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The effects of the limited exhaustibility of knowledge on firm size and the direction of technological change

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Abstract
The new knowledge intensive direction of technological change is magnified at the firm level by the limited exhaustibility of knowledge. This limited exhaustibility triggers cumulability and extensibility for which the larger the firm, the lower the knowledge generation costs from using a larger stock of existing knowledge, and the lower the knowledge exploitation costs related to a larger output based on use of the same piece of knowledge. The consequences for the direction of technological change are twofold. First, the larger the firm size, the larger the share of intangible capital in total capital. Second, the output elasticity of intangible capital increases with the size of the firm. We test our hypotheses on data on US listed companies over the period 1977–2016. The results of ordinary least squares, two-stage least squares and production function estimations confirm our theoretical expectations.

Keywords Knowledge exhaustibility · Cumulability · Extensibility · Knowledge costs · Firm size · Knowledge intensive direction of technological change

JEL Classification 031

1 Introduction

The investigation of the new knowledge intensive direction of technological change is enriched by the analysis of the properties of knowledge as an economic good. Much attention has focused on the limited appropriability of knowledge and its consequences for knowledge exploitation. However, fewer investigations focus on the limited exhaustibility of knowledge, its effects on knowledge generation and exploitation and on the direction of technological change (Antonelli, 2019a, b).

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The limited exhaustibility of knowledge means that knowledge is not subject to the wear and tear suffered by other standard economic goods: it can be used repeatedly to produce other goods and to generate new knowledge. The limited exhaustibility of knowledge has substantial implications for both the generation and exploitation of technological knowledge. With respect to the generation of knowledge, its limited exhaustibility triggers powerful cumulability effects. New knowledge vintages add to the existing stock of knowledge and increase the pool of knowledge on which the firm can draw to generate yet more new knowledge. In terms of the exploitation of knowledge, its limited exhaustibility has powerful extensibility effects. That is, the same piece of knowledge, the blueprint, can be used to produce increasing quantities of output at decreasing marginal costs. Compared to other economic goods, knowledge is more scalable since the costs of its reproduction do not vary with the output volume produced (Haskel & Westlake, 2018).

The limited exhaustibility of knowledge and its resulting prolonged contribution to the firm's production process motivates its capitalization on the firm's balance sheet (Griliches, 1979). The capitalization of knowledge as an intangible asset has caused radical changes not only to national accounting figures but also to firms' accounting procedures and allows detailed study of firm strategies related to use of knowledge as an input (Corrado et al., 2005, 2009).

This article investigates how the limited exhaustibility of knowledge shapes the relationship between firm size and the direction of technological change. We hypothesize that due to the cumulative and extensible character of knowledge stemming from its limited exhaustibility, large firms have stronger incentives to use knowledge and intangible capital in the production process than do small firms.

The importance of knowledge and intangible capital for firm productivity and performance has been well documented (Adarov et al., 2022; Battisti et al., 2015; Bontempi & Mairesse, 2015; Marrocu et al., 2012; O'Mahony & Vecchi, 2009). Some studies show that sector leaders are characterized by the largest shares of intangible and digital capital in total assets (Crouzet & Eberly, 2018; Tambe et al., 2020). Therefore, investing in intangible capital is crucial for long-term competitive advantage.

This paper focuses on the role of knowledge properties in the growth of intangible assets and the direction of technological change at firm level. Specifically, using the tools provided by the economics of knowledge, we propose that the trend stirred by globalization towards the increasing knowledge and intangibles-intensity of technological change in advanced countries is led by large firms.

Large firms can deploy knowledge as an input to larger volumes of output. Indeed, the larger the stock of internal knowledge, the lower the average cost of its initial generation and subsequent exploitation. Larger firms benefit from the cumulative character of knowledge which allows them to increase their stocks of knowledge at decreasing marginal costs, and simultaneously, to take advantage of the increasing returns from using knowledge in the technology production function (Chappell & Jaffe, 2018). Therefore, we hypothesize that the current bias toward the knowledge-intensive direction of technological change will be stronger for larger sized firms, with important consequences at the aggregate level for the knowledge-intensive direction of technological change which is stronger in economic systems that are characterized by the predominance of large firms.

To test our hypothesis, we combine two main sources of data. First, accounting and financial data extracted from the Compustat North America database for an unbalanced panel of 5871 US-listed companies observed during the period 1977–2016. Second, the data on organizational and knowledge capital provided in Ewens et al. (2020) for Compustat firms which we use to measure the firm's knowledge intensity. Thus, the present study complements recent work on the determinants of intangible assets at firm level (Arrighetti et al., 2014; Audretsch & Link, 2018; Montresor & Vezzani, 2016, 2022). However, our intangible capital data are richer and more accurate than the firm balance sheet data or the survey data used by other studies.

Our empirical results contribute in two ways. First, we show that the rate of growth of intangible intensity defined as the intangible to total capital ratio, increases with firm size. The empirical analysis uses standard panel data regression techniques with firm fixed effects and an original instrumental variable (IV) analysis which confirm a positive and economically significant effect of firm size on the growth of intangibles. Specifically, building on recent contributions highlighting the negative effects of openness to international markets on the performance of US firms (Autor et al., 2013, 2019), we instrument firm size with Mexico's and Canada's import penetration in other high-income countries, weighted by each firm's distance from the nearest border crossing point. The underlying idea is that Canadian and Mexican exports to other countries than the US are correlated with their exports to the US but are uncorrelated with US firms' specific productivity shocks, and therefore plausibly are exogenous to US firms' decisions to invest in intangible assets. Moreover, the novelty of our IV strategy is that it allows an exogenous variation which exploits both industry and firm heterogeneity in the exposure to import penetration from the Canadian and Mexican markets whereas previous studies rely only on cross-industry variation (Hombert & Matray, 2018). The results of the first stage of the IV analysis show that increased import penetration from Canada and Mexico has a substantial adverse effect on the performance of US manufacturing firms.

Second, the new knowledge-intensive -and tangible capital saving- direction of technological change, induced in advanced countries by the increase in the supply of human capital and stirred by the aggressive entry in global product markets of new economies specializing in traditional manufacturing industries, with its strong bias towards knowledge capital—measured by its output elasticity- is disproportionately larger for larger firms. We estimate the intangible output elasticity relying on the Olley and Pakes (1996) estimation method which corrects for endogeneity of factor inputs. We deal with the identification problems typical in this setting by implementing the standard 'control function' modification proposed by Ackerberg et al. (2015).

Several studies examine how firm size varies with its knowledge generation and exploitation, innovation strategy, and access to external knowledge and resources (Acs & Audretsch, 1988; Akcigit & Kerr, 2018; Kortum & Lerner, 2000). However, few provide evidence of the relationship between firm size and the direction of technological change and there are no works which provide proof of a link between firm size and the output elasticity of intangible capital. Our results show that the increase in the output elasticity of intangible capital due to a sharp reduction in the output elasticity of tangible capital is much greater for larger compared to smaller firms.

