TECHNICAL NOTE Nº IDB-TN-03078

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Cataloging-in-Publication data provided by the

Inter-American Development Bank

Felipe Herrera Library

Heterogeneous returns to ICT capital: insights from Colombian manufacturing firms / Juan Miguel Gallego Acevedo, Alejandro Nieves, Fernando Vargas, Lina Díaz, José Saboin.

p. cm. — (IDB Technical Note ; 3078)

Includes bibliographical references.

1. Manufacturing industries-Effect of technological innovations on-Colombia. 2. Technological innovations-Colombia. 3. Labor productivity-Colombia. I. Gallego, Juan Miguel. II. Nieves, Alejandro. III. Vargas, Fernando. IV. Diaz, Lina M. V. Saboin, José Luis. VI. Inter-American Development Bank. Country Department Andean Group. VII. Series.

IDB-TN-3078

JEL-codes: D24, L25, O33.

Keywords: ICT, ICT capital, productivity, firm heterogeneity, output elasticities, technology adoption

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Heterogeneous Returns to ICT Capital: Insights from Colombian Manufacturing Firms

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Abstract

The persistent productivity gap between Latin America and the Caribbean and high-income countries is partially attributed to low levels of innovation and limited adoption of technologies, such as information and communication technologies (ICT). ICT capital has been shown to enhance firm performance, yet its role in emerging markets remains underexplored. In this study, we analyze the impact of ICT capital on output in Colombian manufacturing firms from 2013 to 2018. Using an augmented production function, we estimate the output elasticity of ICT capital while addressing potential endogeneity and measurement concerns. Here, we show that ICT capital contributes significantly to output, with elasticities comparable to non-ICT capital and labor. The results reveal substantial heterogeneity: innovative, high-tech, exporting, and big firms have higher ICT capital elasticities than their noninnovative, low-tech, nonexporting, and smaller counterparts. These patterns suggest that complementarities exist between ICT and firms' assets related to innovation, export orientation, and growth. The findings presented here contribute to the literature on ICT capital's role in firm productivity and inform policy making by emphasizing the need for different strategies to foster digital transformation in SMEs and in low-tech sectors.

JEL-codes: D24, L25, O33.

Keywords: ICT, ICT capital, productivity, firm heterogeneity, output elasticities, technology adoption

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1. Introduction[1]

Increasing productivity is one of the most relevant challenges for Latin America and the Caribbean (LAC) (OECD, 2019). Labor and total factor productivity (TFP) are low in the region and their growth rates have decreased recently; on the firm level, productivity consistently exhibits significant heterogeneity both across and within industries. Moreover, GDP growth has fluctuated over time, responding to variations in commodity prices. The theoretical and empirical literature attributes stagnant productivity to innovation and technology adoption deficiencies, particularly in the uptake of information and communication technologies (ICT), which are considered critical for improving firm performance.

In the last 20 years or so, a great deal of research has shown that the adoption of ICT by firms is associated with improvement in labor productivity and TFP (Black & Lynch, 2001; Brynjolfsson & Hitt, 2003; Badescu & Garcés, 2009; Bloom et al, 2012). The literature on the relationship between ICT investments and productivity has been growing (Bloom et al., 2012; Acharya, 2016 and includes case studies in the LAC region (Aboal & Tacsir, 2018; Álvarez, 2016; Grazzi & Jung, 2016). These studies have provided partial evidence supporting the hypothesis that ICT adoption enhances firms' productivity, mainly through increasing the capacity for innovation.

Understanding the influence of ICT on productivity at the firm level is essential to upgrade innovation policy, especially with the rise of recent ICT-driven technologies like big data, cloud computing, and artificial intelligence. New evidence can help with the designing of a new policy agenda to promote more effectively the adoption of ICT by firms; along these lines, Gallego et al. (2015) show that the digital agenda is encouraging the adoption and investment in ICT by micro, small and medium enterprises (MSMEs). Following these authors, this paper shows how the ICT capital positively contributes to firms' output in Colombia.

We calculate the stock of ICT capital by considering almost a decade of ICT investments at the firm level. This ICT capital is included in an augmented production function (PF). Our primary interest variable is TFP, constructed under a control function approach. These results provide empirical evidence to support efforts made by governments in the LAC region and emerging economies in incentivizing firms to adopt ICT. This will contribute to the debate about the ICT impact on productivity and growth. While Robert Solow famously pointed out in the 1980s that the effect of computers was *visible everywhere except in productivity*, several high-income economies benefited from the positive effects of ICT in economic growth, especially in the second half of the 1990s (Colecchia & Schreyer, 2002). In this context, this paper identifies ICT capital and quantifies its returns between 2013 and 2018, combining methodological innovations with rich data from structural surveys in Colombia.

[1] The authors have edited the text using ChatGPT-4o. After using this tool, the authors reviewed and edited the content as needed. The authors remain exclusively responsible for the content and any remaining errors.

This document has five sections in addition to this introduction. The next section presents the context, and a brief review of the literature related to the subject. Section 3 describes the methodological strategy to estimate TFP by a control function, followed by section 4, which presents data and descriptive statistics. The results of estimations are presented in section 5. Finally, section 6 concludes.

2. Context and literature review

The gap between the income per capita in LAC and high-income countries has increased considerably over the past six decades. In 1960, the income per capita in OECD countries was 2.9 times higher than LAC's income per capita, but in 2020, it was 5.3 times higher.[2] There is reason to think that this gap is driven by the gap in productivity growth rather than factor accumulation, as the latter in LAC has been in line with the rest of the world while the former has decreased (Fernández-Arias, 2014). In 2013, LAC's TFP stood at 56 percent of that of the United States,[3] whereas it had been 73 percent in 1960 (Grazzi & Pietrobelli, 2016).

Several factors have been identified as the main determinants of the low productivity rate in LAC. At the macroeconomic level, factors such as foreign direct investment, macro-regulations, education (Duryea & Pages-Serra, 2002), and public consumption (Gómez, Posada & Rhenals, 2018) have been put forth. At the firm level, Grazzi & Pietrobelli (2016) emphasize the role of innovation for productivity growth in LAC, which depends on the availability of additional complementary assets, such as access to finance and external markets, on-the-job training, and access to and use of digital technologies. This paper focuses on digital technology adoption and its effect on the TFP in the region.

LAC is a heterogeneous region in terms of country, industry, and firm productivity. Garone et al. (2020) find that a firm in the 90th percentile of the productivity distribution produces almost seven times as much output (using the same measured inputs) as one in the 10th percentile. Considering the high heterogeneity within LAC and the need for country-specific and sector-specific analyses to design targeted policy, we focus on one industry, the manufacturing sector, and one country, Colombia. Although the role of innovation is likely comparatively small in the manufacturing industry than in the services sector,[4] studying the manufacturing industry in Colombia is relevant because of its importance in the economy. In 2020, the manufacturing sector value-added was 11 percent as a share of the Colombian GDP,[5] and it provided 15 percent of employment in the main cities of the country in 2016 (Olarte-Delgado, 2017).

