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REGULAR ARTICLE

# The knowledge-intensive direction of technological change

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## Abstract

The paper articulates and tests the hypothesis that the current direction of technological change is knowledge- rather than capital intensive. The new accounting procedures that identify and quantify intangible assets allow us to test the role of capitalized knowledge as an input in the technology production function. The micro-level evidence from US listed companies included in Compustat, over the period 1977–2016, confirms that the direction of technological change has been increasingly knowledge intensive and tangible-capital saving. It also shows that this trend has increased in its strength over time and across all US sectors. The most dramatic increase in the output elasticity of knowledge occurred in the high-tech and manufacturing sectors. Furthermore, the output elasticity of tangible capital has constantly reduced in the consumer and high-tech sectors over time.

**Keywords** Knowledge exhaustibility · Intangible capital · Induced technological change · Technology production function · Knowledge intensive direction · Knowledge output elasticity

**JEL Classification** 031 · 033

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## 1 Introduction

This paper elaborates and tests the hypothesis that the direction of technological change has become knowledge rather than capital intensive. We contrast the current understanding of the skill-biased technological change approach and implement the knowledge intensive hypothesis using the recent advances of the economics of knowledge, the resource-based theory of the firm, the routine biased technological change approach and the analysis of the strategic direction of technological change biased towards the intensive use of locally abundant inputs.

There is a large literature showing that technological change has, for long, been characterized by a strong capital intensive direction (Karabarbounis & Neiman, 2014). This claim is consistent with the induced technological change approach, supported by the steady decline in the user costs of capital triggered by the sharp increases in savings and wages.

Significant changes have occurred over the last several years, in relation to the economy and accounting procedures, which question the validity of the capital intensive direction of technological change and support the hypothesis that, now, technological change is biased towards knowledge intensity (Antonelli, 2019a, 2019b; Haskel & Westlake, 2017).

The radical innovation in accounting procedures, introduced in 2008, involving identification and quantification of intangible assets as a separate item in national accounts and in firm balance sheet, allows an assessment of knowledge capital as an input in the production process.[1] This paves the way to an empirical exploration of the actual direction of technological change, whether capital or knowledge intensive (Corrado et al., 2013).

Recent empirical evidence for the advanced economies points to the increasing role of knowledge for driving economic growth (Autor et al., 2003; Brynjolfsson & McAfee, 2014). The emergence and diffusion of new Information and Communication Technologies (ICTs) has made knowledge the most abundant factor in industrialized countries, providing firms with a cheaper input compared to fixed capital and standard labor (Antonelli & Feder, 2020; Van Roy et al., 2018). Globalization is stressing the sharp differences in knowledge endowments and knowledge costs, between the advanced and industrializing countries. Firms based in industrializing countries incur high costs to imitate new knowledge intensive technologies due to their limited transferability. Moreover, industrializing countries cannot replicate the cost conditions in advanced countries, because of the sharp differences in the costs of accessing and using the stocks of quasi-public knowledge rooted in the advanced economies. As a result, knowledge has emerged as an essential and strategic input, rooted in advanced countries that can access and use their large stocks to achieve

[1] As explained in Sect. 3, from 2008 the System of National Accounts (SNA) has included five new standard accounting items: 1) ICT equipment included as a new category under machinery and equipment; 2) intellectual property practices (in place of 'Intangible fixed assets'), which include R&D outcomes; 3) other intellectual property products (replacing 'Other intangible fixed assets'), which include R&D, mineral exploration and evaluation, computer software and databases, literary or artistic originals; 4) mineral exploration and evaluation (replacing 'Mineral exploration' to conform with international accounting standards; 5) computer software modified to include databases.

competitive advantage and has shifted firms' investment decisions towards greater use of intangible and knowledge assets.

In the present article, we show how the new attempts to correctly assess the generation, exploitation and accumulation of knowledge in growth accounting, enabled by the capitalization of knowledge, make it possible to test the hypothesis that the direction of technological change is knowledge intensive rather than capital intensive.

We review the literature on the tangible capital and labor saving direction of technological change, to frame the empirical analysis showing a growing output elasticity of intangible capital and a parallel and complementary reduction in the output elasticity of tangible capital. The new knowledge intensive direction is the outcome of the search for competitiveness, based on use of knowledge that now can be stored and capitalized as an asset to justify its enduring contribution to productivity growth.

The capitalization of knowledge and its role as an input in the production function was identified first by Griliches (1979, 1984, 1986). The capitalization of knowledge is motivated by its limited exhaustibility. Compared to other economic goods, knowledge has slow rates of obsolescence and can be reused repeatedly for the production of other economic goods and further technological knowledge. Moreover, recent contributions by Corrado et al. (2005, 2009) shed light on the need to account for an increased share of intangible assets, such as R&D, software and databases that, previously, were treated as intermediary or labor inputs.

This paper contributes to and extends the recent literature on the relationship between intangible capital and economic growth. Previous empirical studies have mainly focused on the role of intangible assets in growth accounting at the macro-level (Borgo et al., 2013; Piekkola, 2018), or on the productivity-enhancing effect of intangible investments at the micro-level (Bontempi & Mairesse, 2015; Marrocu et al., 2012). However, the output elasticity of intangible capital as a proxy for knowledge intensity in the production function has rarely been quantified empirically.

We therefore estimate a firm-level technology production function, augmented with the inclusion of externally purchased and internally created intangible assets. We show that, in the last 40 years, the output elasticity of intangible capital has accelerated in US listed firms with, on average, a sequential reduction of both labor and physical capital output elasticities.

The recent work by Ewens et al. (2020) provides a measurement for knowledge and organizational capital, which proxies for the firms' intangible resources and allows both to estimate the output elasticity of knowledge and to track its dynamics. Therefore, building on the technology production function developed by Griliches (1979), we assess empirically the contribution of those resources, such as organizational capital and knowledge capabilities, which the Resource Based View theory of the firm acknowledges, are the sources of sustained firm heterogeneity and competitive advantage (Barney, 1991; Kogut & Zander, 1992).

This paper uses a sample of US listed companies, observed over the period 1977–2016, with financial data available from Compustat. This allows us to evaluate the direction of technological change over a more extended period compared to previous studies. Our results point to a sizeable and increasing contribution of intangible capital to the production process, which has resulted in a shrinking output elasticity of physical capital and standard labor. The significant drop in the output elasticity of physical capital confirms that the capital-bias of technology no longer applies to advanced economies in the new knowledge economy. We show also that this radical change was dramatic in the manufacturing sector. The evidence for the high-tech and consumer sectors points to substantial substitutability between knowledge capital and physical capital, with the output elasticity of the latter almost halving in the last 40 years.

The rest of the paper is organized as follows. Section 2 describes the theoretical background. Section 3 presents the data and the methods used for the empirical analysis. Section 4 discusses the results. Section 5 concludes the paper by summarizing our conclusions.

## 2 Theoretical analysis

### 2.1 Knowledge as a key input

The skill-biased technological change approach has become the basic frame of analysis of the direction of technological change. It articulates the view that current technological change is skilled intensive because of the large increase in the supply of human capital triggered by the college boom (Acemoglu, 2002, 2003). However, the skilled intensity may be compatible either with the capital intensive direction – and the consequent need for skilled workers to operate sophisticated and capital intensive machinery – or with the opposite hypothesis that technological change is knowledge intensive but capital saving. This chapter implements and supports that latter interpretation taking advantage of the recent advances in the economics of knowledge: the resource-based view, the routine biased technological change approach and the analysis of the strategic direction of technological change towards the intensive use of exclusive and selected inputs that are only locally abundant. We consider each of these elements in turn.