Third, our study contributes the stream of recent empirical contributions showing that the higher the investment in intangible assets, the greater the share of industry value added appropriated by a few large firms (Crouzet & Eberly, 2019; Autor et al., 2020; Bajgar et al., 2021). In contrast to these studies, we show that investment in intangible capital is explained by firm size since large firms choose to invest more in intangible as opposed to tangible capital. The IV analysis confirms that the direction of causality runs from firm size to growth of intangibles, and not vice versa.

Section 2 theoretically explores the limited exhaustibility of knowledge and its consequences for: (1) the cost of knowledge, and (2) the knowledge-intensive direction of technological change based on firm size. Section 3 describes the data and the econometric models used to test our hypotheses, and Sect. 4 discusses the results. Section 5 summarizes the results of the analysis and concludes the paper.

2 Theoretical background and hypotheses

2.1 Knowledge extensibility and the cost of knowledge

Relying on Arrovian analysis of the properties of knowledge as an economic good, Griliches (1979, 1984, 1986) implemented the first empirical appraisal of the role played by the limited exhaustibility of knowledge in the economics of innovation, proposing the stock of knowledge as an input to the technology production function.

Unlike other economic goods, knowledge is unaffected by physical and economic depreciation and its repeated use does not reduce its productivity. Hence, knowledge is characterized by limited exhaustibility which enables its cumulativeness and extensibility.

Firms with large stocks of internal knowledge can use it to produce new knowledge which saves on other complementary inputs including the search for external knowledge and the performance of internal R&D activities. The stock of internal knowledge is a powerful input in the generation of new knowledge: it results from the accumulation of multiple knowledge vintages that have been acquired or generated in the past. Its availability reduces the need to access external knowledge and perform additional research and learning activities.

Thus, the larger the stock of internal knowledge, the lower are the firm's total knowledge costs (Antonelli & Colombelli, 2015; Cohen & Levinthal, 1990). Firms with large internal stocks of accessible knowledge whose use involves low access and use costs are able to produce desired amounts of new knowledge more easily than firms with small internal knowledge stocks (Weitzman, 1998).

Holding the firm's R&D expenditure and access to external knowledge constant, it is evident that the larger the stock of internal knowledge, the lower the unit knowledge costs. Moreover, a larger stock of internal knowledge implies better absorptive capacity enabling access to external knowledge (Qian & Acs, 2013). Absorptive capacity allows more efficient integration of external knowledge which leads to a positive virtuous circle and ultimately lower need to mobilize internal resources to integrate additional external knowledge (Da Silva, 2014).

Let us now explore the relationship between firm size and the limited exhaustibility of knowledge and its extensibility, and the direction of technological change.

The new knowledge intensive direction of technological change in advanced countries can be regarded as a creative response induced by the changes in factor and product markets (Schumpeter, 1947). The creative response combines the induced technological change with the rivalry in product markets. Let us analyse them in details.

In the induced technological change approach, the rate and direction of technological change are respectively triggered and biased by the changing conditions in factor markets. Induced technological change is considered a meta-substitution process allowing firms to bias their technology to cope with the relative cost of their inputs beyond the limits of the technical changes within a given technology.

In a given map of isoquants, a change in the relative and absolute cost of inputs promotes technical change: firms move along the existing isoquant mapping to increase the intensity of the factor that has become relatively less expensive and reduce the intensity of the input that has become relatively more expensive. However, the notion of induced technological change posits that the change in the cost of inputs may trigger both technical and technological change i.e., the introduction of a new superior technology which increases the scope for substitution of the production factors that have become less expensive for the production factors that have become more expensive. This changes the isoquant map.

The direction of technological change reflects the changes in relative factor costs. When wages increase, firms are induced to introduce new labor-saving, and hence, capital-intensive technologies (Allen, 2011). When relative capital user costs increase, firms may focus on capital-saving technological change. History suggests that labor has become relatively more expensive which provides firms with a strong incentive to use labor less intensively and introduce new capital-intensive technologies (Acemoglu, 2002, 2003, 2015). The secular increase in wages and the decline of capital user costs triggered by the accumulation of savings were entirely consistent with the conspicuous increase in the output elasticity of capital and the complementary reduction of the output elasticity of labor that paralleled and augmented the sharp increase of the capital intensity of production activities (Elsby et al., 2013; Rognlie, 2016). There is a large theoretical and empirical literature showing that technological change has been capital-intensive over quite long stretches of historical time (Zeira, 1998).

However, current technological change seems biased towards other directions. The induced technological change approach helps to capture these recent changes in the direction of technological change. By the mid XX century, technological change was exhibiting a significant energy-saving bias. The sharp increase in oil costs triggered the introduction of new technologies that reduced the energy intensity of production processes (Newell et al., 1999).

By the end of the XX century, the selective fall in the cost of knowledge had induced a new direction of technological change, especially in the advanced countries, that can take advantage of the large stocks of quasi-public knowledge available in their systems at costs that are much lower with respect to their competitors based in knowledge poor countries. The new direction of technological change has proven to be ever more knowledge-intensive and capital-saving. The large increase in the supply of skilled labor in the advanced countries triggered by the college boom and the general increase in revenue, has reduced the cost of knowledge as an input to both the generation of knowledge and the technology production functions (Galor & Moav, 2004). The generation of knowledge is a highly skilled labor-intensive activity, and the reduced relative and absolute cost of skilled labor has had direct and strong effects on reducing the costs of knowledge as the outcome of both top-down and bottom-up knowledge generation processes. The strong increase in the supply of skilled labor triggered a decline of the relative cost of scientific labor, supporting the generation of codified knowledge and augmenting the accumulation of tacit knowledge through learning by doing, learning by using, and learning by interacting. The use of new information and communication technologies which radically improved access to, and screening, processing and storing of information and data, empowered the generation of recombinant technological knowledge resulting in manyfold increases to knowledge efficiency and further reductions to its costs.

The new global competition is characterized by rivalry in quasi-homogeneous product markets among firms based in heterogeneous factor markets. Firms based in advanced countries enjoy large knowledge externalities triggered by the low cost access to large stocks of quasi-public knowledge rooted in their own economic systems, and can rely on less expensive skilled labor and knowledge generation costs far lower than those incurred by competitors based in industrializing knowledge-poor countries which have to pay more to access the stocks of knowledge held in advanced countries (Goel & Saunoris, 2021). High levels of knowledge intensity in firms based in knowledge-abundant advanced countries become an effective source of enduring competitive advantage and a barrier to entry and imitation by competitors based in industrializing countries. This enhances -in advanced countries- firms' levels of de facto knowledge appropriability and larger and persistent mark-ups (Antonelli & Feder, 2021; Bloom et al., 2016).

The economics of knowledge helps grasping the role of firm' size in augmenting the new knowledge intensive direction of technological change. From the analyses of Nelson (1959) and Arrow (1962), it is well understood that knowledge is only partially appropriable: inventors can retain only a portion of the economic benefits from knowledge they produce. The intuition of Griliches (1979, 1992) has focused on the positive effects of the limited appropriability of knowledge. Indeed, the part of knowledge that its inventors cannot appropriate spills over into the economic system and, because of its limited exhaustibility, contributes to the stock of quasi-public knowledge that third entities can use at a relatively low cost (Hall et al., 1984). Because of the non-exhaustible and cumulative character of knowledge, the same knowledge can be used at a decreasing marginal cost by third parties. However, third parties can access knowledge produced by other firms but cannot benefit from the same cost conditions as the first inventors do (Goel & Saunoris, 2016).