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[2] Authors' calculations using the World Bank's data catalog.
[3] Colombia's TFP is close to LAC's overall average (see Figure 4 in Fernández-Arias, 2014.)
[4] See a comparison of these sectors in Uruguay by Aboal and Tacsir (2018).
[5] For the data for 2020, see World Bank's data catalog, https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=CO.

A significant challenge over recent decades has been finding one or more answers to Solow's productivity paradox: "You can see the computer age everywhere but in the productivity statistics" (Solow, 1987). This paradox exists in both emerging and advanced economies. Even when the implementation of these technologies seemed to have no impact in the 1970s and 1980s, later empirical studies did show a positive effect of ICT on productivity, especially after the middle of the 1990s in the United States and other high-income countries. Today, more and better data on ICT are available, allowing for a better understanding of the factors that affect the impact of ICT on various performance measures (Pilat, 2004).

The relationship between ICT and firm performance has been studied using country-, industry-, and firm-level data. In general, aggregated and industry-level studies using data from the United States and Europe show divergent effects of ICT on productivity growth. In contrast, firm-level data show more similarities between countries. Furthermore, the evidence suggests that this effect is positive, significant, and increasing over time (Cardona, Kretschmer, & Strobel, 2013). For example, Matteucci et al. (2005) analyze the use of ICT as a driver of productivity differences between some European countries and the United States using industry-level data for the period 1979–2000 and firm-level data for the period 1995–2000. Both approaches find an impact on labor and total factor productivity, although it was much greater in the United States than in European countries.

Díaz et al. (2015) also use labor productivity as a performance measure. Based on a study of 2009 survey data from Spanish SMEs, they find an indirect effect of ICT capital and innovation on labor productivity via the capacity to export. A positive impact of ICT and R&D on innovation and productivity was also found using an unbalanced panel data of Italian manufacturing firms with four waves from 1995 to 2006. Although the impact of ICT investment on productivity was stronger, it was neither complementary nor a substitute for the investment in R&D (Hall, Lotti, & Mairesse, 2013). Mohnen, Polder and van Leeuwen (2018) find that there are complementarities between investments in ICT, R&D, and organizational innovations: investing in one increases the probability of investing in another and altogether leads to higher TFP; Crespi, Criscuolo, and Haskel (2007) find that IT investment and organizational change interact in their effect on productivity growth, even in the early stages of investment. Finally, Arvanitis and Loukis (2009) evaluate the positive effect of physical, ICT, and human capital on labor productivity growth in Swiss and Greek firms, finding that Swiss firms maximize ICT exploitation more effectively.

The work of Fulgenzi et al. (2024) provides new evidence on the positive impact of ICT on labor productivity growth across 24 OECD member countries from 1995 to 2019. Using a nonparametric production frontier approach, they decompose labor productivity growth into four components: technological change, efficiency change, non-ICT physical capital change, and ICT capital change. Their results confirm that technological change and both non-ICT and ICT capital changes are significant sources of economic growth. Additionally, they find evidence that ICT's contribution to technological progress is positive but lagged, because it takes time for ICT use to be efficiently assimilated and absorbed by a country's workforce.

In any case, most research has focused on high-income countries, while the effect in other types of economies has not been studied with the same depth. However, Aboal and Tacsir

(2018), analyzing data from Uruguay, find that ICTs play a bigger role for innovation and productivity in services than in manufacturing and that nontechnological innovations provide a more important contribution to firm productivity. The World Bank (2006) did conduct a study using survey data from 20,000 firms in 56 low- and middle-income countries gathered between 1999 and 2003. Their results confirm the positive impact of ICT on enterprise growth, profitability, investment, and productivity, but they also identify some barriers that prevent firms from using or taking advantage of ICT, such as lack of employees skilled in ICT and uncertainty about the returns of this kind of investments. Similarly, the adoption of ICT in Brazil and India has had positive consequences on productivity, but the poorer the infrastructure, the lower the returns on the ICT investments (Commander, Harrison, & Menezes-Filho, 2011). A significant statistical relationship between the level of ICT and firm performance, measured through economic profitability or net return, has been found using 2009 survey data from small and medium Tunisian firms in the electrical and electronic sector (Piget & Kossaï, 2013).

With regard to Colombia, Alderete and Gutiérrez (2012) study the effect of ICT investments, human capital, and organizational changes on labor productivity, as well as product and process innovations as complementary factors for ICT use. Labor productivity is measured by these authors through value added per worker and sales per worker. Using the Survey of Development and Technological Innovation (2005) and the Annual Manufacturing Survey (2004), the authors develop two cross-sectional econometric estimations using ordinary least squares (OLS). The results show a positive impact of ICT investment and human capital on labor productivity; however, there is not sufficient statistical evidence to confirm a relationship between organizational changes and the dependent variable. In addition, the study found that there is a positive effect of innovation in the presence of ICT.

Campoverde et al. (2022) use a novel and comprehensive data set of 27,489 formal Ecuadorian firms to study the impact of ICT capital on production and TFP. They find that ICT capital has a positive and statistically significant impact on production, with magnitudes comparable to the impact attributable to non-ICT capital. However, the effects vary significantly across sectors, being larger for oil, mining, and service firms and smaller for manufacturing and agricultural sectors. In terms of TFP, the analysis finds that increasing ICT capital's share in total capital has important effects, suggesting that strategic decisions about capital investment distribution in favor of ICT could generate significant returns. Larger, exporting firms located in large cities tend to benefit more from ICT investments. However, firms above the median in terms of ICT capital show lower productivity levels, suggesting that large ICT investments do not necessarily translate into higher TFP.

Related to the role of ICT capital, Brambilia and Tortarolo (2018) use a database of Argentine firms to evaluate whether changes in ICT investment during the period 2010–2012 had impacts on wages and labor productivity. These authors provide evidence of an increase in labor productivity and wages, but the effects are larger for firms that had high productivity and highly qualified workforces to begin with.

The review of empirical evidence conducted for this paper also reveals that ICT capital's influence on firm performance is conditioned by the existence of complementary investments in organizational, human, and intangible capital. Brynjolfsson and Hitt (2000) document that ICT adoption demands complementary changes in firm organization and that it leads to higher productivity gains in better-managed companies. Additionally, several authors point out that ICT acts as a general-purpose technology (Cardona et al., 2013; Liao et al., 2016), requiring technical improvements and innovative complementarities to increase returns to scale, a phenomenon that can determine the rate of technological progress. However, these spillover effects and consequent technological improvement are not immediate, a phenomenon described as the J-productivity curve (Brynjolfsson et al., 2018).

The need for complementary investments and organizational changes can generate a negative short-term relationship between ICT investments and efficiency. Companies may only experience ICT investment benefits if the organizational context (having high managerial skills or achieving organizational innovation) has been delineated and prepared for full absorption of new ICT technologies (Basu et al., 2003; Liao et al., 2016). If these changes are not implemented, efficiency changes representing catching up in terms of realizing maximum productive potential may not occur. This highlights the importance of considering investments in complementary intangible assets such as human resource training and organizational improvements to maximize ICT's impact on productivity.