The seminal contribution by Arrow (1962) led to much discussion about the properties of knowledge compared to other standard economic goods, emphasizing its limited appropriability and non-rivalrous use. More recently, the emphasis has been on the extended duration of knowledge as an input to generate economic growth. Indeed, knowledge is subject to limited exhaustibility, which implies high levels of cumulability and extensibility. Tangible capital goods are eventually fully exhausted by wear and tear and obsolescence. Because of knowledge extensibility, frontier knowledge instead can be used repeatedly in the technology production function, with decreasing marginal costs: the same blueprint technology can be used for very large production batches. Because of knowledge cumulability, "old" knowledge is an essential input – even when it becomes partly obsolete – in the recombinant generation of new technological knowledge (Antonelli, 2018, 2019a and b).

The assessment of the repeated use of the existing knowledge, both internal and external to the firm and available in the system, provides the underpinnings for understanding the knowledge generation process as cumulative and recombinant, based on existing knowledge items (Weitzman, 1996, 1998). Thus, the firm existing knowledge and how it exploits it are a primary source of competitive advantage: firms in systems with superior knowledge endowments in terms of size, composition and access mechanisms are able to generate new knowledge at much lower costs than firms based in systems with inferior knowledge endowments and knowledge governance mechanisms.

The limited exhaustibility of knowledge means that firms can accumulate stocks of knowledge composed of an array of heterogeneous items. Analysis of firm heterogeneity, based on its resources and capabilities, was undertaken first by Penrose (1959). This work paved the way to the development of the Resource-Based View (RBV) theory, which was adopted by multiple research fields. According to this view, firms possess heterogeneous and imperfectly imitable resources, which are a source of 'sustained competitive advantage' (Barney, 1991). The firm's competitive advantage is determined not only by its positioning in the product market, but also by its possession of scarce, idiosyncratic and, hence, difficult to imitate resources. Generic assets, capabilities and organizational practices, which are long lasting and cannot be appropriated by other firms, represent these resources. Ultimately, they become the firm's knowledge base.

Most tangible goods can be purchased and sold in open markets. However, intangible resources are highly idiosyncratic and firm specific, which prevents their being traded in specific markets. In addition, the market for these assets is imperfect. As a result, firms prefer to build and accumulate internally the resources required to develop competition strategies (Dierickx & Cool, 1989). The competencies and capabilities embedded in these assets are (largely) inimitable due to the causal ambiguity surrounding the firm's performance, which is based on the uncertainty among the firm and its rivals about future performance (Lippman & Rumelt, 1982).

The absence of stringent rules on the disclosure of such assets, makes them almost invisible to competitors and, hence, difficult, if not impossible, to imitate. Therefore, causal ambiguity, path-dependence and time compression diseconomies represent major natural barriers to entry and contribute to sustained competitive advantage. Specifically, time compression diseconomies might imply, at most, diachronic imitation by competitors. However, the competitor is unable to achieve the same level of competitive advantage as the original owner of the asset simply by investing the same resources. The primary implication of this phenomenon is that firm heterogeneity and firm innovative performance are persistent and not subject to the standard rules of creative destruction (Cefis & Orsenigo, 2001). In turn, firms' capabilities turn out to be dynamic since they provide the firm with flexible and timely tools to respond to changes in product and factor markets (Teece et al., 1997).

These unique assets and resources contribute to the firm's positioning in the product markets and allow it to differentiate from competitors in markets where demand is highly elastic and competition is based on price discrimination. As a result, a few dominant firms, whose sustained competitive advantage is based on network externalities and digital marketplaces where the value of knowledge rises with the number of its users (Shapiro & Varian, 1998), increasingly characterize high-tech sectors. In addition, advances in Information and Communication Technologies have lowered the costs of information searches and online price discrimination, leading, ultimately, to superstar effects which allow the firms that offer the best products to appropriate large shares of the market (Bessen, 2020; Forman & Goldfarb, 2020).

The new digital economy requires substantial investment in branding recognition and reputation, complemented by organizational and managerial practice changes (Bloom et al., 2012; Bresnahan et al., 2002). Hence, information technology is requiring firm-specific investments to enable accumulation of digital and intangible assets. These assets are not accounted for as capital but represent a significant source of productivity growth (Tambe et al., 2020).

The accumulation of digital and intangible assets has positive and substantial effects on the appropriability of innovative output. The adoption and use of digital tools favor access to – and screening and selection of – external knowledge, and facilitate its recombination in subsequent knowledge generation waves (Antonelli, 2017). In turn, this reduces the costs related to absorbing external knowledge to well below the prices implied by its marginal cost (Cohen & Levinthal, 1990). Moreover, the accumulation of digital and intangible resources and knowledge capabilities facilitates cooperation among workers and knowledge interactions within firms, enhancing the role of existing knowledge in the technology production function (Garicano & Rossi-Hansberg, 2006).

Recent advances in the induced technological change approach provide additional support for predictions about the new knowledge intensive direction of technological change. According to Acemoglu (2002, 2003, 2015), the sharp reduction in the relative cost of skilled vis-à-vis unskilled workforce would have favored the introduction of capital intensive technologies where skilled labor is strictly complementary. Capital intensive technologies require workers with high levels of human capital and competence. Therefore, reducing the relative wages of skilled labor would reduce the total costs of capital intensive production processes and promote the capital intensive direction of technological change.

However, it could equally be argued that it is the reduction in the relative wages of skilled workers – due to the well-known college boom in the advanced economies in the second part of the twentieth century and the strong increase in the supply of labor with high levels of human capital – that has favored the introduction of knowledge intensive technologies (Goldin & Katz, 2010). In the context of the generation of technological knowledge, skilled labor is far more than an input complementing high levels of capital intensity: it is the key input in an activity with low levels of capital intensity. This argument is supported by rich empirical evidence of high levels of complementarity between knowledge intensive activities and high-skilled workers (Autor et al., 2003; Berman et al., 1994; Falk & Hagsten, 2021; Leiponen, 2006).

In fact, skilled labor, combined with the firm's existing stock of knowledge, form the key input for the generation of knowledge. The reduction of the relative wages of skilled -and creative- labor, should favor the generation of new knowledge and its use as an input in the production of all other goods. In our interpretation of the Skill-Biased-Technological-Change (SBTC) theory, the reduction in the cost of human capital leads to a knowledge intensive and capital saving direction of technological change where knowledge substitutes physical capital, rather than a capital intensive direction where skilled labor complements the higher levels of capital intensity of the production process. The latter interpretation has long been considered the prevailing one in studying the direction of technological change during the twentieth century, along the lines paved by Griliches (1969) and Zeira (1998), who provided evidence of the strong complementarity between skilled labor and physical capital.

On the contrary, our interpretation is fully consistent with the Routine Biased Technological Change (RBTC) literature, according to which the diffusion of information and communication technologies played a pivotal role in the delocalization of capital intensive manufacturing industries in industrializing countries within global value chains supported by intense flows of foreign direct investments and systematic global outsourcing (Autor et al., 2003; Ebenstein et al., 2014; Goos et al., 2014). Firms in advanced countries progressively shifted the core of their activities towards knowledge intensive activities such as R&D and engineering with low intensity of physical capital. The new knowledge intensive and capital saving direction of technological change is the outcome of the re-organization of the production activities and the new specialization of advanced countries (Baldwin, 2016).

Tangible capital plays a marginal role in the generation of new knowledge, which is a high skilled, labor intensive activity. The increase in the supply of skilled labor and the reduction in the related wage, combined with the rapid increase of the flow of R&D activities in the advanced countries in the last several years and the consequent increase in the stock of quasi-public knowledge, has moved in parallel with reductions in the cost of knowledge and, along with the notion of induced technological change approach, has favored the increase in the knowledge intensive direction of technological change.