The heterogeneity in factor markets and the application of the induced technological change approach implies that the cost of the output for the competitor is higher than the cost of the original inventor especially when competitors cannot replicate the actual costs of the innovator. Therefore, in the new global economy, the heterogeneity in factor markets and the application of the induced technological change approach implies that the cost of the output for the competitor is higher than the cost of the original inventor especially when competitors cannot replicate the actual costs of the innovator. Therefore, in the new global economy, the heterogeneity in factor markets and especially the strong differences in the size and composition of the stocks of technological knowledge embedded in the economic systems of advanced countries act as effective market barriers that strengthens the levels of de facto knowledge appropriability.

A large empirical literature acknowledges that this general trend towards using more knowledge and intangible assets to enhance productivity and profitability is especially strong in large firms (Battisti et al., 2015; Cucculelli & Bettinelli, 2015; Hall et al., 2013; Marrocu et al., 2012).

In the advanced countries, the combined effect of the reductions in the absolute and relative costs of knowledge and the competitive advantage in global product markets provided by the selective access to the localized stocks of quasi-public knowledge rooted in their economic systems leads to the new knowledge-intensive direction of technological change. The analysis of the cost of knowledge implemented so far becomes relevant and supports the hypothesis that in advanced countries large firms guide the new knowledge-intensive direction of technological change. The costs of knowledge are lower for larger firms. The limited exhaustibility of knowledge and its cumulability and extensibility effects cause the reduction in unit knowledge costs for large firms. The incentive for knowledge-intensive technological change becomes more significant and effective for large firms compared to smaller ones.

Intangible products incorporate and magnify the limited exhaustibility, extensibility, and cumulability of knowledge and their direct effects on knowledge costs. For example, software involves high implementation sunk costs but negligible reproduction costs. It can be sold in open markets at a null marginal cost. Therefore, the larger the output volume, the lower the average cost of the software. The new digital revolution assigns a prominent role to knowledge since it can be stored in products that can be diffused instantaneously and everywhere at almost no additional cost. This is creating superstar economies in which a few large firms dominate the market (Rosen, 1981). Diffusion of the Internet of Things and big data is allowing storage of ideas in bits and products that are ubiquitous and can be accessed at quasi-zero marginal cost by competent producers (Guellec & Paunov, 2017).

The knowledge-intensive bias of current technological change is especially strong in large firms. Large firms are able more efficiently to complement availability of external local sources of knowledge and factor inputs with formal internal R&D activities conducted by high-skilled personnel. There is a large body of empirical evidence showing that large firms use more advanced technologies and employ greater shares of high-skilled non-production workers (Dunne & Schmitz, 1995; Troske, 1999).

The general new trend at work in the advanced countries towards increasing levels of knowledge-intensity of technological change is stronger for larger firms. The limited exhaustibility of knowledge increases the incentive for its more intensive use: the efficient generation of new knowledge and its exploitation increases with firm size. This greater efficiency leads to greater knowledge-intensity in the direction of technological change and significant changes to the stock of capital in terms of an increased share of intangible capital and a declining share of physical-tangible capital.

2.2 The cost of knowledge and the direction of technological change

The technology production function provides the context for an investigation of the effects of knowledge costs on the direction of technological change. The stock of knowledge T enters the production function for goods Y alongside the standard tangible capital (K) and labor (L) inputs:

$$Y = (K^{\alpha}, L^{\beta}, T^{\gamma}) \tag{1}$$

The standard cost equation complements the technology production function. Total costs (TC) are the sum of the unit cost of tangible capital® times its amount K, the unit cost of labor (w) times the number of labor units L, and the unit costs of knowledge (t) times its amount T:

$$TC = rK + wL + tT \tag{2}$$

Larger firms can generate and exploit technological knowledge at lower costs—the larger the firm size the lower these costs. We can formalize this relationship as follows:

$$t = f(Y), \text{ where } dt/dY < 0 \tag{3}$$

Large firms which benefit from relevant advantages based on the combined effects of knowledge cumulability in knowledge generation and knowledge extensibility in knowledge exploitation, have much stronger incentives than do smaller firms to use knowledge as an input since the costs of both knowledge generation and exploitation decline with firm size. Employing the induced technological change approach allows us to explain why the knowledge intensive direction of technological change is stronger for larger firms:

$$\gamma = g(Y), \text{ where } d\gamma/dY > 0 \tag{4}$$

The output elasticity of the stock of knowledge will be larger for larger sized firms. Moreover, we expect that the rate of growth of the share of intangible capital in the firm's total capital will increase with firm size.

2.3 Hypotheses

Building on the previous subsection, we formulate our working hypotheses that:

1. The growth in the intensity of intangible capital increases with firm size: the larger the firm, the more than proportionately larger is the incentive to accumulate knowledge capital, and the greater its intensity.
2. The knowledge-intensive direction of technological change increases with firm size. The larger the firm, the larger the output elasticity of technological knowledge as an input alongside capital and labor in the technology production function.

Section 3 presents the empirical analysis.

3 Empirical methods

3.1 Data and variables

Based on the theoretical section we predict an increase in knowledge intensity with firm size. In the empirical analysis, we measure the stock of knowledge, and thus the firm's knowledge intensity and stock of intangible assets. Intangible capital is the amount of knowledge that can be added to the firm's capital due to the limited exhaustibility of knowledge. Corrado et al., (2005, 2009) (from hereon CSH) led the assessment of intangible assets in growth accounting.

CSH focused on an array of investment expenditure which was treated as intermediary or cost inputs but could have an enduring impact on productivity. They justify their accounting for intangible assets by arguing that "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" (CSH, 2005, p. 13).

In 2008, the System of National Accounts (SNA) revised the 1993 SNA rules to allow accounting for a large range of intangible assets.[1]

The current system enabling capitalization of intangible assets is based on the notion that the contribution of such assets is not confined to the year of the expenditure but persists over many years. Therefore, capitalization of assets which previously were considered intermediary inputs adds to the stock of capital figures to provide a measure which increases as the rate of depreciation decreases. The depreciation of intangible products occurs at a slower rate than the depreciation of tangible assets: the recent estimates by De Rassenfosse and Jaffe (2018) based on data from a survey of Australian

[1] The current SNA 2008 introduces changes to the identification of capital stock as follows: (1) ICT equipment is separated from other capital stock to allow for more precise definition of intangible ICT; (2) the term "intangible fixed assets" is changed to "intellectual property products" and includes R&D expenditures; (3) minerals exploration is renamed "mineral exploration and evaluation" to conform to international accounting standards; (4) computer software now includes databases; (5) the "other intangible fixed assets" category has been replaced by "other intellectual property products", and includes R&D, mineral exploration and evaluation, computer software and databases, and literary or artistic originals.

patents, show that the rate of depreciation of the value of intellectual property products is within a 2–7% range.