3. Empirical strategy

In this paper, we estimate an augmented PF by considering the inclusion of the stock of ICT capital. First, we discuss the standard methodology to estimate a PF, which is typically composed of state variables (i.e., physical capital) and a free factor (i.e., labor). This classification is commonly assumed in microeconomics, because firms can fix labor in both the short and long run, but capital only in the latter. We consider ICT capital to also be a long-run decision variable. For a given firm i at any point in time t, the most used PF is Cobb Douglas, as we see in equation (1) below, where K stands for capital, L for labor, and α is capital's share in total output, whereas β is labor's participation. The A term is technological progress, from now on referred as total factor productivity (TFP).

$$y = AK^{\alpha}L^{\beta} \tag{1}$$

However, estimating a PF by OLS has omitted variable bias. In fact, the A term is not exogenous and is correlated with the residual. In addition, equation (1) does not consider the productivity not observed by the econometrician. Unobserved productivity, ω_{it}, is correlated with the demand for the flexible inputs of labor, l_{it}, and materials, m_{it}, because after productivity shocks, firms respond by demanding more inputs. The control function approach is the most widely used in PF estimation (Rovigatti & Mollisi, 2018) and proposes different estimates to solve this problem. This approach was first developed by Olley and Pakes (1996) and has received numerous contributions from Levinsohn and Petrin (2003), Ackerberg et al. (2015) and Wooldridge (2009).

3.1 Control function

Semiparametric models instrument the endogenous variables to avoid the associated bias. Olley and Pakes (1996), in solving a firm's optimization problem, use investment as an instrument of unobserved productivity, ω_{it}. Each year, the firm decides how much to invest and hire in the next period based on its productivity.

As per Rovigatti and Mollisi (2018), the control function approach is consistent under the following assumptions: (1) $i_{it} = f(x_{it}, \omega_{it})$ is the investment policy function, invertible in ω_{it}. Moreover, i_{it} is monotonically increasing in ω_{it}; (2) the state variables (typically capital) evolve according to the investment policy function i_{it}, which is decided at time $t - 1$; and (3) the free variables $\boldsymbol{w}_{it}$ (typically labor inputs and intermediate materials) are nondynamic, in the sense that the choice of them at t does not impact future profits and they occurs at time t after the firm realizes productivity shock. Assuming that unobserved productivity is monotonic, it can be defined as

$$\omega_{it} = \mathrm{f}^{-1}(k_{it}, i_{it}) \tag{2}$$

From this transformation, the estimation is performed in two steps. First, an approximation of the function from investment and capital using OLS to estimate the labor parameter l. In the second step, the capital parameter k is estimated, assuming that the unobserved productivity depends on the observed productivity in the previous period; the simultaneity problem is solved, because k_{it} was determined by i_{it-1} of the previous period and is therefore exogenous. The above relies on the assumption that labor is completely elastic.

Levinsohn and Petrin (2003) propose to replace the i_{it} investment instrument with intermediate consumption, because when the available data present investment gaps, the assumption that it is monotonic cannot be maintained. With the new instrument, this assumption does holds and the procedure described by Olley and Pakes can be continued, while the elastic labor assumption holds.

On the other hand, the Ackerberg et al. (2015) model excludes the assumption that labor is perfectly adjustable, considering it to be a function of unobservable productivity i_t and capital k_{it}, which is determined at time s, being $0 < s < 1$. That is, the capital of the next period is selected first and then the amount of labor.

When we take the logarithm from equation (1) and unobserved productivity, ω_{it}, is included in the estimation, as seen in equation (3), we observe that the β parameter is associated with state variables (capital, w_{it}) while γ is related to the free variables (labor measured by wages or number of workers and materials, x_{it}). However, ω_{it}, the productivity not observed by the econometrician, does not have an associated parameter. In addition, equation (3) below assumes that productivity shocks affect only free variables (not state variables).

$$\mathrm{y_{it}} = \alpha + \mathrm{w_{it}}\beta + \mathrm{x_{it}}\gamma + \omega_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{3}$$

Under the seminal approach first developed by Olley and Pakes (1996), productivity evolves as equation (4) below, where Ω_{it-1} is the information set at the previous time period and ξ_{it} the productivity shock, which is uncorrelated with state variables and productivity (Rovigatti

& Mollisi, 2018). In equation (5) below, Olley and Pakes (1996) find that the optimal solution to a firm's demand for free variables (labor and materials) can be used as a proxy of unobserved productivity. This approach works under the assumption that $f(x_{it,}\,\omega_{it})$ is the firm's investment policy function, invertible in ω_{it}, where capital evolves according to the investment policy function decided at time $t-1$, whereas labor, l_{it}, and materials, m_{it}, are chosen at time t after the firm realizes its productivity shock. These demands are obtained through the dynamic problem of the firm. Once the proxy is obtained, it is incorporated into the PF.

$$\omega_{it} = E(\omega_{it}|\Omega_{it-1}) + \xi_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \quad (4)$$

$$\omega_{it} = f^{-1}(i_{it,}\,x_{it}) = h(x_{it,}\,m_{it}) \quad (5)$$

Rovigatti and Mollisi (2018) developed a Stata command "prodest," which estimates the PF under different methodologies (e.g., Olley & Pakes, 1996; Levinsohn & Petrin, 2003). Using the Wooldridge (2009) method, this command performs a consistent estimation within a single-step generalized method of moments (GMM) framework. We prefer the estimation of Wooldridge because it offers many advantages. First of all, its robust standard errors are easily obtained and account for both serial correlation and heteroskedasticity. In addition, this estimation overcomes the potential identification issue highlighted by Ackerberg et al. (2015) in the first stage, such as the correlation between the intermediate input and the error term, given the firm's response to technology efficiency shocks.

This method does yields econometrically robust standard errors that the instrumental variables may overestimate. Yet it also addresses the problems of Olley and Pake (1996) and Levinsohn and Petrin (2003) by replacing the two-step estimation procedure with a GMM setup. It presents the relevant moment constraints in terms of two equations, both of which have the same dependent variable (y_{it}), but each of which is characterized by a different set of instruments. There are two equations because the productivity is constructed (1) without imposing any functional form on the control function $\omega_{it} = h(.,.)$ and (2) by exploiting the Markovian nature of productivity (f{...}), as observed in equations (6) and (7) below. The two advantages of using this approach are that it overcomes the potential identification problem highlighted by Ackerberg et al. (2015) in the first stage and robust standard errors are easily obtained, considering both serial correlation and heteroscedasticity.

$$y_{it} = \alpha + w_{it}\beta + x_{it}\gamma + h(x_{it}, m_{it}) + \upsilon_{it} \quad (6)$$

$$y_{it} = \alpha + w_{it}\beta + x_{it}\gamma + f\{h(x_{it-1}, m_{it-1})\} + \eta_{it} \quad (7)$$

The use of simultaneous equations allows us to recover unobserved productivity ($\phi(\dots)$) by means of a semiparametric equation, as can be observed in equation (8), which combines both equations (6) and (7). y_{it} corresponds to total product, w_{it} contains state variables (capital), x_{it} contains free variables (labor and materials), and both $h(i_{it}, x_{it})$ and $\phi(i_{it}, x_{it})$ indicate the unobserved productivity simultaneously.