Finally, the integration of the analysis of competition in the global economy and the characteristics of knowledge as an economic good enable the identification of a third mechanism, which accounts for the knowledge intensive direction of technological change. There is a large literature showing that knowledge, as an economic good, is characterized by its limited appropriability. Imitators based in the same economic system can easily exploit the technological knowledge and related technological innovations introduced by their 'inventors'. The implications of this limited appropriability of knowledge within a single economy, in terms of reduced incentives for its generation and the high risks of market failure involved, are well known. However, in a global economy, the implications of limited appropriability of knowledge do change. The global economy is characterized by competition in homogeneous product markets among firms based in heterogeneous factor markets.

Industrializing countries can rely on the abundance of labor and the favorable access conditions provided by global financial markets that have worked to sharply reducing the differences in the cost of capital in the global economy. Advanced countries can no longer rely of the cheaper user costs of capital as in the standard Heckscher and Ohlin framework of analysis of the specialization of countries in international markets.

The access and use of the large stocks of knowledge accumulated in advanced economic systems become the new exclusive sources of competitive advantage. The cost of knowledge remains far lower in the advanced with respect to industrializing economies. The economic systems of advanced countries have not only accumulated large stocks of quasi-public knowledge but also implemented effective mechanisms to access and use it. Because of the key role of geographic, institutional and cultural distance in the cost of accessing and using the required stocks of knowledge and the cost of creative labor, the actual cost of knowledge is much lower in advanced countries than in industrializing ones.

The case for a strategic bias towards a high knowledge intensive direction of technological change characterizes more and more competition in the global economy. In global product markets, de facto appropriability of knowledge is much larger than *de jure* appropriability. Competitors based in economies with scarce skilled labor and small knowledge stocks incur substantial imitation costs. As a result, industrializing economies cannot produce knowledge intensive goods at the same costs that the first inventors in skill-abundant countries achieve. The differences in knowledge costs and the limited transferability of knowledge beyond its localized sources and context of generation increase the costs for imitators based in skill-scarce economic systems compared to firms based in skill-abundant and knowledge-rich economic systems. The larger the knowledge intensity of a new product, the larger the appropriability of the mark-ups associated with the increase in productivity. The introduction of knowledge intensive products reinforces the gap between *de jure* and de facto appropriability, and becomes a powerful strategic determinant of a knowledge intensive bias in the introduction of product and process innovations (Antonelli, 2019a, 2019b).

In sum, the literature provides strong support for the hypothesis that knowledge is now a selective and strategic source of growth persistence and competitive advantage and is pushing firms to increase its role as a key input in the production process and enhancement of the accumulation of intangible capital. The next subsection focuses on the concept of knowledge capitalization.

### 2.2 Capitalization of knowledge and intangible assets

The acknowledgement of the limited exhaustibility of knowledge made by Griliches (1979, 1984 and 1986) opened the way to empirical assessments of knowledge as both an input in the production of other goods and an output in a dedicated activity. This culminated in the implementation of the CDM model (Crépon et al., 1998), which provides a unified and simultaneous treatment of knowledge, in its input and output roles.

Knowledge conceived as a bundle of disembodied items and the analysis of its role in growth accounting began with Corrado et al. (2005, 2009). Their work underlines the urgency related to accounting for a large array of assets that contribute persistently and significantly to productivity, but have been treated as intermediary or cost inputs. Indeed, "*the determination of what expenditures are current consumption and what are capital investment is governed by consumer utility maximization, and any outlay that is intended to increase future rather than current consumption is treated as a capital investment*" (Corrado et al., 2005, p. 13). Corrado and colleagues observed that traditional macroeconomic data exclude more than $3 trillion of intangible assets from the standard capital stock measure. By including intangible capital in growth accounting, they found that capital deepening was the primary source of productivity growth.

In 2008, the System of National Accounts (SNA) acknowledged the possibility of accounting for intangible assets, by revising the previous SNA 1993. It changed how capital stock was defined, in the following way: i) ICT equipment is included separately from other categories of capital stock to allow for a more precise definition of intangible ICT; ii) the term ‘intangible fixed assets’ was replaced by the term ‘intellectual property products’ and includes R&D expenditure; iii) mineral exploration became ‘mineral exploration and evaluation’, to conform with international accounting standards; iv) computer software now includes databases; v) the category ‘other intangible fixed assets’ was replaced by a new category ‘other intellectual property products’, and includes R&D, mineral exploration and evaluation, computer software and databases, literary and artistic originals.

Hence, the new accounting procedures enable the capitalization of knowledge inputs that previously were assumed to be fully expended in a particular year. Their capitalization implies that their contribution to productivity extends for more than one year. However, it depends on the depreciation rate. The capitalization of these assets is usually in line with the Perpetual Inventory Method (PIM) in which capital stock, at each moment, depends upon the past value of the capital stock properly depreciated, plus current investment expenditures.

Therefore, the PIM implies that the lower the depreciation rate, the longer the assets duration is on the firm balance sheet and the larger the effect of its capitalization. The empirical literature has long used the PIM to compute capital stocks from firms’ expenditures, allowing for different depreciation rates based on the asset to be capitalized (Nadiri & Prucha, 1996; Hall, 2007; Ortega-Argilés et al., 2014, 2015; Zhang & Mohnen, 2022). However, according to the US listed firms accounting rules, while the capitalization of tangible assets (such as plants, equipment and machines) is based on the purchase price and their depreciation is made considering its conjectured useful life, the General Accepted Accounting Principles (GAAP) treatment for US listed firms considers R&D, brand recognition, advertising and marketing activities as yearly expenditures. Indeed, the GAAP does not allow for their capitalization because of the difficulties and uncertainty surrounding the estimation of their value and their estimated useful lives.[2]

On the contrary, the intangible assets acquired by a US listed firm ensuing the acquisition of another firm are recorded in the balance sheet of the acquiring firm as either identifiable intangible assets or goodwill. Indeed, goodwill represents an assessment of any economic activity that has some value but that is not recorded in the book value of the target firm. On the contrary, if these assets meet specific criteria, they can be capitalized, entering the balance sheet of the acquiring firm at fair market value.

Recognizing intangibles as an additional input in the production function led to many studies investigating the link between intangibles and productivity. Several papers establish a connection between accounting for intangibles and productivity growth at the industry or macro-level (Borgo et al., 2013; Piekkola, 2018). There

[2] https://asc.fasb.org.

is also a rich stream of work that, at the micro level, examines the role of intangibles. Remarkably, several studies find evidence of an influential but marginal role of intangibles for explaining the productivity of European firms (Bontempi & Mairesse, 2015; Marrocu et al., 2012; Ortega-Argiles et al., 2015). Other studies show that more intangibles-intensive firms have a higher probability of innovating (Montresor & Vezzani, 2016, 2022) and that there are many differences in the propensity of firms to invest in intangibles, in the Italian case (Arrighetti et al., 2014, 2015). There is also some evidence of strong complementarities among several intangible inputs in the technology production function and high levels of complementarity between intangibles and the demand for skills (Añón Higón et al., 2017; Hendarman & Cantner, 2018; Piva & Vivarelli, 2009).

Our paper builds on these studies, but departs from them by analyzing a 40-year panel of US listed companies and using data that are more accurate on intangible capital. These data are drawn from Ewens et al.'s (2020) recent work, which proposed original firm level estimates of knowledge and organizational capital, for the universe of US companies recorded in the Compustat database.

Specifically, we compute the firm-level output elasticities of labor, physical capital and intangible capital and compare their evolution over time (1977–2016) and across macro-sectors. This approach is in line with work that focus on the technology production function, in the spirit of Griliches (1979), but in place of capitalized R&D expenditure, in our study we use intangible capital, which includes both knowledge and organizational capital as well as goodwill. Some recent studies estimate the technology production function in a similar way, but focus only on firms' use of digital and ICT technologies (Bartelsman et al., 2019; Hagsten, 2016).

Our approach is distinct from previous empirical investigations that explore the effects of intangible assets on the production processes using the Constant Elasticity of Substitution (CES) production function (Bassanini & Manfredi, 2014; O'Mahony et al., 2021). The focus of our analysis is on the direction of technological change where the use of a Cobb–Douglas production function is more appropriate than of a CES production function, which enables investigation of intangible assets by focusing on the value of the elasticity of substitution but at the cost of ignoring the changes in the output elasticities of the inputs.

