. Hence, white-collar workers are defined as skilled and blue-collar ones as unskilled ones. We are aware that this approximation is not perfect but this is the best possible approximation for skills given the data we have.[11] We highlight that proxies are often used to categorize workers in terms of skills in previous works: cognitive occupations versus manual positions, production vs non-production, routine vs non-routine occupations, education level, and cognitive level (Autor and Dorn, 2013; Mallick and Sousa, 2017; Atalay et al., 2018; Chen, 2020; Cortes et al. 2020; Perez-Laborda and Perez-Sebastian, 2020; Vom Lehn, 2020; Castex et al., 2022; Hendricks and Schoellman, 2023). Finally, we highlight that,

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[10]https://ec.europa.eu/eurostat/databrowser/view/teina110/default/table

[11]For instance, blue-collar workers are mainly production workers, and white-collar workers are mainly non-production or office workers. It is also possible that among white-collar workers, there are employees who have a low level of education, such as secretaries, and maintenance workers.

from 2014, a new reform has been introduced in Belgium, which removes the status of workers. In other words, from 2014, it is no longer possible to distinguish between blue and white collars.

In Table 1, we present the descriptive statistics of the variables used in our empirical study for our initial (2006) and final (2013) periods.

Table 1: Descriptive statistics

2006	Output (euro)	Capital (euro)	Unskilled workers (number)	Skilled workers (number)	Total workers (number)
Unskilled (148 firms)					
average	359,286,226	1,252,583,761	25.77	0	25.77
median	53,982,472	22,335,686	13.50	0	13.50
total	53,174,361,450	185,382,396,757	3,814	0	3,814
Skilled (4,234 firms)					
average	457,488,294	738,309,714	0	27.33	27.33
median	61,270,346	36,597,214	0	8	8
total	1,937,005,439,300	3,126,003,330,885	0	115,698	115,698
Unskilled and skilled (3,466 firms)					
average	284,931,867	439,163,249	63	37	100
median	62,952,128	28,453,937	19	12	37
total	987,573,846,016	1,522,139,791,360	217,500	128,094	345,594
2013	Output (euro)	Capital (euro)	Unskilled workers (number)	Skilled workers (number)	Total workers (number)
Unskilled (148 firms)					
average	418,465,395	1,177,173,510	30.99	0	30.99
median	52,466,780	28,848,670	11.50	0	11.50
total	61,932,878,536	174,221,679,596	4,586	0	4,586
Skilled (4,234 firms)					
average	470,348,233	815,284,472	0	28.35	28.35
median	69,160,292	40,189,966	0	8	8
total	1,991,454,418,577	3,451,914,456,524	0	120,034	120,034
Unskilled and skilled (3,466 firms)					
average	274,391,674	437,443,394	59	41	100
median	62,359,530	31,199,192	17	13	37
total	951,041,523,712	1,516,178,767,872	204,092	141,097	345,189

A first observation is that firms that use only one type of worker are, on average, small and medium-sized enterprises, whereas those that use both types of workers

are, on average, larger firms, as evidenced by their total worker averages. Moreover, 74.30% (73.47%) of the total employment is due to firms using both labor types in 2006 (2013). This represents 52.54% (54.03%) of the skilled and 98.28% (97.80%) of the unskilled workers in 2006 (2013). Capital is more intensive in the firms employing skilled workers only: 64.67% in 2006 and 67.13% in 2013. This probably explains why these firms generated more than 65.05% of output in 2006 and 66.28% in 2013.

Output has positively changed for firms that use only skilled (+0.40%) and only unskilled workers (+2.20%), but the change is negative for firms using both types of workers (-0.54%). For the inputs, capital has only increased for firms that use only skilled labor (+1.43%), while labor has only slightly decreased for firms using both types of workers (-0.02%). Note that these firms have, on average, increased their number of skilled employees at the expense of unskilled employees.

In the past few decades, the Belgian economy, like most other industrialized economies, made a substantial transition away from manufacturing (which traditionally employs more unskilled labour) to a more and more services-based economy and knowledge-based industries (which employ more skilled workers). This ongoing structural change in the Belgian economy has implications first on employment and firm size across sectors and, second, on economic growth across time. For example, the impact on employment can be directly observed in firms that employ both skilled and unskilled workers. Over our analysed period, while the share of skilled labour has risen slightly, that of unskilled workers has slightly decreased. However, other factors such as globalization and offshoring, demographic changes, and education can also explain these changes. The contribution of the service sector constitutes the main core of the Belgian GDP. For instance, the service sector contributed almost 69% to the GDP, while that of manufacturing was almost 20% in 2023 (SPF Economie, 2023). We present the shares of firms, output, capital, and workers in the service sector for our sample in Table 2.[12]

A first observation is that all firm types have their highest firm, output, and input shares in the service sector. Also, the growing importance of the service sector in Belgium over time is highlighted as we see an increase in the input and output shares in the service sector between 2006 and 2013. An exception is the capital share for the unskilled and skilled firms.

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[12]To obtain the shares for the manufacturing sector, it suffices to subtract the shares in Table 2 from 100%.

Table 2: Service sector shares

Year	Firm	Output	Capital	Skilled	Unskilled
Unskilled (148 firms)					
2006	87.16%	98.87%	99.60%	–	90.33%
2013	87.16%	99.35%	99.63%	–	91.32%
Skilled (4,234 firms)					
2006	98.06%	96.91%	98.40%	96.43%	–
2013	98.06%	97.49%	98.84%	96.87%	–
Unskilled and skilled (3,466 firms)					
2006	79.75%	75.91%	73.68%	58.73%	56.06%
2013	79.75%	78.02%	70.39%	62.32%	59.63%

Next, a bit more than 20% of unskilled and skilled firms are part of the manufacturing sectors, this share is 13% for unskilled firms and 2% for skilled firms. It is therefore not a surprise to see that firms employing both unskilled and skilled workers have smaller input and output shares in the service sector. It is worth noticing that while the capital share reaches 70% for these firms, the worker share is around 60%.

For firms employing skilled workers only, the capital and worker shares are very close in the service sector (98% and 96%, respectively). The contribution of these firms to the manufacturing sector is therefore negligible. Also, firms relying on unskilled workers have only a bit less than 10% of their workers in the manufacturing sector and less than 1% of their capital in the same sector. Output production is less than 1% in the manufacturing sector for this firm type.