$$\begin{aligned} y_{it} &= \alpha + w_{it}\beta + x_{it}\gamma + h(i_{it,} x_{it}) + \varepsilon_{it} \\ &= \alpha + w_{it}\beta + x_{it}\gamma + \phi(i_{it,} x_{it}) + \varepsilon_{it} \end{aligned} \tag{8}$$

Once the productivity proxy is included on the PF, the TFP can be obtained by predicting output using the contribution of each factor and obtaining the difference between observed and estimated output, because Solow residuals are obtained, as is seen in equation (9). TFP is therefore the output that cannot be attributed to the accumulation of capital, labor, and materials.

$$\widehat{\omega_{it}} = y_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_k} k_{it} - \widehat{\beta_m} m_{it} \tag{9}$$

Once the required variables are constructed, we proceed to estimate TFP with the prodest package. The following options are specified: (1) the state variable is capital (as is typical in firm optimization problems, where capital is fixed in the short run but flexible in the long run); (2) the proxy is materials (labor can also be a proxy of productivity; however, we are interested in recover labor participation in the PF); (3) the free variable is labor; (4) the method is Wooldridge, with GMM and the Robinson-Wooldridge variation;[6] (5) the polynomial is third degree; and (6) the number of repetitions is 50. By default, the maximum number of iterations to achieve convergence under this command is 10,000. In addition, an attrition correction was considered. However, this estimation do not yield drastically different results.

4. Data and Descriptive Statistics

The main survey used for calculating the TFP is the Encuesta Anual Manufacturera (EAM, Annual Manufacturing Survey), which contains information relevant to the estimation of the PF from 2004 to 2019. This survey captures basic information related to the manufacturing sector that facilitates an understanding of its structure, evolution, and development. EAM is designed to determine the composition of production and consumption in the sector by obtaining the sector's economic indicators, which in turn allow for the generation of basic statistics that provide the basis for calculating the sector's economic aggregates and national accounts.

Therefore, the required variables for the firm's PF estimation can be recovered from EAM. To begin with, labor (L) can be obtained on the basis of either wages or number of workers. To construct the capital variable (K), on the other hand, we use equation 10, where K_{it} is the

[6] Using an instrumental variable (IV) estimation of the autocorrelation function (ACF) that employs an IV version of Robinson (1988) for estimating output elasticities.

capital stock corrected by depreciation (compared to k_{it}). In addition, gross capital formation, GCF_{it}, is gathered on EAM and is also considered.

$$K_{it} = (1 - \text{depreciation}_{it})k_{it} + GCF_{it} \tag{10}$$

As we see in equation (10), in addition capital measurement by the firm, depreciation values and GCF are required to estimate capital properly. In this regard, depreciation rates can be gathered directly from EAM or sector- and capital-specific depreciation rates can be used. This difference allows two possible estimations, (1) book value and (2) Kapital Labour Energy Material Services (KLEMS). The former takes depreciation values from EAM—these values are reported directly by the firm—while the latter uses specific rates for each type of capital, as seen in equation 11. We use different depreciation rates to see whether the PF estimates are sensitive to depreciation parameter changes. However, heterogeneity exercises are carried out by means of equation (12) below. In addition, the labor factor is divided into white-collar and blue-collar workers in order to capture the heterogeneity of labor. EAM identifies both groups as follows: white-collar workers are either managers, administration workers, professionals, technicians, or technologists whereas blue-collar workers are laborers or operators. This division is frequently used in productivity literature.[7]

4.1 Depreciation Parameters

The KLEMS database methodology employs a standardized approach to capital measurement, applying uniform geometric asset depreciation rates across all countries. In addition, these depreciation rates differ by asset type and industry, but not by country or time. They are based on industry depreciation rates by asset type from EU KLEMS, which in turn come from the U.S. Bureau of Economic Analysis (BEA) (BID, 2020) (Table *1*). One advantage of using BEA rates is that they are derived from empirical research, rather than on ad hoc assumptions based, for example, on tax legislation. The validity of these depreciation rates for Latin American countries are attested to in the literature.

4.2 ICT Capital

In order to estimate ICT returns, it is necessary to differentiate ICT from other types of capital. EAM disaggregates the capital account into (1) buildings and structures, (2) machinery and equipment, (3) transportation equipment, (4) technology and communications equipment, (5) office equipment, and (6) land. To collect ICT returns, regardless of capital estimation (book value or KLEMS), the capital variable will keep ICT capital separate from the other types (referred to as “capital without ICT”). For this reason, ICT participation in the PF will be seen as a different factor.

The Encuesta de Desarrollo e Innovación Tecnológica (EDIT, Technological Development and Innovation Survey) also collects data on ICT investments, specifically those aimed at introducing innovations. However, this data may lead to double-counting issues, as ICT-related hardware used for innovation could also be recorded as fixed assets.[8] To address this

[7] See, for example, Doraszelski and Jaumandreau (2013).
[8] Table 13 in Appendix 1 provides further details on the types of questions used to capture these variables in the surveys.

concern, our analysis primarily relies on data from the EAM survey. Nonetheless, a robustness check will incorporate ICT investment data from the EDIT survey.

Table 1 Geometric Depreciation Rates Used in LAKLEMS, by Assets and Industries

Industries	**IT**	**CT**	**Soft**	**TraEq**	**OMach**	**OCon**	**RStruc**	**Cult**	**RD**	**OIPP**
Agriculture, livestock, hunting, forestry and fisheries	0.315	0.115	0.315	0.170	0.129	0.024	0.011	0.151	0.200	0.129
Mining and quarrying	0.315	0.115	0.315	0.170	0.129	0.024	0.011	0.207	0.200	0.129
Manufacturing industries	0.315	0.115	0.315	0.174	0.108	0.033	0.011	0.207	0.200	0.108
Electricity, gas and water	0.315	0.115	0.315	0.191	0.094	0.023	0.011	0.207	0.200	0.094
Construction	0.315	0.115	0.315	0.195	0.139	0.034	0.011	0.195	0.200	0.139
Commerce, hotels and restaurants	0.315	0.115	0.315	0.213	0.135	0.029	0.011	0.188	0.200	0.135
Transportation, storage and communications	0.315	0.115	0.315	0.165	0.103	0.027	0.011	0.197	0.200	0.103
Financial intermediation, real estate, business and renting activities	0.315	0.115	0.315	0.179	0.138	0.039	0.011	0.204	0.200	0.138
Social community and personal services	0.315	0.115	0.315	0.202	0.139	0.034	0.011	0.207	0.200	0.139

Source: BID (2020).
Note: Assets included in LAKLEMS database. IT: Computer equipment; CT: Communication equipment; Soft: Software; TraEq: Transportation equipment; OMach: Other machinery and equipment; OCon: Non-residential construction; RStruc: Residential structure: Cult: Arable assets; RD: Research and development and OIPP: Other intellectual property assets.