Section 2.3 presents our main hypotheses, which are tested in the empirical analysis.

### 2.3 Hypotheses

The new accounting procedures, which allow the capitalization of intangible assets, led us to reconsider standard microeconomic analysis mostly grounded on a two-input production function. To formalize this more precisely, we assume a production process that is represented by a standard Cobb–Douglas production function with constant returns to scale. Here, overall capital $OK$ is split into fixed tangible capital $TK$ and intangible capital $IK$ (so that $OK = TK + IK$), which enter the production function as two distinct inputs, alongside labor $L$, to produce the output $Y$. Hence, the Cobb–Douglas production function can be written as follows:

$$Y_t = \left(TK_t\right)^{\alpha}\left(L_t\right)^{\beta}\left(IK_t\right)^{\gamma}$$

$\alpha$, $\beta$ and $\gamma$ are the respective output elasticities of tangible capital, labor and intangible capital. The subscript $t$ refers to time. In the empirical analysis, we also estimate the output elasticities, for different separate 10-year periods, in order to assess their evolution over time.

This modified version of the technology production function takes account of the role of knowledge and organizational capital in the production process. Our empirical analysis aims to assess the magnitude of $\gamma$, the output elasticity of intangible capital, and its evolution over time. The main prediction of the theoretical framework is that $\gamma$ has increased over the last several years.

We are also interested in whether including intangible capital affects the magnitude of the contribution to output of the other inputs, paying particular attention to the effects on the magnitude of the physical capital output elasticity. Our interpretative framework implies that, in recent decades, in advanced economies, knowledge has been the primary input. Advanced countries are no longer reliant on fixed capital to gain competitive advantage, and their direction of technological change is biased towards greater use of knowledge. In turn, this would imply that we should observe a reduction in the output elasticity of physical capital if intangible capital is included in the production function.

However, our analysis is not aimed primarily at establishing a connection between the increase in the output elasticity of knowledge and the sequential reduction in the output elasticity of labor. It should be remembered that a Cobb–Douglas production function constrains the elasticity of substitution among production factors, to unity. There is a long tradition of empirical studies that analyze the evolution of the output elasticity of labor in a CES framework, where the elasticity between capital and labor is constant but not equal to unity (Bassanini & Manfredi, 2014). The empirical assessment of the impact of knowledge capital on labor compensation requires some additional assumptions about the magnitude of the substitutability and complementarity among production factors. This poses some substantial problems, especially if the tendency of the elasticity of substitution is to increase over time (Ziesemer, 2021).

Therefore, the present analysis aims only to assess whether the increase in the output elasticity of intangible capital coincides with a reduction in the elasticity of tangible capital, to provide evidence of a transition from a fixed and tangible capital intensive direction of technological change to an intangible intensive direction of change.

Section 3 presents the data and the estimation methods.

# 3 Data and methods

## 3.1 Sample and variables

We estimate firm-level production functions using Compustat data for the period 1977–2016. The Compustat database contains detailed financial information on all publicly traded US companies. Using the Compustat database presents several advantages compared to other data sources. First, it provides long time series (since the 1950s). No comparable databases for European or US companies cover a similar time span. Second, Ewens et al. (2020) provide us with new and rich data on intangible capital for the universe of Compustat firms since 1970s, including both knowledge and organizational capital. Therefore, the combination of financial and intangible assets data observed for a large sample of US firms over a long time span represents a novelty compared to previous studies, mostly based on surveys and cross-section analyses (Arrighetti et al., 2014; Montresor & Vezzani, 2016, 2022).

We restrict the sample to US-based firms whose business is conducted in US dollars, with at least two consecutive years of observations and positive values for sales, numbers of employees, gross property, plant and equipment, depreciation, accumulated depreciation, general and administrative expenses, and physical capital expenditures. We exclude regulated utilities (SIC Codes 4900–4999), financial firms (6000–6999) and firms categorized as public services, international affairs or non-operating establishments (9000 +).[3] We winsorize all regression variables at the 1% level to remove outliers.[4] The resulting sample is an unbalanced panel of 7,140 firms observed over the period 1977–2016. The total number of firm-year observations is 59,528.

The key variables used to estimate the firm-level production functions are value added, employment stock, physical capital stock and intangible capital stock. Value added is measured as the difference between sales and materials, deflated using the output deflator. Sales is net sales derived from Compustat (Compustat item SALE). Materials is computed as the difference between total expenses and labor expenses. Total expenses are approximated as Sales minus Operating Income Before Depreciation and Amortization (Compustat item OIBDA). When not directly reported by the firm, labor expenses are calculated by multiplying the number of employees recorded in Compustat (Compustat item EMP) by the average wage for the matching

[3] We exclude firms in these SIC Codes, following a standard practice in related studies (e.g., Chen et al., 2015), because regulated utility and financial firms have different Compustat Balancing Models and reporting standards.

[4] We follow a standard practice in the literature when winsorizing the main variables at the 1% level to minimize the influence of possible spurious outliers (e.g., Borisova and Brown, 2013; Green et al., 2022). However, we check the robustness of our preferred winsorizing threshold by either removing it or setting it at 0.5% and 2%, respectively. The results of these robustness checks, available from the authors upon request, confirm the validity of our preferred estimates.

**Table 1** Summary statistics

| Variable | | Mean | Std. Dev | Min | Max | Observations |
|---|---|---|---|---|---|---|
| *VA*(log) | Overall | 4.482029 | 1.786834 | 0.0009395 | 12.36036 | $N=59{,}528$ |
| | Between | | 1.619095 | 0.4597794 | 8.427894 | $n=7140$ |
| | Within | | 0.6789188 | − 1.16584 | 9.396597 | T bar = 8.33725 |
| *LAB*(log) | Overall | 6.874815 | 1.758069 | 1.098612 | 12.46921 | $N=59{,}528$ |
| | Between | | 1.639048 | 2.171903 | 10.73604 | $n=7140$ |
| | Within | | 0.5272927 | 2.417931 | 10.2604 | T bar = 8.33725 |
| $K^{phy}$(log) | Overall | 4.082399 | 1.941 | 0.0063338 | 10.64679 | $N=59{,}528$ |
| | Between | | 1.789019 | 0.2765187 | 8.675188 | $n=7140$ |
| | Within | | 0.6687657 | − 1.395764 | 7.251904 | T bar = 8.33725 |
| $K^{int}$(log) | Overall | 3.946959 | 1.946682 | 0 | 10.79507 | $N=59{,}528$ |
| | Between | | 1.709465 | 0.0109989 | 8.381353 | $n=7140$ |
| | Within | | 0.8092703 | − 2.102862 | 9.27981 | T bar = 8.33725 |

industry (2-digit SIC).[5] The stock of labor is the number of employees as recorded in Compustat (Compustat item EMP).

Firm-level physical capital stock is given by gross plant, property and equipment recorded in Compustat (Compustat item PPEGT), deflated following Hall (1990) and Brynjolfsson and Hitt (2003).

Firm-level intangible capital stock is measured as the sum of externally purchased and internally created intangible assets. We measure externally purchased intangible capital as the balance sheet item Intangible Assets (Compustat item INTAN). In the case of missing values, we set this item to zero. We retain Goodwill in Intangible Assets since Goodwill includes the fair cost of acquiring intangible assets not separately identifiable (Peters & Taylor, 2017). Internally created intangible capital is the sum of organizational capital and knowledge capital. The measures for the two components of firm-level internally created intangible capital stock are from Ewens et al. (2020). Based on original capitalization parameters for intangible capital – computed by exploiting the price paid for intangible assets in an acquisition – Ewens et al. (2020) impute values of off-balance sheet firm-year stocks of knowledge and organizational capital, for the universe of firms included in Compustat, for the period 1975–2016.