All in all, the descriptive analysis highlights important differences between sectors and skills in terms of outputs and inputs. This implies that we have to take both features into account in our empirical analysis.

3   Theoretical decomposition

Assume we observed a panel database consisting of n firms for a particular sector. Each firm combines capital, denoted as K_t, and labor to generate output, denoted as Y_t, at time t. A specificity of our set-up is to distinguish two types of labor: unskilled workers, captured by U_t, and skilled workers, captured by S_t. We aim to analyze and decompose the change in capital productivity, i.e. output divided by capital, over time. In particular, we want to obtain a decomposition into four

parts: (in)efficiency change (change in the movements toward or away from the best practices), technological change (change in the best practices), skilled labor–capital accumulation, and unskilled labor–capital accumulation (changes in the labor–capital ratios). Formally, such decomposition is given as follows:

$$KPROD = EFF \times TECH \times SKACC \times UKACC. \tag{1}$$

Only $KPROD$ is observed in the database. The other factors have to be estimated. To do so, our starting point is the modeling of a standard macroeconomic production process with technological change and (in)efficiency:

$$Y_t = F_t(K_t, S_t, U_t) \times e_t(Y_t, S_t, U_t, K_t). \tag{2}$$

Firms use three inputs (K_t, S_t, U_t) to generate output (Y_t) at each period t. Technological change is possible as the production function is time variant. $F_t(K_t, S_t, U_t)$ represents the maximal output at time t. When it differs from Y_t, we say that the firm is inefficient at time t. In that case, output may, in principle, be increased without requesting more inputs. At this point, we notice that the firm's performance could be affected by its capacity utilization (CU) (see Ray et al., 2021, for an overview). As a result, higher productivity could just reflect higher CU and not "true" productivity. From an output-based approach, CU is defined as "the maximum quantity that the firm can produce given the quantity of its fixed input(s) even with unrestricted availability of variable inputs"(Johansen, 1968). In (2), CU is therefore incorporated in the efficiency factor (Fare et al., 1989). We acknowledge, however, that efficiency could reflect other factors beyond CU. Decomposing thus, efficiency into multiple factors could help to understand which one really drives its changes. This latter not being the aim of our analysis, we assume that our efficiency factor reflects CU.

An advantage of the capital productivity decomposition is that it is not based on a particular functional form of the production function. Nevertheless, this function has to fulfill certain properties to remain coherent with macroeconomic standards. In particular, we assume that it is quasi-concave and homogenous of degree one (i.e. constant returns-to-scale).[13] It turns out that the production process can equivalently

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[13]Such assumptions can be dropped or changed if needed. They can also be tested (Walheer, 2019). We also note that capacity utilization is, in a sense, included in the efficiency factor in (2).

be written as follows:

$$y_t = F_t(1, s_t, u_t) \times e_t(Y_t, S_t, U_t, K_t), \tag{3}$$

where $y_t = Y_t/K_t$, $s_t = S_t/K_t$, and $u_t = U_t/K_t$ are output, skilled labor, and unskilled labor per unit of capital, respectively. To simply our notation let us define $f_t(s_t, u_t) = F_t(1, s_t, u_t)$ and $e_t = e_t(Y_t, S_t, U_t, K_t)$. By taking a simple ratio between output per capital at two different type periods, say b (base) and c (current), we obtain the following:

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{f_c(s_c, u_c)}{f_b(s_b, u_b)}. \tag{4}$$

On the left-hand side, we have $KPROD$: the capital productivity change between b and c. On the right-hand side, we have two factors: the first is (in)efficiency change between b and c, i.e. $EFF = \frac{e_c}{e_b}$, while the second factor has no clear meaning (for the moment). We can thus rewrite (4) as follows:

$$KPROD = EFF \times \frac{f_c(s_c, u_c)}{f_b(s_b, u_b)}. \tag{5}$$

Next to make technological change appear, we notice that there are two ways to define technological change in our context:

$$TECH_c = \frac{f_c(s_c, u_c)}{f_b(s_c, u_c)},$$
$$TECH_b = \frac{f_c(s_b, u_b)}{f_b(s_b, u_b)}. \tag{6}$$

Both indexes measure technological change but for a different couple: (s_c, u_c) for the first and (s_b, u_b) for the second. These two indexes do not yield the same results but are valid candidates to measure technological change.[14] In a sense, each measures technological change for a certain path. To overcome the path dependence of the decomposition, it suffices to take the geometric average of both indexes. Such a simple procedure, known as the Fisher Ideal decomposition (Caves et al., 1982; Fare et al., 1994), is recognized as the best way to obtain path-independent indexes (Kumar

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[14]The two decompositions are equal only if the neutrality of technological change is assumed (as in Solow (1956) and the many studies building on his pioneering article).

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and Russell, 2002; Henderson and Russell, 2005; Walheer, 2016, 2021; Chambers and Pieralli, 2020). Taking the geometric average of the two indexes in (6) gives us our measurement of technological change:

$$TECH = (TECH_b \times TECH_c)^{1/2}. \tag{7}$$

The next step is to plug our definition of technological change in (7) in our decomposition equation in (4). By doing so, two additional ratios appear. They have no clear meaning but are directly useful to obtain our two last factors ($SKACC$ and $UKACC$).

$$KPROD = EFF \times TECH \times \left(\frac{f_c(s_c, u_c)}{f_c(s_b, u_b)} \times \frac{f_b(s_c, u_c)}{f_b(s_b, u_b)} \right)^{1/2}. \tag{8}$$

The first factor $\frac{f_c(s_c, u_c)}{f_c(s_b, u_b)}$ can be decomposed in two different manners highlighting the impact of one specific variable:

$$\frac{f_c(s_c, u_c)}{f_c(s_b, u_b)} = \frac{f_c(s_c, u_c)}{f_c(s_b, u_c)} \frac{f_c(s_b, u_c)}{f_c(s_b, u_b)} = SKACC_c(u_c) \times UKACC_c(s_b),$$

$$\frac{f_c(s_c, u_c)}{f_c(s_b, u_b)} = \frac{f_c(s_c, u_c)}{f_c(s_c, u_b)} \frac{f_c(s_c, u_b)}{f_c(s_b, u_b)} = UKACC_c(s_c) \times SKACC_c(u_b). \tag{9}$$