We implement the same methodology as for physical capital to obtain the ICT capital, as is formulated in equation (10). For ICT capital depreciation rates in manufacturing, we use the average rate among the first three columns in Table 1, i.e. IT, CT, and Software, as we observe by means of equation (11). In addition, monetary quantities are presented in real terms (taking the base Consumer Price Index of 2018), along with intermediate consumption, which (considered as other factor production, deflated by a firm-specific price index) is key to estimating the control function approach. As a robustness check, we also use the average, minimum, and maximum values present in them. These are, respectively, 0.248, 0.115, and 0.315, as shown in columns 1 to 3 in Table 1.

$$D_{ict} = \frac{\left(D_{it} + D_{ct} + D_{soft}\right)}{3} \tag{11}$$

The estimation of the PF considers several possibilities. Given the 2 methods of calculating capital (KLEMS and book value), the 2 calculations of the labor variable (number of workers and wages earned by them) in the structural estimation of productivity, and the 3 different methods of calculating the production function (Olley and Pakes, OP; Levinsohn and Petrin, LP; Wooldridge and Wooldridge-GMM), there are 12 possible combinations of the TFP estimations and are considered in the first instance. One possible combination is using wages in labor, KLEMS in capital, and Wooldridge-GMM for PF estimates. In addition, outliers were excluded from the estimation based on the price index availability.

4.3 Descriptive Statistics

In this section we present some statistics on firm characteristics such as age in years, number of workers, value of production, value of physical capital, value of ICT capital, and total investment on R&D in average for the period of reference. We calculate the same descriptive figures for different firm characteristics, such as size, exporting vocation, innovation investment decisions, technology requirements according to which the firm operates, and whether the firm is in a manufacturing sector associated to the extractive industry. Tables 2–4 present the statistics. In each form of heterogeneity we divide the sample into two groups.

Table 2 Descriptive Statistics, by Firm Size and Exporting Status (Average Values at 2013 USD Exchange Rate)

Variable	SMEs	Big firms	Nonexporting firms	Exporting firms
Age (years)	25	33.9	25.3	27.9
Workers	40.9	388.4	55.1	126.1
Product (COP, thousands)	$13,200,000	$75,900,000	$16,400,000	$26,000,000
Total capital (COP, thousands)	$2,800,308	$32,100,000	$3,922,967	$10,600,000
Total capital without ICT (COP, thousands)	$2,718,330	$31,200,000	$3,815,576	$10,300,000
Total ICT (COP, thousands)	$71,575	$677,405	$89,976	$261,566
ICT investment from EDIT (COP, thousands)	$5,798	$555,622	$42,557	$406,733
N	4207	553	3922	784

The statistics are presented as follows: first, we divide the sample according to the type of heterogeneity. The following heterogeneities were considered: (1) firm size: (categorical—SMEs: up to 200 employees and big firms: more than 200 employees); (2) exporting firms: 10 percent or more of revenues are from exports; (3) innovative firms: those that invest in innovation (e.g., R&D, human capital); (4) extractive firms: this classification is according to ISIC-rev4 at three digits. The ISIC codes are specified in Appendix I; (5) technological requirements: high-tech, medium-tech, or low-tech according to ISIC-rev4 at three digits; (6) and (7) ICT capital: sample split in half, a bottom and top 50 percent, according to ICT capital median according to KLEMS and book value method; and (8) ICT: capital sample split into four groups according to ICT capital, but taking only the first and fourth quartiles (bottom and top 25 percent, also by KLEMS and the book value method.

Table 3 Descriptive Statistics by Innovating Firms, Extractive Firms, and Technological requirements (Values at 2013 USD Exchange Rate)

Variable	Noninnovating firms	Innovating firms	Nonextractive firms	Extractive firms	Low- and medium-tech	High-tech
Age (years)	25.0	28.8	25.7	25.5	25.6	28.2
Workers	51.6	125.2	63.4	71.1	65.3	52.4
Product (COP, thousands)	$13,400,000	$36,700,000	$17,500,000	$17,900,000	$17,700,000	$11,000,000
Total capital (COP, thousands)	$3,160,386	$12,400,000	$4,379,384	$6,385,545	$4,853,457	$3,721,811
Total capital without ICT (COP, thousands)	$3,074,190	$12,000,000	$4,243,582	$6,251,505	$4,718,896	$3,496,046
Total ICT capital (COP, thousands)	$80,578	$263,408	$111,012	$123,418	$114,061	$92,844
ICT investment from EDIT (COP, thousands)	$12,756	$141,419	$51,505	$369,396	$126,205	$31,113
N	2956	1750	3638	1076	4597	117

As can be observed in Table 2, big firms are on average older (23.9 to 25 years) and invest more in ICT (COP 677,405,000 to COP 71,575,000) when compared to SMEs. Exporting firms similarly are slightly older; they have considerably more workers (126) than do nonexporting firms (55). Turning to innovating firms, they are slightly older when compared to noninnovating firms (28 and 25 years, respectively) and invest substantially more in ICT (per EDIT, COP 141,419,000 compared to COP 12,756,000). On the other hand, extractive-linked and non-extractive-linked firms are almost the same age (25 years) and are similar in the numbers of workers (71 and 63, respectively). Extractive-linked firms report a higher average of product and also total capital. However, ICT capital is only somewhat higher for them than it is for non-extractive-linked firms (COP 123,418,000 to COP 111,012,000). Finally, when considering technological requirements, high-tech firms are almost the same age as low- and medium-tech firms, whereas the latter have more workers (65) than do the former (52) and have higher product value, capital, and ICT capital.

In addition, we compare the same figures with the firms that invest more than the industry median on ICT capital versus those that invest less and consider the lowest and the highest 25 percent in terms of investment in ICT capital. As expected, after dividing firms according to the ICT capital median value, firms located in the top 50 percent are older, employ more workers, and have higher values of product, total capital, total capital without ICT, and ICT capital, as can be observed in Table 4. This pattern can also be observed in Table 5.

Table 4 Descriptive Statistics, by Subsamples (Values at 2013 USD Exchange Rate)

Variable	**Bottom 50% ICT – Book value**	**Top 50% ICT – Book value**	**Bottom 50% ICT – KLEMS**	**Top 50% ICT - KLEMS**
Age (years)	23.2	28.1	23.1	28.7
Workers	20.9	111.6	23.4	115.3
Product (COP, thousands)	$7,464,424	$28,000,000	$7,476,206	$29,800,000
Total capital (COP, thousands)	$716,958	$9,146,784	$779,274	$9,703,988
Total capital without ICT (COP, thousands)	$680,250	$8,922,445	$744,121	$9,463,555
Total ICT capital (COP, thousands)	$8,292	$224,339	$8,364	$240,433
ICT investment from EDIT (COP, thousands)	$9,142	$15,956	$8,177	$16,857
N	1746	1668	1866	1556

Table 5 Descriptive Statistics (Values at 2013 USD Exchange Rate)

Variable	Bottom 25% ICT – Book value	Top 25% ICT - Book value	Bottom 25% ICT - KLEMS	Top 25% ICT - KLEMS
Age (years)	22.7	31.3	22.8	31.7
Workers	16.8	174.3	19.3	179.4
Product (COP, thousands)	$5,305,602	$37,100,000	$5,336,625	$38,100,000
Total capital (COP, thousands)	$554,912	$16,200,000	$628,533	$17,300,000
Total capital without ICT (COP, thousands)	$498,250	$15,800,000	$576,137	$16,900,000
Total ICT capital (COP, thousands)	$2,842	$401,983	$2,463	$438,443
ICT investment from EDIT (COP, thousands)	$23,743	$23,368	$20,004	$24,146
N	901	828	983	753

5. Results

5.1 Production Function Estimates

In Table 6, the capital is estimated according to the book value method. The depreciation rate is fixed at 0.248 for ICT capital, as is the mean of depreciation of software, technological, and communication assets. We estimated using three different methods: Wooldridge, and Wooldridge with GMM correction, and Wooldridge (Robinson estimator), because the OP and LP methods have several drawbacks. For example, if a shock in productivity immediately translates into free inputs, Wooldridge methods correct these setbacks using a set of moments. In addition, the labor factor was estimated in two ways, counting the number of workers or wages paid.