Our dataset is based on financial accounting data for a panel of US-listed firms observed over 1977–2016, extracted from the Compustat North America database. The companies included in the sample conduct their business in US dollars and show positive values for at least two consecutive years for sales, numbers of employees, gross property, plant and equipment, depreciation, accumulated depreciation, general and administrative expenses, and physical capital expenditures. Firms belonging to regulated utilities (SIC codes 4900–4999), financial firms (6000–6999) and public services, international affairs and non-operating establishments (9000+) are excluded. To remove outliers which could induce bias in the results, we winsorize all the variables employed in the regression analysis at 1%. The final sample is an unbalanced panel of 5871 firms over the period 1977–2016.

The main variables used in the analysis are sales, value added, employment levels, physical capital stock, and intangible capital stock. Sales are equivalent to the Compustat item *SALE*, which measures net sales. Value added is calculated as the difference between sales and materials. Materials are equal to the difference between total expenses and labor expenses. In turn, total expenses are computed as the difference between sales and the Compustat item Operating income before depreciation and amortization or *OIBDA*. Labor expenses are extracted directly from firms' balance sheets. For firms that do does not report the level of wage compensation, this is derived by multiplying number of employees by average wage in the firm's industry based on the 2-digit SIC code. Employment level is extracted directly from Compustat item *EMP*.

We derive physical capital stock as the sum of gross plant, property and equipment, Compustat item *PPEGT*. We use both internal and external intangible capital to measure the intangible capital stock. Externally purchased intangible capital is recorded directly on Compustat under item *INTAN*. The data on internally created intangible capital are from Ewens et al. (2020) and include both organizational and knowledge capital. The variables in Ewens et al. (2020) were constructed using new capitalization parameters derived from the intangible assets prices obtained from firms' acquisition deals. The authors built an intangible capital time series for all the firms in Compustat from 1977 to 2016. All the monetary variables used in the analysis are deflated using the output deflator.

Our analysis takes into account implicitly the heterogeneity of knowledge in relation to the limited exhaustibility of knowledge and the direction of technological change. Indeed, knowledge is a heterogeneous good and the value of the output may increase more than proportionally with the increase in the variety of knowledge inputs (Jacobs, 1969). In relation to the limited exhaustibility of knowledge, the heterogeneity in knowledge implies that knowledge assets may possess different depreciation rates. The data on intangible stock taken from Ewens et al. (2020) address this issue, since they estimate depreciation parameters separately for knowledge capital and organizational capital, and across different industries. Secondly, the heterogeneity in knowledge may have consequences for the relationship between firm size and the direction of technological change. Large firms likely possess a greater variety of knowledge with respect to small firms. Moreover, our data reveal that the composition of knowledge for large firms has shifted toward a large share of externally acquired knowledge and a lower share of knowledge internally produced. To the extent to which external knowledge offers more opportunities to recombine existing knowledge and contributes to generate more technological knowledge, firm size and knowledge variety are directly correlated. Since the scope of our paper is to shed light on the new knowledge-intensive—and tangible-capital saving—direction of technological change, we leave to future research the analysis of how knowledge variety and the composition of knowledge contribute to the new direction of technological change in relation to firm size.

3.2 Econometric models

The econometric analysis tests the hypotheses formulated in Sect. 2. We hypothesized that the incentives to accumulate knowledge capital grow with the firm size. Larger firms benefit from the smaller knowledge costs deriving from the non-exhaustible and extensible character of knowledge as an economic good and its input to the production process. This allows us to assess whether the rate of growth of the share of intangible capital in the firm's total capital increases with firm size. We predict that the tendency to accumulate intangible and knowledge capital compared to other financial assets increases as firm size increases.

We estimate the following equation:

$$GrowthInt_{it} = \alpha_0 + \alpha_1 ln(SIZE)_{it} + X'_{it-1}\alpha_2 + \theta_i + \rho_t + \mu_{jt} + \varepsilon_{it} \tag{5}$$

The dependent variable $GrowthInt_{it}$ is the logarithmic difference of firm i' s share of intangible capital in total capital (the sum of physical and intangible capital) between year t and year $t-1$ for. The variable $SIZE_{it}$ is firm size measured by the natural log of the number of the firm's employees. The vector X'_{it-1} includes firm age (number of years since firm foundation) and leverage (ratio of total debts to total assets). These control variables allow us to interpret the coefficient of size as net of the number of years the firm has had to accumulate knowledge assets and the propensity to invest in risky activities. Finally, θ_i and ρ_t are respective firm and year fixed effects. The inclusion of these fixed effects allows us to control for unobservable and time-invariant firm-specific features, and shocks reflecting business cycles and changes in relative prices, and especially interest rates that are common to all firms in a year. In a more demanding specification, we add the term μ_{jt} for industry-by-year fixed effects[2] which allows us to identify our coefficient of interest α_1 in comparison to other firms in the same industry-year. Indeed, the incentives to use and substitute intangible with tangible capital may vary across industries. While firm fixed effects subsume any time-invariant difference across industries, the use of industry-by-year fixed effects allows capturing those factors that vary also across industries and year (Goel, 1990). Moreover, changes in relative prices, tax policies or investment opportunities that affect the allocation investment decision and, hence, the incentive to use intangible rather tangible capital, occur at the industry level and are absorbed by industry-by-year fixed effects (Bena et al., 2021; Zwick & Mahon, 2017).

The error term ε_{it} captures unobservable firm-specific factors that affect the firm's knowledge intensity. Equation 5 is estimated using the fixed-effects panel data estimator. Based on our hypothesis, we expect the coefficient α_1 to be positive. Standard errors are clustered at the industry-year level. Appendix Table 6 reports the descriptive statistics for the variables used in our analysis.

Since the effect of firm size on intangible capital may be endogenous to the firm's investment in intangible assets, we employed the original IV strategy described in Sect. 4.2.

We aim to show also that the output elasticity of knowledge increases with firm size. We assume a production process represented by a Cobb–Douglas production function

[2] Industries correspond to 3-digit SIC.

with constant returns to scale and three factor inputs. Knowledge is proxied by the intangible capital IK and enters as a third input alongside labour L and tangible capital TK. The Cobb–Douglas production function takes the following form:

$$Y_{it} = \left(TK_{it}\right)^{\alpha}\left(L_{it}\right)^{\beta}\left(IK_{it}\right)^{\gamma} \tag{6}$$

where Y_{it} is output of the firm i in year t, and α, β and γ are the respective output elasticities of tangible capital, labour and intangible capital. According to our hypotheses, we expect a higher γ for larger firms. Equation 6 is can then be re-estimated and written as:

$$y_{it} = \alpha + \beta_1 l_{it} + \beta_2 k_{it}^{phy} + \beta_3 k_{it}^{int} + \omega_{it} + \varepsilon_{it} \tag{7}$$

where I and t are indexes for firm and time, y_{it} is the log-transformed firm-level value added, l_{it} is the log-transformed number of employees, k_{it}^{phy} and k_{it}^{int} are the log-transformed physical and intangible capital stock, ω_{it} is an unobservable random component which captures unobservable productivity or technical efficiency and evolves according to a first-order Markov process, and ε_{it} is an idiosyncratic output shock distributed as a white noise.