In a similar vein, we apply the same principle to the second factor in (8), i.e. $\frac{f_b(s_c, u_c)}{f_b(s_b, u_b)}$ to obtain two different decompositions:

$$\frac{f_b(s_c, u_c)}{y_b(s_b, u_b)} = \frac{f_b(s_c, u_c)}{f_b(s_b, u_c)} \frac{f_b(s_b, u_c)}{f_b(s_b, u_b)} = SKACC_b(u_c) \times UKACC_b(s_b),$$

$$\frac{f_b(s_c, u_c)}{y_b(s_b, u_b)} = \frac{f_b(s_c, u_c)}{f_b(s_c, u_b)} \frac{f_b(s_c, u_b)}{f_b(s_b, u_b)} = UKACC_b(s_c) \times SKACC_b(u_b). \tag{10}$$

We end with four different manners of measuring unskilled labor–capital accumulation ($UKACC$) and skilled labor–capital accumulation ($SKACC$). Following the same spirit applied before to obtain the path-independent version of the technological

change component, we obtain the following:

$$SKACC = (SKACC_b(u_b) \times SKACC_b(u_c) \times SKACC_c(u_b) \times SKACC_c(u_c))^{1/4} \,,$$
$$UKACC = (UKACC_b(s_b) \times UKACC_b(s_c) \times UKACC_c(s_b) \times UKACC_c(s_c))^{1/4} \,.$$
$$(11)$$

By replacing the definition of $SKACC$ and $UKACC$ in equation (8), we end up with the quadripartite decomposition of capital productivity change between periods b and c. The benchmark value of each factor is unity indicating a status quo. Larger (smaller) values imply a progression (regression). In practice, several production functions have to be estimated to obtain the decomposition. Some of them are even counterfactual as they involve several periods. The computational aspect is the topic of the next section.

4   Estimation

The theoretical decomposition defined previously does not depend on a specific estimation method. In light of our application, we prefer to follow a non-parametric estimation method. Indeed, as we use firm-level data for two sectors in several periods, assuming a particular functional form for the production functions is not insidious. Moreover, we allow for technological change and (in)efficiency behavior. Both aspects complexify the estimation process.

We make use of a non-parametric linear programming technique. The basic principle is to compute (in)efficiency using other firms as peers such that the linear programming is coherent with the properties imposed on the production functions (here: quasi-concavity and homogeneity of degree one). An important aspect is that linear programming has to be defined in a general manner as counterfactual concepts have to be computed.

The main advantage of the selected estimation method is that it avoids making a functional assumption for the production process, which is not insidious. In our multi-dimensional contexts (one output, three inputs, two sectors, several periods, technological change, inefficiency behaviour), finding convincing arguments to support a specific functional form is not easy. Moreover, even if we can come up with such arguments, the important number of parameters to be estimated complexified the

task. Finally, we are interested in the overall change and not only the first (or second) moment (Silbersdorff et al., 2018).

To be fair, we remark that a disadvantage of using linear programming is that measurement errors and potential outliers are ignored. To mitigate this shortcut, we adopt the well-known order-m estimator to compute the potential outputs (Daraio and Simar, 2007). The basic principle is to compute expected potential outputs obtained with random sub-samples of m peers.[15]

Finally, to avoid unfairness in our estimation protocol, we make use of external variables when defining peer firms. The sector and region are two obvious external variables. We also consider size and ownership These three distinctions have been taken into account since studies show that the size of a firm or its ownership has an impact on its productivity.[16] The size of a firm is measured either by its total number of employees, its value-added, or its market share. The ownership is approximated in the literature by the type of management and by the country in which the group's parent company or head office is located. In this paper, the size of a firm is measured by its total number of employees. The ownership will be approximated by whether the firm is owned by a Belgian or foreign entity.

The linear programming for firm i in a particular sector evaluated at $(Y_{ib}, S_{ib}, U_{ib}, K_{ib})$ with respect to sub-sample h of m peers in period c (denoted $S_c^h(m)$) is given as fol-

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[15]Practically, the sampling procedure is repeated B times to obtain the expected potential output. In this study, we set $B = 1,000$, and $m = 50$. If we take a too large m then the robust procedure has no impact as it is the same as taking the full sample. If we take too small m, we may have infeasabilities when running the linear programming. The m selected reflects this balance (Simar, 2003).

[16]See, for size (Yasin et al., 2021; Ciani et al., 2020; Sari et al., 2016; Diaz and Sanchez, 2008; Hsieh and Klenow, 2009; Toma, 2020); and ownership (Berle and Means, 1932; Ehrlich et al., 1994; Barbera and Moores, 2013; Huang and Zhang, 2017).

lows:

$$\hat{e}_c^h(Y_{ib}, S_{ib}, U_{ib}, K_{ib}) = \min_{e \geq 0; \lambda_1 \geq 0, \ldots, \lambda_n \geq 0} e$$

$$\text{(C-1)} \ \frac{Y_{ib}}{e} \leq \sum_{s \in S_c^h(m)} \lambda_s Y_{sc}, \text{for}$$

$$\text{(C-2)} \ S_{ib} \geq \sum_{s \in S_c^h(m)} \lambda_s S_{sc}, \tag{12}$$

$$\text{(C-3)} \ U_{ib} \geq \sum_{s \in S_c^h(m)} \lambda_s U_{sc},$$

$$\text{(C-3)} \ K_{ib} \geq \sum_{s \in S_c^h(m)} \lambda_s K_{sc}.$$

The constraints in (12) capture the properties imposed on the production function: quasi-concavity and homogeneity of degree one. The former can be seen by noticing that convex combinations of the inputs and output are considered, while the latter implies that the weights $(\lambda_1, \ldots, \lambda_n)$ must only be positive. The objective of linear programming is to select the weights such that the (in)efficiency score is minimized. That is, the firms are evaluated in the best possible light. The peers are different for each firm. In practice, each time the linear programming is run, peers are defined in light of the external variables (sector, region, size, and ownership). Next, m peers are selected randomly defining sub-sample h, denoted as $S_c^h(m)$. Once the linear programmings are solved B times, i.e. one time for each sub-sample h, we can obtain the expected efficiency score for each firm i:

$$\hat{e}_c(Y_{ib}, S_{ib}, U_{ib}, K_{ib}) = \mathbb{E}[\hat{e}_c^h(Y_{ib}, S_{ib}, U_{ib}, K_{ib})] \tag{13}$$

The estimated efficiency score $\hat{e}_c(Y_{ib}, S_{ib}, U_{ib}, K_{ib})$ has to be interpreted as the theoretical counterpart $e_c(Y_{ib}, S_{ib}, U_{ib}, K_{ib})$: the benchmark value is unity and lower values reflect greater inefficiency behavior.