Table 1 reports summary statistics for the four key variables used to estimate firm–level production functions (Appendix Tables A1 and A2).[6] Figure 1 depicts

[5] This approach presents some drawbacks to the extent to which firms are heterogeneous based on the workforce composition regarding skills and educational attainment. Indeed, skilled wages usually earn a wage premium on lower-skilled workers; therefore, wage heterogeneity among firms, due to different skill compositions, might be artificially flattened. We thank an anonymous referee for this remark. To limit the concerns raised by this caveat, we also conduct estimations using average wages calculated at finer levels of industry disaggregation (i.e., 3-digit SIC and 4-digit SIC). Results are robust to these checks and are available from the authors upon request.

[6] Tables A1 and A2 in the Appendix report, respectively, the description and the summary statistics for manufacturing, consumer and high-tech, separately.

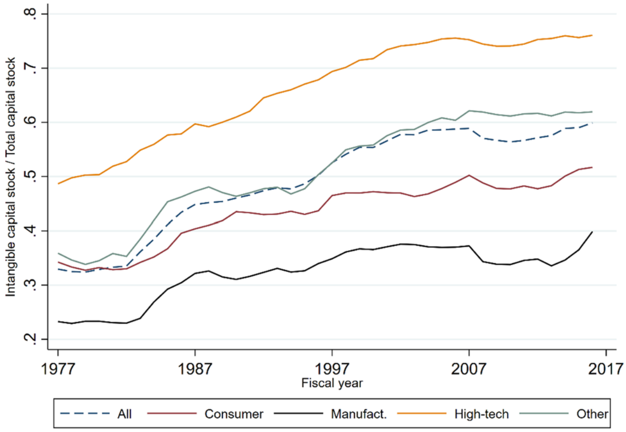


**Fig. 1** Intangible capital intensity

the evolution, over time, of the intangible capital stock intensity, calculated as the ratio between intangible capital stock and total capital stock (i.e., physical capital stock + intangible capital stock), for the full sample of US firms considered, in four aggregated industries (manufacturing, consumer, high-tech and other).[7] Overall, the average intangible intensity increased from ~ 33% in 1977 to ~ 60% in 2016 (dashed line). As expected, intangibles intensity is higher in high-tech industries (above 76% in 2016) compared to (traditional) manufacturing (~ 40% in 2016) and consumer industries (~ 51% in 2016).

### 3.2 Empirical methods

Our empirical analysis starts with the estimation of a traditional Cobb–Douglas production function that takes the following form:

$$y_{it} = \alpha + \beta_1 l_{it} + \beta_2 k_{it}^{\text{phy}} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where $I$ and $t$ are the firm and time, respectively; $y_{it}$ is the log-transformed firm-level value added; $l_{it}$ is the log-transformed number of employees; $k_{it}^{phy}$ is the log-transformed physical capital stock; $\omega_{it}$ is a random component that captures unobservable productivity or technical efficiency and evolves according to a first-order Markov process; $\varepsilon_{it}$ is an idiosyncratic output shock distributed as white noise.

We augment (1) with the firm-level log-transformed intangible capital stock ($k_{it}^{int}$). The 'augmented' firm-level production function takes the following form:

$$y_{it} = \alpha + \beta_1 l_{it} + \beta_2 k_{it}^{\text{phy}} + \beta_3 k_{it}^{int} + \omega_{it} + \varepsilon_{it} \tag{2}$$

[7] Figure 1 (which is adapted from Ewens et al. (2020), Fig. 6), provides time series trends for intangible capital intensities, on average and by industry, as discussed by the same authors.

To provide consistent estimates of the parameters of interest in (1) and (2), we cannot rely on Ordinary Least Squares (OLS). It has been shown conclusively that the correlation between the observable input levels and the unobservable productivity shocks is a major source of bias in OLS estimates used to estimate firm-level production functions. In other words, productivity shocks force firms to respond by modifying the levels of both their output and their demand for inputs: negative shocks lead to a decrease in both output and demand for input; positive shocks can lead to the opposite reaction from the firm. Due to this simultaneity issue, OLS estimates are not consistent. Moreover, it is unlikely that this issue of simultaneity can be solved by applying fixed-effect estimators. Indeed, to be consistent, fixed-effect estimators must assume that $\omega_{it}$ is firm specific and time invariant. However, unobserved productivity changes over time, which causes bias in fixed-effect estimates.

One of the most relevant contributions in this context was by Olley and Pakes (1996) (hereafter, OP), who proposed the 'control function' method to resolve this major issue. OP provided the first formalized consistent two-step procedure to estimate firm-level production functions. They suggested using firm investment levels to proxy for $\omega_{it}$, under specific assumptions. First, that firm investments are a function of variable inputs (e.g., labor) and $\omega_{it}$, are invertible in $\omega_{it}$ and, also, are monotonically increasing in $\omega_{it}$. Second, capital evolves according to investments, which are decided at time *t-1*. Third, variable inputs (e.g., labor) are non-dynamic (i.e., their choice at *t* does not affect future profits, and are chosen at *t* after observation by the firm of a productivity shock).

Levinsohn and Petrin (2003) (LP) advanced the OP method by suggesting use of firm demand for intermediate goods to proxy for productivity, instead of using demand for investments. They argue that OP's assumptions related to monotonicity and timing of demand for investments might be too strong in many real-world cases. They suggest that demand for intermediate goods is more sensitive to productivity shocks and, therefore, captures them better.

The major drawback related to both the OP and LP methods, is collinearity issues. Both OP and LP assume that, when faced with a productivity shock, firms can instantly adjust some inputs (especially labor) at no cost. This is difficult to confirm and is unlikely, with the result that using either the OP or LP methods to estimate the first stage of the two-step estimation procedure suffers from collinearity. Ackerberg et al. (2006) (ACF) proposed a modified version of the traditional 'control function' approach to solve the collinearity issue, which also allowed consistent estimates of labor elasticities. In their method, all (unbiased) estimates of the production function parameters are obtained in the second step of the estimation procedure.

For reasons of data availability, we employ the OP two-stage estimation strategy, corrected according to the ACF method. Compustat data allow us to systematically observing firm demand for investments, but, in most cases, we cannot measure demand for intermediate goods directly. This means that, for our sample of firms, the LP method is largely unfeasible.

Since we are interested, also, in investigating how the elasticities of labor, physical and intangible capital evolved over time, we split the 1977–2016 timespan into four 10-year periods. We also present estimates for the separate subsamples

**Table 2** Output elasticities

| | Full sample | | Manufacturing | | Consumer | | High-tech | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LAB* | 0.704*** | 0.609*** | 0.587*** | 0.460*** | 0.588*** | 0.508*** | 0.890*** | 0.838*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $K^{phy}$ | 0.254*** | 0.216*** | 0.349*** | 0.326*** | 0.297*** | 0.204*** | 0.114*** | 0.0840*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) |
| $K^{int}$ | | 0.166*** | | 0.168*** | | 0.222*** | | 0.102*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.002) |
| *N* | 59,528 | 59,528 | 12,901 | 12,901 | 18,676 | 18,676 | 15,496 | 15,496 |

Notes: The dependent variable is the log of firm-level value added. All the models include year dummies. Macro-sector dummies are included for the full sample in columns (1) and (2). Estimates for 'Other' firms are not reported. 'Other' firms are included in the estimates for the full sample. Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

of manufacturing, consumer and high-tech firms, over the entire timespan and by 10-year period. Section 4 presents and discusses the main results.

# 4 Results

## 4.1 Baseline results

Table 2, Columns 1 and 2, present the results of the main analysis, performed on the full sample described in Sect. 3.1. Column 1 refers to Eq. (1) and Column 2 to Eq. (2). In Column 1, the estimates of the firm-level production function do not include the intangible capital stock, which instead is included in Column 2.