Column 1 indicates that with the Wooldridge method, the participation of wages of white-collar workers was 13 percent, whereas blue-collar workers' wages had a participation of 7 percent. On the other hand, we observe that capital without ICT is statistically significant, and its participation is 2.8 percent. Finally, ICT capital has an output elasticity of 1.9 percent in the PF. As the dependent variable is the value of production, the output elasticity of materials must also be included and accounts for more than 50 percent of the PF. The following columns are interpreted similarly, where we see that ICT capital participation oscillates between 1.5 and 2.9 percent.

Table 6 Production Function Estimates (Values using Books Capital Method)

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*
Labor variable	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Labor, White collar	0.137***	0.123***	0.138***	0.243***	0.238***	0.244***
	(0.00451)	(0.00560)	(0.0131)	(0.00987)	(0.0126)	(0.0301)
Labor, Blue collar	0.0743***	0.0779***	0.0768***	0.365***	0.391***	0.374***
	(0.00499)	(0.00703)	(0.0180)	(0.0110)	(0.0152)	(0.0345)
Capital, without ICT	0.0281***	0.00675	0.0294***	0.0265***	0.0124	0.0276***
	(0.00936)	(0.00870)	(0.0101)	(0.00919)	(0.00779)	(0.00889)
Capital, ICT	0.0197***	0.0295***	0.0205***	0.0158***	0.0239***	0.0165***
	(0.00567)	(0.00475)	(0.00584)	(0.00557)	(0.00443)	(0.00573)
Materials	0.505***	0.633***	0.518***	0.440***	0.441***	0.447***
	(0.0231)	(0.0867)	(0.0335)	(0.0227)	(0.0664)	(0.0328)
Observations	18,834	18,834	18,834	18,834	18,834	18,834
Number of groups	3,532	3,532	3,532	3,532	3,532	3,532

Across all columns, the fact that ICT capital has returns comparable with other types of capital (1.6 and 2.7 percent, respectively) is remarkable, because it reveals the importance of firms' connecting digitally with suppliers and consumers from 2013 to 2018. This time period was chosen because it has a homogeneous nomenclature of inputs and outputs. Currently, the Central Product Classification (CPC 2.1) is in force, which was introduced in 2013. In the previous years an earlier version was used. On the other hand, PF estimates using the KLEMS method lead to 12 different estimations, which are presented in Table 7. Each specification can be observed in Table 8.

With the KLEMS method, ICT capital participation is considerably more prominent than capital without ICT, as it oscillates between 4.5 and 5.9 for columns 1, 3, 4, and 6. These are the columns where all parameters are statistically significant at 99 percent. The results are surprising and reveal the growing importance of ICT technologies and the difference between depreciation rates under the book value-reported and KLEMS-specific rates.

Table 7 Definitions of Estimations Using Production Function, Capital, and Labor Methods

Model specification	**Production function method**	**Capital method**	**Labor variable**
(1)	*Wooldridge*	*Book value*	*Wages*
(2)	*Wooldridge (GMM)*	*Book value*	*Wages*
(3)	*Wooldridge (ROB)*	*Book value*	*Wages*
(4)	*Wooldridge*	*Book value*	*# of workers*
(5)	*Wooldridge (GMM)*	*Book value*	*# of workers*
(6)	*Wooldridge (ROB)*	*Book value*	*# of workers*
(7)	*Wooldridge*	*KLEMS*	*Wages*
(8)	*Wooldridge (GMM)*	*KLEMS*	*Wages*
(9)	*Wooldridge (ROB)*	*KLEMS*	*Wages*
(10)	*Wooldridge*	*KLEMS*	*# of workers*
(11)	*Wooldridge (GMM)*	*KLEMS*	*# of workers*
(12)	*Wooldridge (ROB)*	*KLEMS*	*# of workers*

Table 8 Production Function Estimates Using the KLEMS Capital Method

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*
Labor variable	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Labor, White collar	0.127***	0.115***	0.126***	0.218***	0.217***	0.217***
	(0.00454)	(0.00552)	(0.0128)	(0.0100)	(0.0125)	(0.0297)
Labor, Blue collar	0.0703***	0.0726***	0.0720***	0.359***	0.383***	0.364***
	(0.00485)	(0.00659)	(0.0169)	(0.0109)	(0.0149)	(0.0341)
Materials	0.488***	0.638***	0.498***	0.423***	0.412***	0.429***
	(0.0232)	(0.0798)	(0.0334)	(0.0229)	(0.0630)	(0.0330)
Capital, without ICT	0.0298***	0.00221	0.0302***	0.0275***	0.00951	0.0281***
	(0.0101)	(0.00751)	(0.00963)	(0.00994)	(0.00677)	(0.00923)
Capital, ICT	0.0559***	0.0792***	0.0591***	0.0457***	0.0711***	0.0484***
	(0.0113)	(0.00970)	(0.0115)	(0.0111)	(0.00854)	(0.0113)
Observations	18,808	18,808	18,808	18,808	18,808	18,808
Number of groups	3,516	3,516	3,516	3,516	3,516	3,516

5.2 Robustness Checks

In order to check the sensitivity of the estimates, we use different depreciation rates from Table 1. In Table 9, we use the lower bound (0.115). In column 7 it can be observed that capital without ICT has an output elasticity of 2.77 percent, whereas ICT capital of 5.95 percent in the PF; this trend holds across all methodologies.

Using the upper bound for depreciation rate we obtain the following estimates presented in Table 10. It can be observed in column 7 that white-collar workers have a participation of 12.1 percent, blue-collar workers one of 7.4 percent, capital without ICT one of 2.68 percent, and finally ICT capital one of 6.2 percent. Thus, using the upper bound for depreciation rates leads us to find lower returns for ICT capital in contrast to other types of capital, as is expected.