Our approach consists of estimating Eq. 7 for two separate samples of large and small firms. To distinguish large and small firms we use the standard U.S. Small Business Administration (SBA) threshold of 500 employees and based on the average number of the firm's employees reported in Compustat.[3] For both samples, we estimate firm-level production functions based on splitting the sample period into the two periods 1977–1996 and 1997–2016. Based on our predictions, we expect the output elasticity of knowledge to increase along with the size of firms, and that the expected gap will increase over time.

Using OLS to estimate Eq. 7 would produce inconsistency biases due to the correlation between observable input levels and the unobservable productivity shock. To solve both endogeneity and selection problems, we applied the Olley and Pakes (1996) approach. OP proposed a two-step procedure to enable consistent estimation of the production function. They suggest using firm investment to proxy for ω_{it} under the following assumptions. First, firm investments are a function of the variable inputs (e.g., labor) and ω_{it}. Second, firm investments must be invertible and monotonically increasing in ω_{it}. Third, capital evolves with investments which are decided at time *t-1*. Fourth, variable inputs (e.g., labor) are non-dynamic (i.e., their choice at t does not affect future profits, and they are chosen at t after the firm's observation of a productivity shock).

The major drawback of the OP method is that it induces collinearity issues. It assumes that firms facing a productivity shock can instantly adjust some of its inputs (especially labor) at no cost. If this is not the case, the OP method to estimate the first stage of the two-step estimation procedure suffers from collinearity. Ackerberg et al. (2006) proposed using a modified version of the traditional 'control function' approach to solve collinearity issues while also allowing consistent labor elasticity estimates. Using their method, all (unbiased) estimates of the production function parameters are obtained in the second step of the estimation procedure.

We applied the OP two-stage estimation strategy, corrected using the ACF method. Compustat data provide systematic information on firms' investment demand; however, for

[3] We acknowledge that on average the companies included in Compustat are not small companies, and that although there is large variability in firm size, small and very small firms are underrepresented. In our sample, 59.4% of the firms have more than 500 employees which means that the distinction we make between small and large firms should be interpreted only in relative terms.

Table 1 Growth in intangible intensity and firm size

	(1)	(2)	(3)	(4)
Size	0.010***	0.011***	0.012***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Age		−0.009**	−0.009**	−0.007*
		(0.004)	(0.004)	(0.004)
Leverage			−0.032***	−0.025**
			(0.009)	(0.011)
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Sector-year FEs				Yes
N	48,990	48,990	48,990	48,990
R^2	0.169	0.169	0.169	0.284

The dependent variable is the growth rate of the ratio between intangible capital and total capital. All the regressor are in log. Age and leverage are measured at time $t-1$. Standard errors clustered by industry and year are in parentheses

*$p<.1$, **$p<.05$, ***$p<.001$

most of our sample, we cannot measure demand for intermediate goods which is the basis for another common estimation procedure, the Levinsohn and Petrin (LP) (2003) method. This means that, for our sample of firms, the LP method is unfeasible.

4 Results

4.1 Baseline results

In this section we discuss the results of the multivariate analysis described in Sect. 3. Table 1 reports the estimation results for Eq. 5 using the panel data fixed-effects estimator. We start by including the bivariate relationship between the rate of growth of intangibles over total capital and firm size, and then introduce control variables to evaluate the stability of our coefficient of interest. Column (1) shows that the coefficient of size is positive and statistically significant ($p<0.01$). Column (2) includes the log of firm age as a control variable. While the coefficient of age is negative and statistically significant, the coefficient of size remains statistically significant and increases in magnitude. This result does not change with the addition of the control variable leverage in column (3). These negative and significant estimates confirm the findings from Montresor and Vezzani's (2022) analysis. Column (4) presents the results of a more demanding specification which also includes industry-by-year fixed effects. This controls for heterogeneous shocks across industries in a particular year which might have influenced the accumulation of intangible capital. The explained variation increases noticeably as the R^2 increases from 0.17 to 0.28. In line with our hypotheses, the coefficient of firm size increases in magnitude and remains highly statistically significant.[4]

The overall results support hypothesis (1) that the growth of intangible intensity is related positively to firm size. On average, compared to small firms, larger firms invest more in intangible than tangible capital. Also, the control variables show that the older the firm the lower its investment in intangible resources, and that greater financial leverage reduces the incentive to accumulate intangible assets.

4.2 Instrumental variable analysis

The relationship between firm size and intangible capital in Eq. (5) could raise endogeneity concerns. Some recent studies show that for large firms the greater the investment in intangible capital the greater the share of value added accrued by the firm (Bajgar et al., 2021). The use of intangible assets such as software and databases increase the share of fixed and sunk costs in the firm' cost structure, creating barriers to entry and enhancing incumbent rents (De Ridder, 2019). Therefore, an increased share of intangible capital may create scale economies favoring large incumbent firms (Covarrubias et al., 2020).

To overcome these endogeneity issues, we apply an original IV strategy based on exposure of Compustat firms to penetration by Canadian and Mexican exports. We adapt our framework following the approach in Autor et al., (2013, 2019). We constructed the following measure of import exposure:

$$Exposure_{ijt} = \frac{1}{ln(MinDist_i)} * \left(\frac{ln(ImportsPenetration_{jt})}{ln(IndustryEmployment_{j1991})} \right) \tag{8}$$

where $Exposure_{ijt}$ is our instrumental variable for firm i active in industry j and year t, $MinDist_i$ is the distance from each firm's i zip code or city to the nearest border crossing point of the USA-Mexico or USA-Canada borders,[5] $ImportsPenetration_{jt}$ is Mexico's or Canada's import penetration in other countries for industry j at time t, and $IndustryEmployment_{j1991}$ is the level of employment in industry j in 1991. The idea is that within-industry imports of Canadian and Mexican good by other high-income countries are correlated with these countries' imports to the US, through their impact on the sales of the firms in those sectors which more likely to be affected by this shock. However, since Canada's and Mexico's import penetration in other countries stems from productivity and trade shocks in a given sector j in those countries, these shocks are likely to be uncorrelated with US firms' unobserved time-varying factors affecting the propensity to invest in intangible assets (Hombert & Matray, 2018).

Recent decades have been characterized by high levels of advanced economy openness to international trade. Increased levels of trade integration combined with relatively labor-abundant countries have resulted in greater penetration of labor-abundant goods and have reduced employment levels in advanced, capital-abundant economies (Antonelli & Feder, 2021).

[4] Appendix Table 7 shows that the results are robust to proxying for firm size using the firm's net sales instead of firm's number of employees.

[5] The geographical distance is measured as the distance in km between the firm's zip code and the border crossings coordinates. In the case of missing zip codes, we geolocated the city or county available from Compustat.