5   Results

In this section, we present the results of our empirical analysis. We start off with some preliminary analysis of the distributions of capital productivity. After, we give our results for the quadripartite decomposition of capital productivity, and we turn

to an analysis of the distribution dynamics of capital productivity and study the relationships between the quadripartite decomposition components. This allows us to investigate the SBTC and CSC hypotheses. Finally, we run several sensitivity analyses and summarize our results.

To support our analysis, we rely on statistical tests (Kolmogorov-Smirnov, Mann-Whitney, χ^2, Cramer's V). We select those tests as they are well-known tests and also since they are non-parametric, as the estimation method used in the paper. Note that there is no connection between the decomposition, estimation, and statistical tests used for the result analysis. We challenge our results using other statistical tests in Sectio 5.4 when running sensitivity analysis.

5.1   Preliminary analyses

We start with one important graphical representation of capital productivity in Figure 1: we display capital productivity ($KPROD$) distributions for our initial and final years for the service and manufacturing sectors while taking the skills into account. We are particularly interested in the distribution shifts and the existence of multiple modes. The first would imply the improvement of capital productivity, and the second one the existence of groups of firms.

An important finding is that the capital productivity distributions seem related to the type of workers used and the sector. First, except for firms using both types of workers, distributions have moved to the right in the manufacturing sector, indicating positive capital productivity change. Next, the distribution shift is less clear in the service sector for all firm types. Moreover, most of the distributions are right-skewed: this indicates that a minority of firms have high capital productivity. Also, firms in the service sector display higher average productivity than those in the manufacturing sector, irrespective of the type of worker used. Finally, multiple modes are observed for most of the distributions suggesting potential firm clusters in each sector.

To formally test whether our observations are statistically true, we rely on two statistical tests. To verify whether the capital productivity distributions have moved to the right, we make use of the nonparametric Kolmogorov–Smirnov (KS) test.[17] Next, we make use of the calibrated Silverman's (1981) test for multimodality.[18] The

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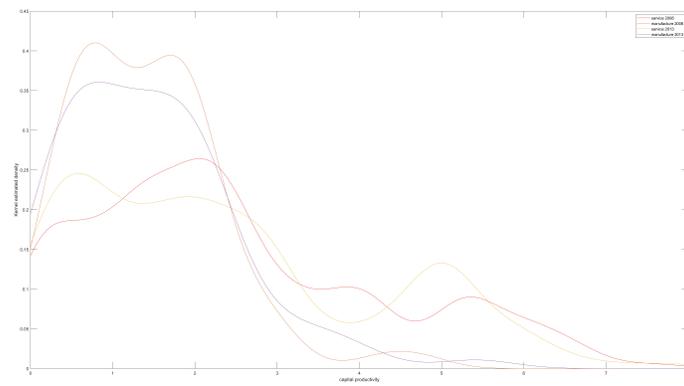[17]H_0: 2013 and 2006 distributions are equal; H_1: 2013 distribution is larger than 2006 distribution.
[18]H_0: the distribution has one mode; H_1: the distribution has more than one mode. We use the bootstrapped version of the calibrated Silverman's (1981) test due to Hall and York (2001).
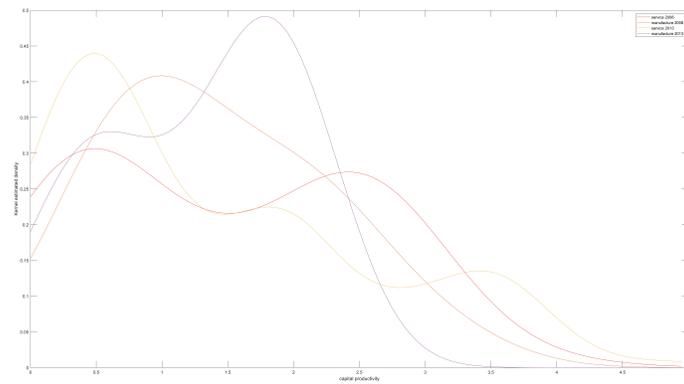
Figure 1: Capital productivity
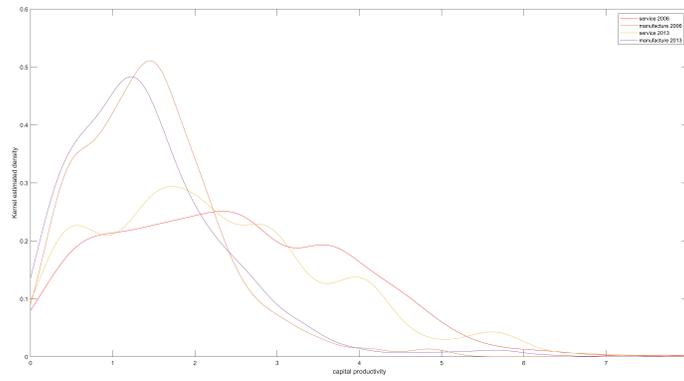
(a) Unskilled and skilled

(b) Skilled

(c) Unskilled

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results are given in Table 3.

Table 3: Capital productivity distribution statistical tests

| Type	KS 2006–2013 $p-$value	Silverman 2006 $p-$value	Silverman 2013 $p-$value
Manufacturing			
Unskilled and skilled	0.0121	0.4588	0.5457
Skilled	0.3545	0.0458	0.5176
Unskilled	0.0127	0.5472	0.2585
Service			
Unskilled and skilled	0.2485	0.4589	0.0511
Skilled	0.5836	0.5411	0.4895
Unskilled	0.3258	0.0358	0.0214

Overall, the $p-$values of the tests confirm our initial claims. The results of the KS test confirm the shifts in the distributions of capital productivity of firms in the manufacturing sector using both types of workers and of firms using only unskilled workers. By contrast, for firms in manufacturing using only skilled workers and for all firms in the services sector, we do not have evidence of a positive distribution shift. Next, the calibrated Silverman's (1981) test for multimodality confirms the existence of multi-modes in the capital productivity distributions in 2006 and 2013, only in three cases. More than one mode is found for firms employing unskilled workers in the service sector for both years and for skilled worker firms in the manufacturing sector in 2006.