Table 9 Production Function Estimates with Depreciation Rate = 0.115 and KLEMS Capital Method

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*
Labor variable	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*
VARIABLES (Depreciation rate: 0.115)	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Labor, White collar	0.122***	0.109***	0.121***	0.220***	0.218***	0.218***
	(0.00516)	(0.00612)	(0.0125)	(0.0117)	(0.0145)	(0.0303)
Labor, Blue collar	0.0741***	0.0760***	0.0755***	0.361***	0.381***	0.364***
	(0.00563)	(0.00778)	(0.0183)	(0.0125)	(0.0171)	(0.0347)
Capital, without ICT	0.0277**	0.00752	0.0286**	0.0236**	0.0158**	0.0246**
	(0.0120)	(0.00845)	(0.0111)	(0.0118)	(0.00766)	(0.0107)
Capital, ICT	0.0595***	0.0854***	0.0624***	0.0454***	0.0763***	0.0480***
	(0.0133)	(0.0114)	(0.0134)	(0.0131)	(0.0101)	(0.0132)
Materials	0.436***	0.536***	0.448***	0.370***	0.334***	0.379***
	(0.0266)	(0.0894)	(0.0385)	(0.0262)	(0.0709)	(0.0379)
Observations	14,049	14,049	14,049	14,049	14,049	14,049
Number of groups	3,487	3,487	3,487	3,487	3,487	3,487

Table 10 Production Function Estimates with Depreciation Rate = 0.315 and KLEMS Capital Method

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*
Labor variable	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*
VARIABLES (Depreciation rate: 0.315)	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Labor, White collar	0.121***	0.108***	0.120***	0.218***	0.216***	0.215***
	(0.00516)	(0.00611)	(0.0125)	(0.0117)	(0.0145)	(0.0303)
Labor, Blue collar	0.0741***	0.0760***	0.0754***	0.359***	0.380***	0.363***
	(0.00563)	(0.00777)	(0.0183)	(0.0125)	(0.0171)	(0.0347)
Capital, without ICT	0.0268**	0.00648	0.0276**	0.0229*	0.0152**	0.0239**
	(0.0120)	(0.00846)	(0.0111)	(0.0118)	(0.00767)	(0.0107)
Capital, ICT	0.0652***	0.0932***	0.0684***	0.0500***	0.0829***	0.0529***
	(0.0135)	(0.0116)	(0.0135)	(0.0133)	(0.0104)	(0.0133)
Materials	0.434***	0.542***	0.446***	0.369***	0.337***	0.378***
	(0.0265)	(0.0890)	(0.0384)	(0.0262)	(0.0708)	(0.0378)
Observations	14,047	14,047	14,047	14,047	14,047	14,047
Number of groups	3,487	3,487	3,487	3,487	3,487	3,487

5.3 Output Elasticities across Sectors and Firm Types

This section explores the heterogeneity in the output elasticity of ICT capital across various firm types and sectors. Understanding these differences is relevant to the understanding of how firms leverage ICT capital and the identification of patterns of technological efficiency. As the literature highlights, the impact of ICT investments depends on complementary assets such as innovation capabilities, organizational structure, and managerial skills (Bloom et al., 2012; Crespi et al., 2007; Gallego et al., 2015).

Using the specification detailed in Model 7 in Table 7, we examine the output elasticity of ICT capital across five key dimensions of firm heterogeneity: innovation activity, technological intensity, firm size, sector (extractive vs. nonextractive), and export orientation.[9] Robustness checks, including alternative specifications, are provided in Appendix III (Tables 16–21).

Innovation-active firms tend to adopt ICT more intensively, leveraging complementarities between ICT and other innovation-related activities. We define innovative firms as those reporting any investments in innovation activities.

Table 11 shows a marked difference between firms that are innovation active and firms that are not. ICT capital elasticity is 8.75 percent for the former, which is significantly higher than

[9] The model assumptions include (1) nonincreasing returns to scale, (2) non-negative estimates, and (3) the statistical significance of labor and physical capital. In addition, Model 9 can be considered the preferred estimation, beause it also adjusts to the model assumptions and thus is in line with Model 7.

the whole sample average (approximately 3 percent). In contrast, noninnovative firms exhibit no statistically significant ICT elasticity. This finding underscores the strong synergies between innovation and ICT adoption, reinforcing the idea that ICT investments are more effective when paired with complementary innovation efforts.

First, firms are analyzed according to their innovative performance. Gallego et al. (2015) find that innovation-oriented firms are more likely to adopt ICT among manufacturing firms in Colombia, suggesting the existence of complementarities between innovation and ICT adoption. We define innovative firms as those investing in innovation activities. The results presented in Table 11 show that estimates for noninnovative firms are not statistically significant for non-ICT capital, whereas innovative firms show a complete set of significant parameters with 8.75 percent participation of ICT capital in the PF. This elasticity is considerably higher than the average of noninnovative firm (around 3 percent), in line with the idea that complementarities exist between ICT and innovation.

Next, we analyze heterogeneity based on the technological intensity of firms' sectors, distinguishing between the low- and medium-tech sectors and high-tech sectors. [10] High-tech firms show a substantially higher ICT elasticity (75.8 percent) compared to their low- and medium-tech counterparts (5.4 percent). This highlights the critical role of ICT in high-tech production processes, where digital technologies are often integral to operations and innovation.

Firm size is another important dimension of heterogeneity. Big firms often have greater capacity to invest in ICT and complementary assets, making ICT capital more impactful. We define big firms as those with more than 200 employees, while smaller firms are categorized as SMEs. Table 11 shows that big firms exhibit an ICT elasticity of 7.56 percent, substantially higher than the 5.10 percent observed for SMEs. However, SMEs show notable heterogeneity depending on the specification. For instance, under the KLEMS method, ICT elasticity ranges between 5.1 and 7.1 percent, (for details, see Appendix II).

The extractive sector plays a significant role in Colombia's economy, yet its relationship with ICT adoption at the firm level remains underexplored.[11] This study finds that firms operating in the extractive sector value chain exhibit a lower ICT capital elasticity (4.68 percent) compared to firms with operations not related to extractive activities (6.04 percent).[12]

Table 11 also shows that extractive value chain firms rely more heavily on physical capital and blue-collar labor, while nonextractive firms make greater use of ICT capital and white-collar labor. These findings suggest that the nature of extractive production processes limits

[10] Using ISIC-rev4 at three digits.

[11] By 2019, according to the Atlas of Economic Complexity, for Colombia the share of extractive industries over total exports was as follows: oil (26.2 percent), coal (9.9 percent), and oil products (4.8 percent). These, in addition to other categories of minerals with a share below 5 percent of total exports individually, together form a significant component of Colombian exports.

[12] Because our sample is limited to the manufacturing sector, the criterion we used to identify the impact of ICTs in the extractives sector was to consider the following five subsectors: (1) crude oil and natural gas; (2) coal, lignite, and peat; (3) coke oven products and refined oil products; (4) metallic and nonmetallic minerals; and (5) basic metals and fabricated metal products.

the role of ICT, possibly due to higher costs or limited applicability. However, enhancing ICT adoption in extractive firms could potentially improve productivity, particularly in downstream activities within the value chain. Further research is needed to explore the mechanisms underlying these differences.

We examine differences in the returns to ICT capital according to firms' exporting performance. Exporting firms often face pressures to improve efficiency and adopt advanced technologies to meet global market standards (Melitz, 2003). The results in Table 11 confirm this, as they show a higher ICT elasticity for exporting firms (8.09 percent) than for nonexporting firms (6.79 percent). These results align with the broader literature, which links export activity to productivity gains, suggesting that ICT adoption is one of the mechanisms driving this relationship.