Several studies highlight the negative effects of exposure to globalization on the wages and employment rates of US domestic workers, and especially those engaged in routine-intensive tasks (Autor et al., 2015). According to these estimates, the increasing trade integration with China is more detrimental to low-skilled workers than the effects of technological advancements. Also, it has been shown that this effect is not limited to Chinese penetration but is related to overall exposure to globalization (Ebenstein et al., 2014). Therefore, we expect that exposure to Canada and Mexico import penetration will have a negative effect on those firms more vulnerable to these shocks. For these reasons and using insights from international economics, we expect that the firms more exposed to import penetration will be those located closer to borders (Vannoorenberghe, 2012).

Although the literature mostly focuses on the surge in China's import penetration, penetration from Canadian and Mexican imports has increased significantly worldwide. Appendix Fig. 1a, b plot respective Canadian and Mexican imports to other high-income countries. They show a respective twofold and a seven-fold increase in these imports to other high-income countries between 1991 and 2014. To isolate Canadian and Mexican exports arising from supply shocks in their local economies, we follow the standard international economics identification strategy and use Canada's and Mexico's import penetration in other high-income countries. Using import penetration to the US could induce endogeneity problems since lower productivity of US firms due to a negative shock could automatically create increased import penetration from other countries. This concern is reduced by a focus only on exports from Canada and Mexico to other countries, while remaining correlated to Canada's and Mexico's import penetration in the US.

Compared to studies that focus only on China's import penetration, our IV relies on both cross-industry variation based on differential import penetration by manufacturing industries, and on cross-firm variation provided by each firm's distance to the nearest border crossing point. To the best of our knowledge, this strategy to create an exogenous variation in firm performance in terms of employment and sales is unique.

The instrument was constructed as follows. First, we searched for Mexican and Canadian border crossings with the US. We selected only crossing-point locations established after 1976 and allowing for transfer by all the means of transport.[6] This identified coordinates for 22 Mexico-US and 111 Canada-US border crossing locations.[7]We then identified the border crossing point nearest to the firm's zip code, or in the case of missing zip code the firm's city or county centroid.[8] To construct our instrument, we consider Canada import penetration for firms with headquarter is in a state bordering Canada, and Mexico import penetration for firms with headquarters is in a state adjacent to Mexico. For the remaining firms, we use the sum of the two import penetration measures.

Data on import penetration from Canada and Mexico come from the UN Comtrade database.[9] Following Autor et al., (2013, 2019), we use data at the four-digit SIC level for the period from 1991 to 2014 on imports from Canada and Mexico to eight high-income

[6] In the case especially of Mexico-US transfers, some border crossing locations allow only pedestrians or do not allow trucks.

[7] Appendix Fig. 1 provides a map of the US showing the positions of the border crossin points.

[8] To reduce measurement errors in this procedure, we drop all the firms at a distance of more than 1000 km from a border crossing points.

[9] Data were retrieved directly from David Dorn's website: https://www.ddorn.net/. They are collated according to the correspondence between 6-digit HS product-level trade data available from UN Comtrade and the 4-digit SIC manufacturing industries in Compustat.

countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland) for which comparable trade data are available from 1991. Since industry employment may be directly endogenous to import shocks, we normalize Canadian and Mexican import penetration at the industry-year level by industry employment in 1991 based on County Business Patterns data.

For trade data constraints reasons, the IV strategy is limited to manufacturing firms observed over the period 1991–2014 which reduced the sample size to a maximum of 1,026 firms depending on the specification used. For completeness and comparison reasons, we also report the sample results of panel fixed effect estimations. Thus, although the size of the sample is smaller compared to the estimates in Table 1, we show that hypothesis 1 holds also for this sub-sample.

Table 2 presents the results. Columns (1)–(4) report the results of the panel fixed effects estimates based on the sample used to perform the IV estimates; columns (5)–(8) present the results of the IV estimations. The coefficient of firm size is positive and statistically significant ($p < 0.01$) across all the specifications reported in columns (1)–(4) and its magnitude is stable (0.015 in column (1), 0.016 in column (4)). This statistically significant and positive coefficient of firm size is robust to the inclusion of firm age in column (2), firm leverage in column (3) and industry-by-year fixed effects in column (4). In this sub-sample, the coefficient of firm age is not statistically different from zero, and firm financial leverage remains negatively and significantly related to intangibles intensity.

Columns (5)-(8) report the IV results. The coefficient of firm size is statistically significant and positive across all the specifications and is also meaningful economically. Specifically, a 1% increase in firm size leads to an increase in the range of 0.08–0.09% in the rate of growth of the intangible/tangible capital ratio. Therefore, the IV estimates do confirm panel data results and show that the impact of firm size on intangibles intensity is six-seven times larger on average when we account for endogeneity.

The last rows in the Table 2 show that as expected the import penetration has a strong negative shock on US firm employment levels. Therefore, increasing import penetration by Canada and Mexico depresses employment levels in those US firms that are more vulnerable to such competition (Ebenstein et al., 2014). The F-statistics (which are based on the Kleibergen–Paap test and are reported in the last row in Table 2) are all well above the accepted threshold of 10, suggesting that the negative effect of Canada and Mexico import penetration is sizable and that the instrument is relevant.[10]

The "Appendix" reports the results of selected robustness checks. First, to demonstrate that the depression in the firm's employment levels is due only to the negative effects of exposure to imports on firm performance and not to other causes, we test also whether the results are robust to measuring firm size by total sales rather than total employees. The results in Appendix Table 8 are based on the specification in Table 2 and support our hypotheses that Canadian and Mexican import penetration has an adverse effect on firm sales and that firm sales have a positive and statistically significant effect on growth of intangibles intensity.

Second, it could be argued that the mechanism we identify is valid only for those firms located close to a trade boundary and have only second-order effects for firms located at a distance from a border crossing, and that this could be confounding our estimates. To alleviate these concerns, the estimates in Appendix Table 9 are based on different distance

[10] The different sample sizes in Table 2 are due to the exclusion or not on singleton points are excluded or not from the estimation in line with the recommendation in Correia (2015).

Table 2 Growth in intangible intensity and firm size—IV estimates

	OLS	OLS	OLS	OLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.015***	0.016***	0.016***	0.016**	0.083**	0.090**	0.085**	0.093**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.028)	(0.030)	(0.030)	(0.042)
Age		−0.005	−0.005	−0.005		−0.020**	−0.019**	−0.020**
		(0.007)	(0.007)	(0.007)		(0.009)	(0.009)	(0.010)
Leverage			−0.055***	−0.046***			−0.063***	−0.054***
			(0.015)	(0.014)			(0.016)	(0.015)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FEs				Yes				Yes
N	8987	8987	8987	8875	8962	8962	8962	8851
					First stage:			
Exposure					−0.013*** (0.001)	−0.012*** (0.001)	−0.012*** (0.001)	−0.010*** (0.002)
F-stat					98.54	87.45	89.11	28.93

The dependent variable is the rate of growth of the ratio of intangible capital to total assets. Age and leverage are measured at time $t-1$. Standard errors clustered by industry and year are in parentheses