It has often been argued that productivity is impacted by firms' efficiency behaviour. Hence, in Figure 2, we plot the distributions of the level of efficiency across firms in the manufacturing and service sectors in 2006 and 2013. These distributions reveal several information. First, like previously for productivity distributions, we can see that there are sectoral differences, with the highest average performance displayed by the service sector. This first observation follows the trend observed for productivity distributions. Second, between 2008 and 2013, in both sectors, some firms have improved while others deteriorated significantly, as evidenced by the dispersion of the distributions. This could potentially be the impact of some economic shock, which affected firms and sectors differently. While some firms adapted or improved, others struggled, and this has increased divergence in performance. Yet another explanation could be the consequence of structural changes (such as heterogeneous technology

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Figure 2: Efficiency distributions
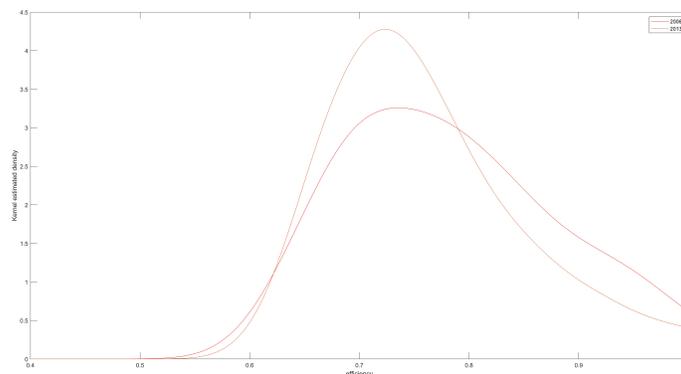
(a) Manufacturing
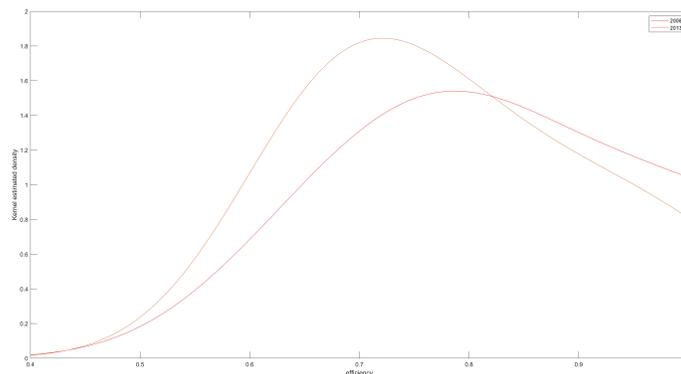
(b) Service

adoption across firms). The lower dispersion in the manufacturing sector could be explained by the standardisation of the production process, resulting in better transferable technology and a more capital-intensive sector. Finally, there is a strong link between the change in efficiency and the change in productivity. However, nothing can be inferred from this link, since other potential factors could explain the change in productivity, and efficiency improvements are not necessarily translated into productivity growth.

All in all, the preliminary analyses highlight the importance of taking the skills and the sectors into account in our analysis. The shapes and changes of the capital productivity distributions seem dependent on these two criteria. Studying these impacts is the goal of the rest of this empirical analysis.

5.2 Decomposition results

We present the results of our quadripartite decomposition of capital productivity. Recall that the factors are: efficiency change (EFF), technological change ($TECH$); skilled labor–capital accumulation ($SKACC$), and unskilled labor–capital accumulation change ($UKACC$), and that the benchmark value is unity. A value higher (lower) than one indicates a positive (negative) contribution. For the computation aspect, we refer to Section 4. The averages and medians for each component by type of workers used and by sector are shown in Table 4.

Table 4: Decomposition results

Type	Statistics	PROD	EFF	TECH	SKACC	UKACC
Manufacturing						
Unskilled and skilled	average	1.0435	1.2465	1.2169	1.0635	1.0830
	median	0.9572	0.9026	1.0447	1.0054	1.0204
Skilled	average	1.0323	0.8837	1.8995	0.9785	–
	median	0.9439	0.7854	1.1869	0.9858	–
Unskilled	average	1.0263	0.8485	1.1229	–	1.1926
	median	0.9638	0.7211	1.0410	–	1.0471
Service						
Unskilled and skilled	average	1.0079	1.9463	1.9935	1.1232	1.0044
	median	0.9739	0.9809	1.4273	1.0411	1.0112
Skilled	average	1.0849	0.8780	1.2458	1.4635	–
	median	0.9615	0.9665	1.2560	1.3210	–
Unskilled	average	1.0258	0.9373	1.6460	–	1.1255
	median	1.0120	0.9205	1.2157	–	1.0040

Average capital productivity change is larger than unity in each case, but higher for firms using skilled workers in both sectors. Averages and medians do not tell the same story: median capital productivity changes are smaller than one. This is probably due to the existence of groups of firms as indicated before with the multi-mode tests (Table 3).

The positive (average) capital productivity change is mostly due to technological change. This component is always larger than one. Largest values are found for skilled worker-based firms in the manufacturing sector and firms employing both unskilled and skilled workers in the service sector. It is also this last type of firms that are the only ones that have benefitted from a positive efficiency change; this is true in both sectors. In the other cases, efficiency change plays a negative role.

In terms of the contributions of the skill-related components, all contributions are positive and non-negligible with an exception for the firms using skilled workers in the manufacturing sector. The largest contribution is found for the skilled labor–capital accumulation for skilled workers only firms in the service sector. This component is, in fact, the main reason for the positive capital productivity change in that case. We also see that the impact of the skill-related components is higher when firms rely on one type of worker only.

While the averages and medians give us an idea of the impact amplitudes of the components, they do not say how each component has contributed to the distribution changes or shifts found in Figure 1. We complete our empirical investigation by constructing counterfactual distributions. The idea is to verify what factor or combination of factors gives us a result close to the final capital productivity distributions. To obtain the counterfactual distributions, we simply multiply the initial capital productivity level (y_b) by one or several components (EFF, $TECH$, $SKACC$, and $UKACC$).[19] Each counterfactual distribution isolates the effect on the distribution shift or change of the selected factors. To formally test the equality between the counterfactual and final distributions, we again rely on the KS test.[20] Not rejecting the null hypothesis for a component or a combination of components would highlight its/their greatest importance. p−values are given in Table 5.