The results of this initial exercise highlight three main features. First, in Column 2, the average intangible capital stock elasticity is 0.166, which is sizeable, especially if compared to the elasticity of physical capital stock which is 0.216. Second, as expected, the largest estimated elasticity is for labor (~0.61). Third, both labor and physical capital elasticities reduce when the production function is augmented by the inclusion of intangible capital stock (the coefficients in Column 2 compared to Column 1). By comparing the results in Columns 1 and 2, we observe that labor and physical capital elasticities drop by ~13.5% (from 0.704 to 0.609) and by ~15% (from 0.254 to 0.216), respectively. In sum, when intangible capital stock is included in the estimates of the firm-level production function, we observe a significant and sizeable contribution to created value added. Also, and as expected, its inclusion reduces the real elasticities of both labor and (especially) physical capital.

Table 2, Columns 3–8, report industry-specific results. Columns 3 and 4 refer to manufacturing, Columns 5 and 6 to consumer goods and services and Columns 7 and 8 to high-tech. The significant and sizeable contribution of intangible capital stock to firm value added is confirmed across industries. Precisely, the estimated elasticities of intangible capital stock range between 0.102 (high-tech) and 0.222

**Table 3** Output elasticities by decade – full sample

| | 1977–1986 | | 1987–1996 | | 1997–2006 | | 2007–2016 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LAB* | 0.673*** | 0.597*** | 0.694*** | 0.609*** | 0.704*** | 0.615*** | 0.731*** | 0.584*** |
| | (0.004) | (0.002) | (0.002) | (0.001) | (0.009) | (0.003) | (0.003) | (0.008) |
| $K^{phy}$ | 0.258*** | 0.228*** | 0.250*** | 0.201*** | 0.253*** | 0.189*** | 0.264*** | 0.185*** |
| | (0.003) | (0.002) | (0.003) | (0.004) | (0.010) | (0.004) | (0.006) | (0.005) |
| $K^{int}$ | | 0.117*** | | 0.156*** | | 0.202*** | | 0.224*** |
| | | (0.002) | | (0.003) | | (0.006) | | (0.005) |
| *N* | 15,480 | 15,480 | 15,502 | 15,502 | 16,063 | 16,063 | 12,274 | 12,274 |

Notes: The dependent variable is the log of firm-level value added. All models include year and macro-industry dummies. We apply the 2-stage estimation method proposed by Olley and Pakes (1996), corrected following Ackerberg et al. (2006). Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

(consumer). These results suggest that knowledge intensity is likely to be larger where knowledge extensibility and cumulability exert stronger effects. Indeed, in the production of consumer goods characterized by large batches that use the very same blueprint, as well as in some subsectors within the manufacturing, the output elasticity of intangible capital shows its highest levels because of the strong positive effects of the extensibility of knowledge. Production processes in the high-tech sector are instead characterized by higher differentiation and customization. As a result, the benefits of knowledge extensibility are smaller in high-tech.[8]

Moreover, it is worth noticing that the elasticity of intangible capital is higher than the elasticity of physical capital for high-tech and consumer firms. Lastly, we can confirm that the inclusion of intangible capital stock significantly reduces the magnitude of both labor and physical capital elasticities, compared with the industry-specific estimates from Eq. (1). Specifically, labor elasticities drop by between 5.8% (high-tech) and 21.6% (manufacturing), while physical capital stock elasticities drop even more, between 6.6% (manufacturing) and 31.3% (consumer).[9]

[8] The higher output elasticity of intangible capital estimated for consumer than high-tech firms may also be explained by the fact that the consumer sector is populated by big corporations that generate and exploit intangibles extensively to increase productivity. On the other hand, firms in the high-tech sector benefit from intangibles in terms of increasing mark-ups and barriers to entry, reflected in higher levels of sales and market shares but less in productivity compared to consumer firms. As a result, the output elasticity of knowledge for high-tech firms may be lower than for consumer firms. Our interpretation is in line with Crouzet and Eberly (2019) and Orhangazi (2019).

[9] The $R^2$ is not reported but all the estimations display high levels of goodness of fit with an $R^2$ above 0.9 across all the specifications. We also implement a Wald test for the joint significance of macro-industry and year dummies in columns (1) and (2) reporting that the dummies are jointly statistically significant at the highest confidence level.

**Table 4** Output elasticities by decade – Manufacturing

| | 1977–1986 | | 1987–1996 | | 1997–2006 | | 2007–2016 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LAB* | 0.623*** | 0.533*** | 0.700*** | 0.570*** | 0.514*** | 0.390*** | 0.578*** | 0.368*** |
| | (0.002) | (0.003) | (0.003) | (0.009) | (0.006) | (0.013) | (0.012) | (0.014) |
| $K^{phy}$ | 0.338*** | 0.306*** | 0.280*** | 0.257*** | 0.413*** | 0.413*** | 0.421*** | 0.384*** |
| | (0.001) | (0.004) | (0.004) | (0.006) | (0.009) | (0.006) | (0.014) | (0.013) |
| $K^{int}$ | | 0.120*** | | 0.172*** | | 0.200*** | | 0.290*** |
| | | (0.004) | | (0.004) | | (0.006) | | (0.026) |
| *N* | 4870 | 4870 | 3229 | 3229 | 2705 | 2705 | 2220 | 2220 |

Notes: The dependent variable is the log of firm-level value added. All models include year dummies. We apply the 2-stage estimation method proposed by Olley and Pakes (1996), corrected following Ackerberg et al. (2006). Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

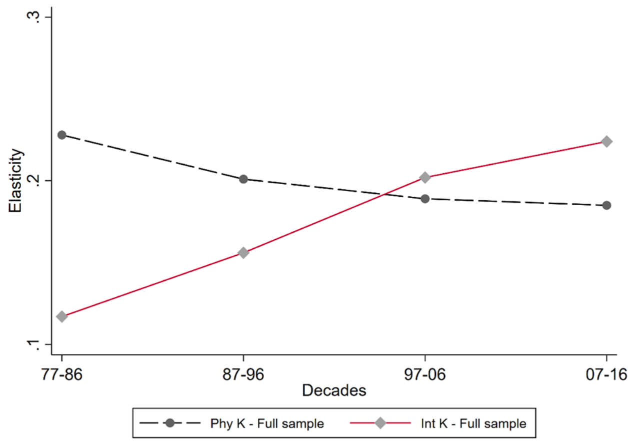


**Fig. 2** Tangible and intangible capital elasticities: Estimates by decade (full sample)

## 4.2 Results by decade

In this subsection, we present a series of estimates for the full sample (Table 3) and by industry (Tables 4–6), respectively, splitting the 1977–2016 timespan into four 10-year periods. Figure 2 is based on the results reported in Table 3 and provides a graphical representation of the evolution of the estimated physical and intangible capital elasticities (full sample). Figure 3 depicts industry specific elasticities relying on the results reported in Tables 4, 5 and 6.