*$p<.1$, **$p<.05$, ***$p<.001$

Table 3 Output elasticities by firm size – 1977–2016

	(1) All	(2) Small	(3) Large
EMP	0.617***	0.538***	0.636***
	(0.000000319)	(0.000000270)	(0.000000270)
TK	0.234***	0.275***	0.174***
	(0.000000297)	(0.000000284)	(0. 000,000,277)
IK	0.192***	0.160 ***	0.187***
	(0.000000297)	(0.00000210)	(0.00000210)
N	56,133	18,669	37,464

Standard errors in parentheses. Small and large firms are distinguished by employment numbers below or above 500

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

thresholds and consider only firms within 750 km and 500 km from a border crossing. This effectively limits the analysis to firms in states bordering Canada or Mexico. Appendix Table 9 reports the results of these tests, conducted on the full specification in Table 2 column (8). Column (1) considers firms within 750 km distance from a border crossing, column (2) considers firms within a 500 km distance from a border crossing and column (3) considers only those firms located in a state adjacent to Mexico or Canada. Overall, the findings in Appendix Table 9 confirm all the results. The first-stage indicates that import penetration has a negative effect on firm employment, and the second stage confirms that firm size has a positive and statistically significant impact on growth of intangibles intensity. The coefficient of firm size varies between 0.082% in column (1) and 0.2% in column (3). The F-statistics are all above the threshold of 10.

4.3 Production function estimation results

In this section we test hypothesis (2) that the output elasticity of intangible capital is higher for large firms. We use the same sample used to estimate Eq. 5. Table 3 presents the results of the production function estimation for the whole period 1977–2016. Column 1 reports the estimation results for the full sample. Columns 2 and 3 present the respective estimates for large and small firms. Starting with the estimates for the full sample (column 1), the results show that the output elasticity of knowledge capital is about 0.19, whereas the output elasticity of tangible capital is larger on average (~ 0.23). In the split sample of large and small firms (respectively columns 2 and 3), we observe a much lower output elasticity of knowledge (~ 0.16) than output elasticity of physical capital (~ 0.27) among small firms. However, in the case of large firms, the output elasticity of knowledge is 0.187 and is larger than the elasticity of physical capital (0.174) and is also larger than the output elasticity of knowledge estimated for small firms. As expected, labor input has the highest output elasticity (0.64 for large firms, 0.54 for small firms).

These results support hypothesis (2), and in combination with the results presented in the previous subsection, confirm that larger firms do bias the direction of technological

Table 4 Output elasticities by firm size 1977–1996

	(1) All	(2) Small	(3) Large
EMP	0.600***	0.542***	0.610***
	(0.000000290)	(0.00249)	(0.000000308)
TK	0.228***	0.264***	0.194***
	(0.000000297)	(0.00154)	(0.000000287)
IK	0.114***	0.127***	0.105***
	(0.00000290)	(0.00149)	(0.000000287)
N	29,625	10,286	19,339

Standard errors in parentheses. Small and large firms are distinguished by employee numbers below or above 500

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Table 5 Output elasticities by firm size 1997–2016

	(1) All	(2) Small	(3) Large
EMP	0.567***	0.537***	0.640***
	(0.000000270)	(0.00409)	(0.000000437)
TK	0.178 ***	0.287 ***	0.140***
	(0.000000284)	(0.00919)	(0.000000307)
IK	0.191***	0.201 ***	0.231***
	(0.00000215)	(0.00653)	(0.000000400)
N	26,508	8383	18,125

Standard errors in parentheses. Small and large firms are distinguished according to employee numbers below or above 500

*$p<0.05$, **$p<0.01$, ***$p<0.001$

change towards a greater use of knowledge- and intangible- capital. These results do warrant the interpretation that their lower knowledge costs and larger de facto appropriability levels, with respect to smaller firms, motivate their choices.

To investigate differences across time between small and large firms in relation to the knowledge output elasticity, we estimate the production function splitting the 1977–2016 timespan into two 20-year periods. Tables 4 and 5 present the respective results for the periods 1977–1996 and 1997–2016. Comparison of the results in the first columns in Tables 4 and 5 shows that on average, between these 20 years periods the output elasticity of knowledge increased sharply from 0.11 to 0.19, while the output elasticity of physical capital decreased from 0.23 to 0.18. These findings support the evidence in Piekkola (2018) and Antonelli (2019a) of a growing knowledge-intensive -and tangible capital saving- direction of technological change.

Comparison between columns 2 and 3 in Table 4 and columns 2 and 3 in Table 5 shows the decrease in the elasticities of the two kinds of capital stock is driven by large companies. In fact, the estimated output elasticity of knowledge in the 1977–1996 period is higher for small than for large firms (respectively 0.127 and 0.105). However, in the next 20 years period these respective elasticities are 0.201 and 0.231. For large companies, this means that the estimated elasticity of knowledge increased by 120% (+58% for small companies). In the case of the estimated output elasticity of physical capital, in the 1977–1996 period it is around twice the estimated output elasticity of knowledge capital for both small and large firms (respectively 0.264 and 0.194) while in the period 1997–2016 it decreases to around 0.14 for large companies (well below the roughly 0.23 estimated elasticity of knowledge) but remains almost steady for small companies (around 0.29). The output elasticity of labor shows no significant variation over time for either small or large companies. In the case of small firms, it is steady at around 0.54, while slightly increasing from 0.61 (period 1977–1996) to 0.64 (period 1997–2016) for large firms.

This provides further support for our hypothesis that the direction of technological change has been more knowledge-intensive for large compared to small firms, and that the divergence in the direction of technological change between small and larger firms has become more noticeable in relatively recent periods.

It is interesting that the direction of technological change in large firms is characterized by a clear substitution of intangible with tangible capital, and substantial stability of the output elasticity of labor. Thus, the new direction of technological change in large firms is knowledge-intensive and capital-saving. This knowledge-intensive direction of technological change led by large firms is leading to a new capital stock composition in which there is an increasing share of intangible capital and a declining share of physical capital. However, it has limited effects on the output elasticity of labor which remains steady. These results are consistent with and further support the theoretical prediction that the incentives to use knowledge are much greater in large compared to small firms, suggesting that the cost of using knowledge declines with firm size.

5 Conclusions

The direction of technological change in advanced countries has shifted radically since the last decades of the XX century. The traditional capital intensive and labor-saving bias has been overtaken by a new knowledge-intensive bias. The new knowledge-intensive direction of technological change is the outcome of the creative response induced by the large increase in the supply of human capital and triggered by the new division of labor in global product markets where emerging countries specialize in the products of the manufacturing industry and advanced countries in the generation and exploitation of technological knowledge. The new knowledge-intensive direction of technological change is profoundly changing the structure of advanced economic systems through the drastic re-composition of capital stock that is becoming ever less physical and ever more intangible (Pagano, 2014; Pagano & Rossi, 2009).

The limited exhaustibility of knowledge with the consequent high levels of cumulability and extensibility yields specific economies of scale that favor larger firms. This paper provides evidence that the larger the firm size, the stronger the bias towards knowledge-intensive -and tangible capital saving- technological change. Evidence based on the US corporate system confirms a direction of technological change that is knowledge-intensive and tangible capital-saving and is led by large corporations. These results are explained by the effects of increased knowledge stocks and increased output combined with the limited exhaustibility of knowledge in terms of cumulability and extensibility on reducing average knowledge costs.