Without a suprise none of the counterfactual distributions when only one component is selected is equal to the 2013 actual distributions. Next, there are cases when the null hypothesis is not rejected, i.e. when a combination of components is found to be the major cause of the distribution changes/shifts. First, for firms employing unskilled and skilled workers, it is a combination of technological changes, skilled labor-, and unskilled labor-capital accumulation. This finding is true in both the manufacturing and service sectors. This implies that technology and skills have to be used together for this type of firm. For firms with only unskilled and firms with only skilled workers, it is the association between technological changes and unskilled labour-capital accumulation; and between technological changes and skilled labour-capital accumulation, respectively. Again, such findings are correct in both sectors.

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[19]The counterfactual distributions are directly connected to the decomposition in (1): $y_c = y_b \times EFF \times TECH \times SKACC \times UKACC$.

[20]H$_0$: 2013 and counterfactual distributions are equal; H$_1$: 2013 and counterfactual distributions are different.

Table 5: Statistical tests for the counterfactual distributions

Component	Unskilled and skilled	Unskilled	Skilled
Manufacturing			
$y_b \times EFF$	0.000	0.000	0.000
$y_b \times TECH$	0.000	0.000	0.001
$y_b \times SKACC$	0.000	–	0.000
$y_b \times UKACC$	0.000	0.000	–
$y_b \times EFF \times TECH$	0.003	0.000	0.000
$y_b \times EFF \times SKACC$	0.004	–	0.001
$y_b \times EFF \times UKACC$	0.000	0.000	–
$y_b \times EFF \times TECH$	0.039	0.001	0.000
$y_b \times TECH \times SKACC$	0.001	–	0.317
$y_b \times TECH \times UKACC$	0.064	0.489	–
$y_b \times SKACC \times UKACC$	0.012	–	–
$y_b \times EFF \times TECH \times SKACC$	0.024	–	0.000
$y_b \times EFF \times TECH \times UKACC$	0.000	0.000	–
$y_b \times EFF \times UKACC \times SKACC$	0.036	–	–
$y_b \times TECH \times SKACC \times UKACC$	0.245	–	–
Service			
$y_b \times EFF$	0.001	0.001	0.000
$y_b \times TECH$	0.000	0.000	0.001
$y_b \times SKACC$	0.000	–	0.000
$y_b \times UKACC$	0.000	0.000	–
$y_b \times EFF \times TECH$	0.004	0.000	0.000
$y_b \times EFF \times SKACC$	0.004	–	0.001
$y_b \times EFF \times UKACC$	0.000	0.001	–
$y_b \times EFF \times TECH$	0.024	0.001	0.000
$y_b \times TECH \times SKACC$	0.001	–	0.472
$y_b \times TECH \times UKACC$	0.081	0.316	–
$y_b \times SKACC \times UKACC$	0.032	–	–
$y_b \times EFF \times TECH \times SKACC$	0.051	–	0.000
$y_b \times EFF \times TECH \times UKACC$	0.000	0.000	–
$y_b \times EFF \times UKACC \times SKACC$	0.022	–	–
$y_b \times TECH \times SKACC \times UKACC$	0.389	–	–

The counterfactual analysis highlights once more the crucial role of technological change in combination with skills. A contrario efficiency change is not found to be a determinant in the capital distribution changes in both sectors.

5.3 SBTC and CSC hypotheses

Using our decomposition of capital productivity, we suggest new ways to look at the skilled-biased technological change (SBTC) and capital-skill complementarity (CSC) hypotheses. In brief, the SBTC hypothesis says that technological progress is biased toward skilled workers, while the CSC hypothesis states that capital and skilled labor are more complementary inputs than capital and unskilled labor.

For the SBTC, we verify how technological change is related to skilled labor- and unskilled labor-capital accumulations utilizing χ^2 tests and Cramer's V.[21] To do so, we partition firms into two categories for technological change: when $TECH \geq 1$ and when $TECH < 1$. We do the same for the skilled labor- and unskilled labor-capital accumulations. If the SBTC hypothesis is verified, we expect to see a connection between technological change and skilled labor- and unskilled labor-capital accumulation (significant χ^2 tests), but that the link is stronger for skilled labor-capital accumulation (i.e. a greater Cramer's V).

For the CSC, we compare the distributions and medians of the skilled labor- and unskilled labor-capital accumulations using the KS and Mann-Whitney tests.[22] Intuitively, if the CSC hypothesis is correct, the skilled labor-capital accumulation has to be larger than the unskilled labor-capital accumulation. We choose to test the CSC hypothesis for firms using both worker types only as the trade-off between skilled workers, unskilled workers, and capital occurs in these firms only.

Results for the tests regarding the SBTC and CSC hypotheses are provided in Table 6.

Let us start with the SBTC. Technological change is found to be related to all

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[21]H_0: technological change and skilled (unskilled) labor-capital accumulation are independent; H_1: technological change and skilled (unskilled) labor-capital accumulation are dependent. Cramer's V is a measure of effect size for the chi-square test of independence; when it is lower than 0.2, a weak association link is observed, when it is between 0.2 and 0.6, there is a moderate association link, and when it is larger than 0.6, there is a strong association link.

[22]H_0: the skilled labor- and unskilled labor-capital distributions (medians) are equal; H_1:the skilled labor-capital distribution (median) is larger than the unskilled labor-capital distribution (median). We note that the skilled labor- and unskilled labor-capital distributions are computed as follows: $y_b \times SKACC$ and $y_b \times UKACC$).

Table 6: SBTC and CSC hypotheses

Type	Worker	SBTC		CSC	
		χ^2	Cramer V	KS	Mann-Whitney
		$p-$value	coefficient	$p-$value	$p-$value
Manufacturing					
Unskilled and skilled	skilled	0.000	0.514	0.258	0.317
	unskilled	0.001	0.225		
Skilled	skilled	0.000	0.689		
Unskilled	unskilled	0.011	0.186		
Service					
Unskilled and skilled	skilled	0.000	0.658	0.012	0.000
	unskilled	0.000	0.235		
Skilled	skilled	0.002	0.725		
Unskilled	unskilled	0.178	0.125		

labor-capital accumulations, with an expectation for firms employing unskilled work-
ers only in the service sector. Next, Cramer's V reveals a strong (greater than 0.6)
link in all cases for firms relying on skilled workers and a more moderate (greater
than 0.2) connection for firms relying on unskilled workers. Note that the connection
is even stronger for firms utilizing skilled workers only. Overall, these findings go in
the direction of the SBTC hypothesis.