Starting with the full sample estimates of the augmented production function (Table 3, Columns 2, 4, 6 and 8), we observe a sharp increase over time of the

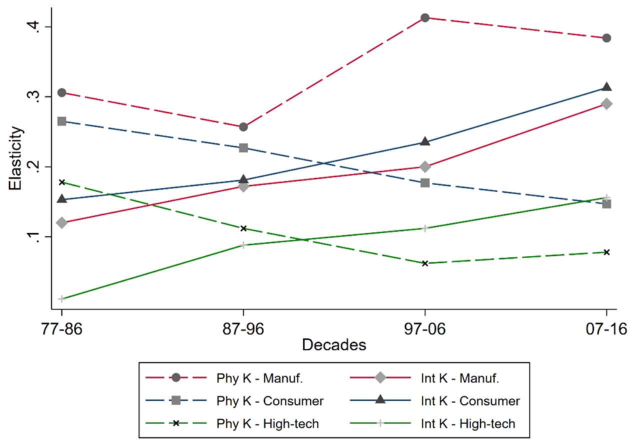


**Fig. 3** Tangible and intangible capital elasticities: Estimates by industry and by decade

**Table 5** Output elasticities by decade – Consumer

| | 1977–1986 | | 1987–1996 | | 1997–2006 | | 2007–2016 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LAB* | 0.609*** | 0.535*** | 0.603*** | 0.532*** | 0.590*** | 0.488*** | 0.568*** | 0.446*** |
| | (0.003) | (0.004) | (0.003) | (0.005) | (0.010) | (0.010) | (0.011) | (0.005) |
| $K^{phy}$ | 0.316*** | 0.265*** | 0.311*** | 0.227*** | 0.315*** | 0.177*** | 0.325*** | 0.147*** |
| | (0.003) | (0.004) | (0.005) | (0.005) | (0.004) | (0.009) | (0.007) | (0.006) |
| $K^{int}$ | | 0.153*** | | 0.181*** | | 0.235*** | | 0.313*** |
| | | (0.003) | | (0.004) | | (0.007) | | (0.009) |
| *N* | 5760 | 5760 | 5502 | 5502 | 4407 | 4407 | 3175 | 3175 |

Notes: The dependent variable is the log of firm-level value added. All models include year dummies. We apply the 2-stage estimation method proposed by Olley and Pakes (1996), corrected following Ackerberg et al. (2006). Standard errors in parentheses. $^{*}$ $p<0.05$, $^{**}$ $p<0.01$, $^{***}$ $p<0.001$

**Table 6** Output elasticities by decade – High-tech

| | 1977–1986 | | 1987–1996 | | 1997–2006 | | 2007–2016 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LAB* | 0.788*** | 0.790*** | 0.862*** | 0.821*** | 0.925*** | 0.887*** | 0.890*** | 0.810*** |
| | (0.006) | (0.008) | (0.005) | (0.005) | (0.006) | (0.006) | (0.003) | (0.005) |
| $K^{phy}$ | 0.195*** | 0.178*** | 0.136*** | 0.112*** | 0.082*** | 0.062*** | 0.125*** | 0.078*** |
| | (0.009) | (0.005) | (0.005) | (0.006) | (0.009) | (0.008) | (0.005) | (0.004) |
| $K^{int}$ | | 0.011 | | 0.088*** | | 0.112*** | | 0.156*** |
| | | (0.008) | | (0.004) | | (0.006) | | (0.005) |
| *N* | 2657 | 2657 | 3781 | 3781 | 5173 | 5173 | 4058 | 4058 |

Notes: The dependent variable is the log of firm-level value added. All models include year dummies. We apply the 2-stage estimation method proposed by Olley and Pakes (1996), corrected following Ackerberg et al. (2006). Standard errors in parentheses. $^{*}$ $p<0.05$, $^{**}$ $p<0.01$, $^{***}$ $p<0.001$

intangible capital stock elasticity. It almost doubles between the decade 1977–1986 (Column 2, coefficient 0.117%) and the decade 2007–2016 (Column 8, coefficient 0.224%). It should be noted that, from 1997, the estimated elasticity of intangible capital stock is higher than the estimated elasticity of physical capital. Notice, also, that the observed significant increase in the relevance of intangible capital stock comes at the cost of a continuous drop mainly in the elasticity of the physical capital stock, which reduces from an estimated 0.228 (decade 1977–1986) to an estimated 0.185 in the last decade considered (a 18.9% decrease). Estimated labor elasticity remains instead fairly stable over time, ranging between 0.584 and 0.615.

Lastly, if we compare production function estimates obtained excluding intangible capital stock (Columns 1, 3, 5 and 7) with estimates obtained from the augmented production function (Columns 2, 4, 6 and 8), the elasticities of both labor and physical capital reduce in magnitude, in each period considered. Moreover, these differences increase over time and, on average, refer more to physical capital than to labor. Precisely, the differences for labor elasticities range between -11.3% (first decade) and -20.1% (last decade), while the differences for physical capital elasticities range between -11.6% (first decade) and -29.9% (last decade).

We replicate the analysis in Table 3 for the manufacturing, consumer and high-tech subsamples, separately. The results by industry, depicted in Fig. 3, provide interesting insights.

Looking at manufacturing firms (Table 4), we observe an increasing trend in capital elasticities (both physical and intangible) over time, at the cost of a significant drop in labor elasticities. Interestingly, the estimated intangible capital stock elasticity increases by more than 1.4 times, from 0.12 (1977–1986) to 0.29 (2007–2016). In the case of the other two inputs, the estimated elasticity of physical capital stock increases from 0.306 (1977–1986) to 0.384 (2007–2016), while estimated labor elasticity (the lowest across industries) decreases from 0.533 in 1988–1986 to 0.368 in 2007–2016. Lastly, we confirm that the estimated elasticities of both labor and physical capital are always higher if the production function is estimated excluding rather than including intangible capital stock.

Table 5 reports the results for the subsample of consumer industry firms and shows that the estimated elasticity of intangible capital increased sharply over time, from 0.153 in the first 10-year period to 0.313 in the last 10-year period (+ 104.5%). Both labor and (especially) physical capital elasticities dropped consistently. Specifically, estimated labor elasticity decreased from 0.535 in the first 10-year period to 0.446 in the last period and the elasticity of physical capital stock dropped even more from 0.265 (first period) to 0.147 (last period).

Overall, we confirm the evidence reported above about considerable differences in the magnitude of labor and physical capital elasticities when estimated using Eq. (1) or Eq. (2). As expected, augmenting the production function by including the stock of intangible capital always leads to significantly lower estimated elasticities of both labor and physical capital.

The last set of results, reported in Table 6, refers to high-tech firms. For this subsample of firms, we observe a similar trend to the general trend observed for the full sample. However, the magnitude of the estimated elasticities is interesting. First, the largest increase is for intangible capital elasticity, which increases from 0.011 (first decade) to 0.156 (last decade). Second, the elasticity of physical capital stock drops by 56.2% between the first and last decade (from 0.178 to 0.078). These two results suggest that, over time, in high-tech industries, intangible capital gains increasing importance relative to physical capital. In the final 10-year period considered, the estimated elasticity of intangible capital stock (0.156) is the double of the estimated elasticity of the physical capital stock (0.78). Third, labor elasticity (ranging between 0.79 and 0.89) does not vary considerably over time and is significantly higher than the labor elasticity estimated on the full sample (Table 3).

## 5 Conclusions

The analysis of the direction of technological change has long recognized its capital intensive bias in advanced economies. The capital intensive direction of technological change was explained by the parallel secular increase in wages and the decline in the cost of capital that together provided inducements to bias technological change toward greater use of capital.

This paper elaborates an alternative interpretation to the standard skill based technological change approach and tests the hypothesis that the new direction of technological change is knowledge intensive but tangible-capital saving. We argue that the new knowledge intensive direction of technological change is the result of the search for competitiveness by firms in advanced countries facing increased levels of competition in the new global economy and their effort to trying to enhance the appropriability of the knowledge output. Firms base the generation of new technological knowledge on their imperfectly imitable resources, which now can be capitalized as assets thanks to the new accounting rules.

The capitalization of knowledge as an intangible asset in the firm's balance sheet results from a long process of recognition of the limited exhaustibility of knowledge and its consequences for the subsequent generation of technological knowledge. The new accounting procedures allow the identification and measurement of intangible assets as a distinct input in the technology production function.

Our empirical analysis uses a sample of US listed firms included in the Compustat North America database, observed for the period between 1977 and 2016. We estimate a technology production function that includes intangible assets as a production factor, alongside tangible capital and labor, and we confirm that the direction of technological change has become increasingly knowledge intensive and actually tangible-capital saving, over time and across industries. This supports theoretical works in the new economics of knowledge, which stress the role, in a global economy, of knowledge as a key input in the production function.