In the theoretical section, we argued that knowledge costs decline with firm size in both the knowledge generation function where knowledge cumulability has an effect and in the technology production function where extensibility matters. The limited exhaustibility of knowledge is the fundamental property at the basis of this mechanism. Knowledge can be reused repeatedly to produce new technological knowledge and additional economic goods. Large firms have strong incentives to use more knowledge since its cost declines with the size of both the internal stock of knowledge and the firm's output.

The greater use that is made of the firm's knowledge as a result of its lower cost is consistent with the induced technological change approach recently revived by Acemoglu (2002, 2003). The rate and direction of technological change in the advanced economies has been due to and been promoted by the changes in factor markets and input prices and by the global rivalry in quasi-homogeneous product markets among firms based in highly heterogeneous factor markets. As long as the cost of capital was lower than the cost of labor, the direction of technological change was capital-intensive and labor-saving. The globalization of financial markets has reduced the spread in capital costs between advanced and industrializing countries and called attention on the radical differences in the costs of knowledge and in the opportunities for its exploitation.

The new trend in the knowledge intensive direction of technological change is driven by two factors: (1) the increased availability of high-skilled workers in advanced countries and (2) the new forms of rivalry in the global economy among firms based in heterogeneous factor markets but competing in quasi-homogeneous product markets that have stressed the radical asymmetries in the costs of accessing and using the stocks of quasi-public knowledge rooted in the economic systems of advanced countries with respect to industrializing ones. Their intertwining effects have biased the direction of technological change in advanced countries towards knowledge and skilled-intensive activities. This trend has been augmented and magnified by large firms that have larger opportunities and incentives to benefit from the effects of the intrinsic cumulability and extensibility of knowledge. The final outcome is that the traditional capital-intensive direction of technological change has been overtaken by a knowledge-intensive and capital-saving direction of change, and this direction is stronger for large firms.

The empirical analysis provided evidence of this stronger knowledge-intensive direction of technological change for large firms. We analyzed a rich sample of US-listed firms recorded in the Compustat database and observed along the period 1977–2016. Our evidence is based on panel fixed effects estimators and IV and production function estimation strategies. First, we showed that firm size drives the growth of intangible capital intensity, and that as firm size increases, the rate of growth of the share of intangibles in the firm's total capital also increases. Second, we found evidence of a higher output elasticity of knowledge for large firms compared to small firms. Finally, we showed also that these dynamics strengthen over time, and have become particularly prominent in recent periods.

Appendix

See Tables 6, 7, 8 and 9 and Figs. 1 and 2.

Table 6 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
GrowthInt	48,990	0.008	0.188	−4.168	8.266
Size	48,990	6.994	1.749	0.693	12.469
Age	48,990	2.184	1.093	0	5.153
Leverage	48,990	0.078	0.193	0	6.916

Table 7 Growth in intangible intensity and firm size

	(1)	(2)	(3)	(4)
Size	0.011***	0.012***	0.012***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Age		−0.009**	−0.009**	−0.008**
		(0.004)	(0.004)	(0.004)
Leverage			−0.033***	−0.026**
			(0.009)	(0.011)
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Sector-year FEs				Yes
N	48,990	48,990	48,990	48,990
R^2	0.169	0.169	0.169	0.284

Firm size measured by net sales

The dependent variable is the growth rate of the ratio between intangible capital and total capital. All the regressor are in log and measured at time $t-1$. Standard errors clustered by industry and year are in parentheses

$^{*}p<.1$, $^{**}p<.05$, $^{***}p<.001$

Table 8 Growth in intangible intensity and firm size—IV estimates

	OLS	OLS	OLS	OLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.008**	0.008**	0.008**	0.009**	0.087**	0.094**	0.089**	0.142*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.031)	(0.033)	(0.032)	(0.074)
Age		−0.004	−0.004	−0.004		−0.019**	−0.018**	−0.027*
		(0.007)	(0.007)	(0.007)		(0.009)	(0.009)	(0.015)
Leverage			−0.054***	−0.045**			−0.057***	−0.048**
			(0.015)	(0.014)			(0.016)	(0.017)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FEs				Yes				Yes
N	8987	8987	8987	8875	8962	8962	8962	8851
					First stage:			
Exposure					−0.012***	−0.011***	−0.011***	−0.006*** (0.002)
					(0.001)	(0.001)	(0.001)	
F-stat					77.68	69.49	70.46	10.56

Firm size measured by net sales

The dependent variable is the growth rate of the ratio between intangible capital and total assets. Age and leverage are measured at time $t-1$. Standard errors clustered by industry and year are in parentheses

$^*p<.1$, $^{**}p<.05$, $^{***}p<.001$

Table 9 Growth in intangible intensity and firm size – IV estimates

	(1)	(2)	(3)
Size	0.082**	0.133*	0.200**
	(0.039)	(0.069)	(0.079)
Age	−0.019*	−0.025*	−0.050**
	(0.011)	(0.013)	(0.020)
Leverage	−0.052***	−0.053**	−0.026
	(0.016)	(0.019)	(0.019)
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Sector-year FEs	Yes	Yes	Yes
N	7904	6394	5110
	First stage:		
Exposure	−0.11*** (0.002)	−0.09*** (0.002)	−0.15*** (0.004)
F-stat	28.15	13.96	13.09

Different distance thresholds and only Mexico or Canada bordering firms

The dependent variable is the growth rate of the ratio between intangible capital and total assets. Age and leverage are measured at time $t-1$. Column (1) considers only firms within 750 km from the nearest crossing-border point, column (2) uses only firms within 500 km, whereas column (3) runs the estimation on the sample of firms in a state bordering with Canada and Mexico. Standard errors clustered at the industry-by-year level are in parentheses

$^{*}p<.1$, $^{**}p<.05$, $^{***}p<.001$

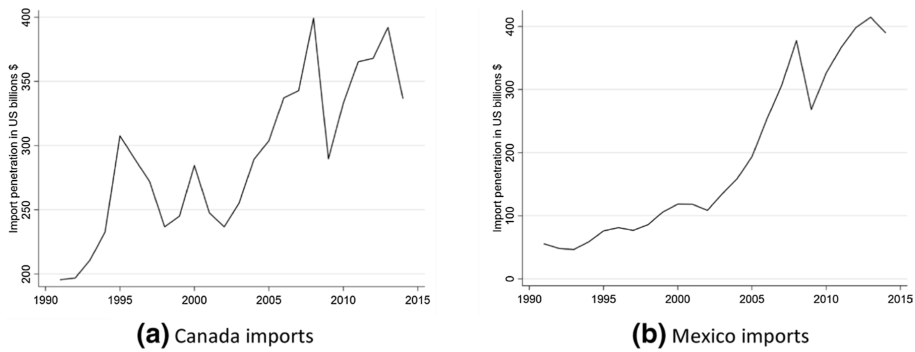

Fig. 1 Imports of Canada and Mexico to other high-income countries

Fig. 2 Position of the US and Mexico cross-boarding points

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