For the CSC, we do not have evidence that the skilled labor-capital accumulation
is stronger than the unskilled labor-capital accumulation in the manufacturing sector.
This is true when looking both at the distributions and the medians. On the contrary,
we find that skilled labor-capital accumulation is stronger than unskilled labor-capital
accumulation in the service sector. This indicates that skilled workers and capital play
together a more important role than unskilled workers and capital, which seems to
support the CSC hypothesis for that sector.

5.4 Sensitivity analysis

In this section, we challenge the stability of our results in several ways. Firstly, we
use another measure of capital which is based on the book value (Chen, 2020; Maliar
et al., 2020; Castex et al., 2022). Second, we modify the parameters of our estimation
method: m (number of peers) and B (number of iterations). Third, we take closures
and new establishments into account by introducing such firms to the peer groups.

Four, we select alternative statistical (nonparametric) tests: Li's test by Simar and Zelenyuk (2006) in place of Kolmogorov-Smirnov, and the nonparametric indicator of Krause (2017) instead of Silverman. (Note that the results of Krause's test (2017) are very similar to the ones obtained before; they are not shown in the following for the sake of compactness. For the same reason, we do not give the averages and medians of the decomposition components for each alternative specification; we prefer to focus our attention on the main tables). Finally, we modify our definition of the firm types by varying the percentage of skilled or unskilled workers.[23]

We present in Table 7, the $p-$values using the adapted Li's test for our initial alternative specifications.[24] For the sake of compactness, we only present the cases where the $p-$values are larger than 5%. We recall that not rejecting the null hypothesis for a component or a combination of components highlights its/their greatest importance. In Table 8, we present the results for the SBTC and the CSC for our alternative specifications.

In Table 7, we see that applying Li's tests to our initial setting does not affect our conclusions for both sectors. For firms employing both skilled and unskilled workers, the combination of technological changes and skilled labour-capital accumulation explains the capital productivity change. For firms using exclusively unskilled (skilled) workers, the major role of technological change is confirmed. Next, modifying our definition of capital or the parameters of the linear programming (m and B) does not change our results. The tests, including closures and new establishments, still highlight the important roles of skills and technological change. This also means that those firms do not represent the best practice. In a sense, we focus our attention on the most important firms in our empirical exercise. Finally, when modifying our definiton of the firm type, we find the same results. This means that firms emplying only one type of workers form the best practice. In Table 8, the $p-$values of the different alternative specifications are lower than 5% supporting the SBTC hypothesis for both sectors. For the CSC, the $p-$values support that hypothesis for the services sector only. All, our sensitivity exercise provides robustness to our initial findings.

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[23]As highlighted in Table 1, we have 148 firms that only use 100% of unskilled workers and 4,234 that use 100% of skilled workers. If we decrease the shares to 90%, we have 382 and 4,474 firms, respectively. For 80%, we find 850 and 4,826 firms, respectively. The results in Tables 7 and 8 are based on the 80% case. Results are in the same vein for 90%.

[24]H_0: 2013 and counterfactual distributions are equal; H_1: 2013 and counterfactual distributions are different.

Table 7: Statistical tests for the counterfactual distributions − sensitivity

Component	Unskilled and skilled	Unskilled	Skilled
Manufacturing			
(1) initial setting			
$y_b \times TECH \times SKACC$	0.000	−	0.354
$y_b \times TECH \times UKACC$	0.053	0.412	−
$y_b \times TECH \times SKACC \times UKACC$	0.125	−	−
(2) capital book value			
$y_b \times TECH \times SKACC$	0.004	−	0.215
$y_b \times TECH \times UKACC$	0.041	0.158	−
$y_b \times TECH \times SKACC \times UKACC$	0.196	−	−
(3) $m = 30$ and $B = 2,000$			
$y_b \times TECH \times SKACC$	0.018	−	0.548
$y_b \times TECH \times UKACC$	0.092	0.508	−
$y_b \times TECH \times SKACC \times UKACC$	0.410	−	−
(4) closures and new establishments			
$y_b \times TECH \times SKACC$	0.045	−	0.412
$y_b \times TECH \times UKACC$	0.158	0.292	−
$y_b \times TECH \times SKACC \times UKACC$	0.141	−	−
(5) alternative firm type defintion			
$y_b \times TECH \times SKACC$	0.000	−	0.398
$y_b \times TECH \times UKACC$	0.041	0.174	−
$y_b \times TECH \times SKACC \times UKACC$	0.098	−	−
Service			
(1) initial setting			
$y_b \times TECH \times SKACC$	0.000	−	0.438
$y_b \times TECH \times UKACC$	0.061	0.361	−
$y_b \times TECH \times SKACC \times UKACC$	0.298	−	−
(2) capital book value			
$y_b \times TECH \times SKACC$	0.000	−	0.3142
$y_b \times TECH \times UKACC$	0.112	0.3408	−
$y_b \times TECH \times SKACC \times UKACC$	0.214	−	−
(3) $m = 40$ and $B = 2,000$			
$y_b \times TECH \times SKACC$	0.002	−	0.347
$y_b \times TECH \times UKACC$	0.111	0.3187	−
$y_b \times TECH \times SKACC \times UKACC$	0.391	−	−
(4) closures and new establishments			
$y_b \times TECH \times SKACC$	0.000	−	0.314
$y_b \times TECH \times UKACC$	0.091	0.296	−
$y_b \times TECH \times SKACC \times UKACC$	0.129	−	−
(5) alternative firm type defintion			
$y_b \times TECH \times SKACC$	0.000	−	0.402
$y_b \times TECH \times UKACC$	0.054	0.354	−
$y_b \times TECH \times SKACC \times UKACC$	0.242	−	−