Moreover, we find that the increasing output elasticity of intangible capital is associated with a concomitant reduction in the output elasticity of physical capital, while the output elasticity of labor remains relatively stable over time. In line with recent findings (Gould, 2019), the aggregate manufacturing sector is the only one wherein we may observe a reduction in the output elasticity of labor. On the contrary, in the consumer and high-tech sectors, the increase over time of the intangible output elasticity parallels the substantial reduction in the physical capital output elasticity.

While our results provide evidence of the knowledge intensive and tangible-capital saving direction of technological change, the data at our disposal do not enable us to disentangle the labor input based on either their educational attainment or the tasks performed. The complementarity between labor and intangible capital we find in the consumer and high-tech sectors, and the substitutability between labor and intangibles in the manufacturing sector, support the hypothesis of complementarity between non-routine, skilled labor and intangibles and a potential substitution between unskilled, routine labor and intangibles. Indeed, the share of high-skilled and creative labor is usually higher in the consumer and high-tech sectors, while the share of unskilled labor is larger in manufacturing. However, our intuitions are only tentative and cannot be tested on our data. Nonetheless, this line of inquiry is worthy of investigation in future empirical analyses.

At the same time, further analyses could be conducted on estimating output elasticities by considering finer levels of sectoral disaggregation. Nonetheless, our analysis is confined to the US. Therefore, expanding the investigation to other developed economies would be of interest.

Lastly, our results may have substantial policy implications. As recognized by a recent, albeit little explored line of research, the capitalization of intangible assets may have distorting effects on growth accounting figures (Koh et al., 2020). Specifically, the capitalization of an item previously accounted for as cost or expenditure directly increases the size of the capital figures. However, this leads to a considerable reduction in the Total Factor Productivity (TFP), measured as the ratio between the actual and the theoretical output. Therefore, even though the expenditures on R&D and other intangible assets may directly increase TFP levels, their capitalization has the opposite effect, reducing the actual increase of the TFP. Hence, policymakers should carefully consider the growing practice of intangibles capitalization, especially in terms of income redistribution to the factor inputs, labor and capital. Since R&D expenditures are based mainly on the wages paid to the researchers, it is evident that the capitalization of these costs contributes to increasing the capital figures in firm balance sheets but reduces the share of income paid to labor, Euler conditions assumed.

## Appendix

**Table A1:** Macro-sectors composition

| | |
|---|---|
| Manufacturing | Coal mining; Oil and gas extraction; Furniture and fixtures; Paper and allied products; Printing, publishing and allied; Chemicals and allied products; Petroleum refining and related industries; Rubber and miscellaneous plastics products; Leather and leather products; Stone, clay, glass, concrete products; Primary metal industries; Industrial, commercial, machinery, computer equipment; Electronic, other electric equipment, ex computers; Electric, gas and sanitary services; Fabricated metal, ex machinery; Transportation equipment; Railroad transportation |
| Consumer | Agriculture; Food and kindred products; Tobacco products; Textile mill products; Apparel and other finished products; Publishing and printing; Leather and leather products; Furniture and fixtures; Consumers of electronic, other electric equipment, ex computers; Wholesale and retail; Consumers of miscellaneous manufacturing industries; Personal services: Miscellaneous repair services |
| High-Tech | Computers and computing equipment; Motors and generators; Electronic installations and communications equipment; Electrical equipment; Optical instruments; Computer related services; Research services; Communications and communications services |

**Table A2:** Summary statistics by macro-sector

| Variable | | Mean | Std. Dev | Min | Max | Observations |
|---|---|---|---|---|---|---|
| Panel A. Manufacturing | | | | | | |
| *VA*(log) | Overall | 4.612938 | 1.861601 | 0.0051775 | 9.886498 | $N=12{,}901$ |
| | Between | | 1.779542 | 0.3121284 | 8.722406 | $n=1432$ |
| | Within | | 0.556072 | 0.6973888 | 7.486065 | T bar = 9.00908 |
| *LAB*(log) | Overall | 6.843044 | 1.856817 | 1.098612 | 11.21723 | $N=12{,}901$ |
| | Between | | 1.84416 | 1.460676 | 10.7386 | $n=1432$ |
| | Within | | 0.4194254 | 3.9881 | 8.728046 | T bar = 9.00908 |
| $K^{phy}$(log) | Overall | 4.675492 | 2.024529 | 0.0491415 | 10.64679 | $N=12{,}901$ |
| | Between | | 1.942392 | 0.395319 | 9.78821 | $n=1432$ |
| | Within | | 0.565738 | 0.7531377 | 7.222618 | T bar = 9.00908 |
| $K^{int}$(log) | Overall | 3.657775 | 1.971733 | 0.0997537 | 9.653311 | $N=12{,}901$ |
| | Between | | 1.760544 | 0.1864216 | 8.056134 | $n=1432$ |
| | Within | | 0.6872218 | − 0.3849529 | 7.508428 | T bar = 9.00908 |
| Panel B. Consumer | | | | | | |
| *VA*(log) | Overall | 4.715482 | 1.718055 | 0.0128411 | 10.44186 | $N=18{,}676$ |
| | Between | | 1.564374 | 0.7271292 | 8.324896 | $n=2299$ |
| | Within | | 0.6265208 | 0.3411308 | 8.600963 | T bar = 8.12353 |
| *LAB*(log) | Overall | 7.438004 | 1.740475 | 1.098612 | 12.57764 | $N=18{,}676$ |
| | Between | | 1.615396 | 3.27554 | 10.94467 | $n=2299$ |
| | Within | | 0.5144557 | 2.98112 | 10.82359 | T bar = 8.12353 |
| $K^{phy}$(log) | Overall | 4.392974 | 1.918091 | 0.0063338 | 10.60254 | $N=18{,}676$ |
| | Between | | 1.773962 | 0.3220612 | 8.549367 | $n=2299$ |
| | Within | | 0.6531046 | − 1.085189 | 7.562479 | T bar = 8.12353 |

**Table A2:** (continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| $K^{int}$(log) | Overall | 4.038243 | 1.921663 | 0.0286518 | 10.75711 | $N$ = 18,676 |
| | Between | | 1.731137 | 0.373914 | 8.616455 | $n$ = 2299 |
| | Within | | 0.7647773 | − 1.068593 | 8.921713 | T bar = 8.12353 |
| Panel C. High-tech | | | | | | |
| $VA$(log) | Overall | 4.146694 | 1.71621 | 0.0046349 | 11.06797 | $N$ = 15,496 |
| | Between | | 1.470694 | 0.5080749 | 8.364461 | $n$ = 1888 |
| | Within | | 0.7359448 | − 1.501176 | 7.305579 | T bar = 8.20763 |
| $LAB$(log) | Overall | 6.38241 | 1.527973 | 1.609438 | 12.46921 | $N$ = 15,496 |
| | Between | | 1.31374 | 2.856169 | 10.13465 | $n$ = 1888 |
| | Within | | 0.5693303 | 2.10652 | 8.987756 | T bar = 8.20763 |
| $K^{phy}$(log) | Overall | 3.414475 | 1.715321 | 0.0623831 | 9.238831 | $N$ = 15,496 |
| | Between | | 1.459851 | 0.2444695 | 7.666317 | $n$ = 1888 |
| | Within | | 0.7145764 | − 1.847717 | 6.205306 | T bar = 8.20763 |
| $K^{int}$(log) | Overall | 4.251752 | 1.792024 | 0.0406698 | 10.69279 | $N$ = 15,496 |
| | Between | | 1.507615 | 0.6102509 | 8.435502 | $n$ = 1888 |
| | Within | | 0.8365538 | − 1.180442 | 8.237065 | T bar = 8.20763 |

**Data availability** The data and the analysis that support the findings of this article are available from the authors upon request.

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