Table 8: SBTC and CSC hypotheses − sensitivity

Type	Worker	SBTC		CSC	
		χ^2 p−value	Cramer V coefficient	Li test p−value	Mann-Whitney p−value
Manufacturing					
(1) capital book value					
Unskilled and skilled	skilled	0.000	0.412	0.185	0.245
	unskilled	0.003	0.116		
Skilled	skilled	0.087	0.135		
Unskilled	unskilled	0.008	0.096		
(2) $m = 30$ and $B = 2,000$					
Unskilled and skilled	skilled	0.006	0.294	0.312	0.451
	unskilled	0.000	0.325		
Skilled	skilled	0.002	0.712		
Unskilled	unskilled	0.000	0.234		
(3) closures and new establishments					
Unskilled and skilled	skilled	0.050	0.214	0.321	0.412
	unskilled	0.005	0.199		
Skilled	skilled	0.054	0.245		
Unskilled	unskilled	0.022	0.285		
(4) alternative firm type defintion					
Unskilled and skilled	skilled	0.050	0.214	0.321	0.412
	unskilled	0.000	0.116		
Skilled	skilled	0.029	0.195		
Unskilled	unskilled	0.011	0.210		
Service					
(1) capital book value					
Unskilled and skilled	skilled	0.000	0.658	0.012	0.000
	unskilled	0.000	0.235		
Skilled	skilled	0.002	0.725		
Unskilled	unskilled	0.178	0.125		
(2) $m = 30$ and $B = 2,000$					
Unskilled and skilled	skilled	0.002	0.712	0.051	0.008
	unskilled	0.006	0.325		
Skilled	skilled	0.005	0.611		
Unskilled	unskilled	0.212	0.611		
(3) closures and new establishments					
Unskilled and skilled	skilled	0.009	0.484	0.021	0.004
	unskilled	0.000	0.358		
Skilled	skilled	0.008	0.851		
Unskilled	unskilled	0.187	0.512		
(4) alternative firm type defintion					
Unskilled and skilled	skilled	0.000	0.895	0.009	0.000
	unskilled	0.000	0.201		
Skilled	skilled	0.000	0.902		
Unskilled	unskilled	0.220	0.492		

Our results and conclusions are not affected by any of the alternative specifications.

5.5   Summary

To summarize, our empirical analysis highlights a couple of stylized facts. First, capital productivity distributions have moved to the right in the manufacturing sector, while the distribution shift is less clear in the service sector for all firm types. This is mostly due to potential firm clusters in the service sector. Moreover, capital productivity changes depend on skills and sectors. This is in line with recent research regarding sector and skill heterogeneity (Chen, 2020; Perez-Laborda and Perez-Sebastian, 2020; Taniguchi and Yamada, 2022).

Second, capital productivity change is mostly due to technological change. The largest contributions are found in firms employing skilled workers. Positive efficiency change is only found in the service sector for firms employing both unskilled and skilled workers. Skilled-related components have a positive and non-negligible role in capital productivity changes. Such impact is higher when firms rely on one type of worker only. This implies that technology and skills have to be used together to foster capital productivity. These findings are still correct under alternative specifications.

Next, skills and technological changes are strongly related to the manufacturing and service sectors, supporting the SBTC. For the CSC, we only find support in the service sector. We may interpret that finding as a more important sensibility to skill movements in the service sector. The sensitivity analysis confirms these findings.

6   Conclusion and discussion

Capital productivity has been recognized as a main driver of economic growth and development by empirical economists. Understanding its role and its connection with skills and technology change are the main focuses. Building on this research, we analyze the capital productivity growth using a new decomposition approach. In particular, we decompose capital productivity change into four parts: efficiency change, technological change, skilled labor–capital accumulation, and unskilled labor–capital accumulation.

Using firm-level data for two sectors (service and manufacturing) and a nonparametric estimation approach, we find that capital productivity changes depend

on skills and sectors. Also, our empirical analysis reveals that technological improvement is the main driver. This being said a combination of technological change with skills is needed to understand capital productivity changes. Finally, our decomposition approach allows us to suggest a new look at the SBTC and CSC hypotheses. While the first is fully supported, the second is only partially correct. All these findings are robust as they are not affected when changing the model specifications.

We end our paper with several important remarks. Our approach offers several advantages in decomposing capital productivity growth, particularly in handling the complex relationships between capital, skills, and technology at the firm level. The method's ability to simultaneously analyze sector-specific differences while accounting for four distinct factors has provided a framework for understanding capital productivity dynamics and the contribution of skills. Moreover, our methodology is not restricted to firm-level applications but can also be used to analyze various levels such as countries, regions, industries, and sectors. We note that related nonparametric approaches have already been used for the countries (Kumar and Russell, 2002; Henderson and Russell, 2005; Walheer 2018; 2021), states (Chambers and Pieralli, 2020), and sectors Walheer (2016). A major difference with our paper is that we focus on capital productivity.

However, one limitation of our method is that it gives results in relative rather than absolute terms. Being a data-based method, it is sensitive to data. Adding or subtracting data can have an impact on the results and hence on the external validity of the results. For this reason, care must be taken when implementing this method. With regard to the data, we acknowledge that our approximation of skills is probably not the best and that the level of education is probably a better proxy (we do not have such data).

Looking ahead, our findings open several promising research avenues from both theoretical and empirical perspectives. Future studies could extend our decomposition framework to other countries or longer periods, potentially incorporating additional factors affecting capital productivity. With this in mind, extending our method by combining it with regression would be a good option. The partial support found for the capital-skill complementarity hypothesis warrants further investigation, particularly in different economic contexts. Moreover, future research could explore how different categorizations of skills and capital types (such as ICT vs. non-ICT) might affect the relationship between technological change and productivity growth,

especially given our findings supporting the skilled-biased technological change hypothesis. Furthermore, recent developments in the literature on SBTC indicate an orientation towards task or occupation-biased technological change, which would be another direction for future research.

Finally, we would like to acknowledge the fact that in this paper, we do not directly account for capacity utilisation (CU). Indeed, CU variations could affect productivity changes, and one may attribute these changes to true efficiency or technological changes, if the latter were not accounted for in the model. One possible extension of our paper is to consider capital as a long-term factor and Labour as a short-term factor. In this case, we would need to adapt our breakdown and distinguish between the short term and the long term. We would probably have more factors or different factors. It should be noted that, as our analysis covers the period 2006-2013, we are ultimately only looking at the short term, and it would not be very interesting to consider CU here. What would have been interesting is a long time period with short periods to analyse CU and then compare them.

7   Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 9: NACE codes

Code	Sector
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply; Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H	Transportation and Storage
I	Accommodation and Food Service Activities
J	Information and Communication
K	Financial and Insurance Activities
L	Real Estate Activities
M	Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
O	Public Administration and Defence; Compulsory Social Security
P	Education
Q	Human Health and Social Work Activities
R	Arts, Entertainment and Recreation
S	Other Service Activities
T	Activities of Households as Employers; Undifferentiate Goods and ServicesProducing Activities of Households for Own Use
U	Activities of Extraterritorial Organisations and Bodies