Finally, differences according to firms' level of investment in ICT capital are explored by separating the sample into quartiles and halves based on ICT capital investment levels (Table 12). Firms in the top 50 percent of ICT investment have significantly higher ICT capital elasticities (13.7 percent) compared to those in the bottom 50 percent (3.37 percent). Similarly, firms in the top quartile exhibit an ICT elasticity of 16.5 percent, while estimates for the bottom quartile are not statistically significant (Table 12). These results highlight the growing returns to ICT capital as firms increase their investment levels, emphasizing the importance of scaling ICT adoption for productivity growth.

It is important to note that while the output elasticity of ICT capital is related to productivity, it is not exactly the same. While output elasticity shows the responsiveness of output to investments in ICT capital, productivity measures the efficiency with which all inputs are used to generate output. Hence, firm types that have higher ICT capital output elasticities are not necessarily more productive overall. Nevertheless, to explore the connection between ICT capital output elasticity and productivity, we perform a series of stochastic dominance tests in terms of TFP, presented in Annex III. These tests reveal that, across all firm types, those with higher ICT capital output elasticities also consistently exhibit higher productivity levels (TFP) than their counterparts. This finding suggests a strong association between ICT capital output elasticity and overall productivity, reinforcing the importance of ICT capital for firm performance.

Table 11 Production Function Methods by Heterogeneities

Production function method	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*
Labor variable	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*
Heterogeneity	**Noninnovative firms**	**Innovative firms**	**Low- and medium-tech**	**High-tech**	**SMEs**	**Big firms**	**Nonextractive firms**	**Extractive firms**	**Nonexporting firms**	**Exporting firms**
Labor, White collar	0.219***	0.269***	0.125***	-0.242	0.120***	0.187***	0.137***	0.107***	0.119***	0.186***
	-0.0365	-0.0251	-0.00453	-0.276	-0.0047	-0.0235	-0.00598	-0.00703	-0.00564	-0.0227
Labor, Blue collar	0.151***	0.0553***	0.0693***	1.844***	0.0637***	0.117***	0.0756***	0.0772***	0.0943***	-0.0042
	-0.0441	-0.013	-0.00483	-0.561	-0.0051	-0.0355	-0.00549	-0.0102	-0.0065	-0.0132
Materials	0.665***	0.190**	0.484***	0.112	0.494***	0.320***	0.439***	0.541***	0.402***	0.292***
	-0.213	-0.0758	-0.0232	-0.545	-0.0247	-0.0716	-0.0303	-0.0358	-0.0297	-0.0714
Capital, without ICT	0.0448	0.0763**	0.0304***	0.144	0.0268**	0.0402	0.0340***	0.024	0.0234*	0.0737**
	-0.066	-0.0319	-0.0102	-0.263	-0.0108	-0.0297	-0.013	-0.0161	-0.0138	-0.0324
Capital, ICT	*0.0379*	*0.0875***	*0.0539****	*0.758***	*0.0510****	*0.0756***	*0.0604****	*0.0468***	*0.0679****	*0.0809***
	-0.0796	*-0.0385*	*-0.0112*	*-0.301*	*-0.0119*	*-0.0352*	*-0.0141*	*-0.0183*	*-0.0149*	*-0.0334*
Observations	318	1,467	18,656	150	16,957	1,571	11,382	7,417	11,343	1,767
Number of groups	872	1,132	3,487	29	3,340	354	2,106	1,416	3,109	694

Note: The specification 7: KLEMS method is used for capital, wages for labor, and GMM for pf estimates for innovative, extractive, and exporting firms.

Table 12 Production Function Estimates by Heterogeneities

Production function method	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*
Labor variable	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*
Heterogeneity	**Bottom 50% - Book value**	**Top 50% - Book value**	**Bottom 50% - KLEMS**	**Top 50% - KLEMS**	**Bottom 25% - Book value**	**Top 25% - Book value**	**Bottom 25% - KLEMS**	**Top 25% - KLEMS**
Labor, White collar – wages	0.0865***	0.215***	0.0920***	0.191***	*0.0739****	*0.253****	0.0722***	0.231***
	(0.00538)	(0.00894)	(0.00528)	(0.00933)	*(0.00608)*	*(0.0165)*	(0.00619)	(0.0165)
Labor, Blue collar – wages	0.111***	0.0466***	0.113***	0.0458***	*0.0922****	*0.0295****	0.0922***	0.0281***
	(0.00853)	(0.00607)	(0.00838)	(0.00614)	*(0.0120)*	*(0.00799)*	(0.0118)	(0.00808)
Materials	0.456***	0.505***	0.478***	0.525***	*0.432****	*0.495****	0.494***	0.542***
	(0.0341)	(0.0331)	(0.0340)	(0.0336)	*(0.0490)*	*(0.0451)*	(0.0509)	(0.0449)
Capital, without ICT	0.0295**	0.0780***	0.0214	0.0797***	*0.0207*	*0.0479**	0.00473	0.0480*
	(0.0149)	(0.0182)	(0.0145)	(0.0191)	*(0.0194)*	*(0.0258)*	(0.0194)	(0.0262)
Capital, ICT	*0.0156*	*0.0842****	*0.0337***	*0.137****	*-0.00357*	*0.106***	*0.0144*	*0.165****
	(0.0163)	*(0.0301)*	*(0.0154)*	*(0.0327)*	*(0.0249)*	*(0.0477)*	*(0.0210)*	*(0.0495)*
Observations	8,574	9,105	8,464	8,922	*3,922*	*4,362*	3,774	4,304
Number of groups	2,298	1,907	2,464	1,933	*1,422*	*1,056*	1,615	1,054

Note: The specification 7: KLEMS method is used for capital, wages for labor and GMM for production function estimates. The sample is divided in half according to ICT median value.

6. Conclusions

This study estimates the output elasticity of ICT capital across different types of firms and sectors in Colombia, shedding light on how ICT investments contribute to output generation under varying firm characteristics. The findings reveal significant heterogeneity in ICT capital's contribution to output. Firms that are innovative, high-tech, large, or export-oriented exhibit substantially higher ICT elasticities compared to their counterparts. For instance, ICT capital elasticity is 8.75 percent for innovative firms and 75.8 percent for high-tech sectors, while SMEs and low- and medium-tech sectors display ICT elasticities of 5.1 and 5.4 percent, respectively. For the extractive industries, ICT elasticity is 4.68 percent, lower than the 6.04 percent observed in nonextractive sectors. These differences highlight how firm characteristics, and sectoral dynamics shape the output returns to ICT capital investments.

The findings illustrate the marked heterogeneity in the output elasticity of ICT capital across firm types, in line with the literature that emphasizes the importance of complementary assets to effective ICT adoption in firms. Indeed, ICT capital is more relevant for production in firms and sectors with the resources and capabilities to integrate them effectively.

This study estimates output elasticities based on a firm-level production function, which is subject to several limitations. The methodology does not allow for the establishment of a causal relationship between ICT capital and output; the elasticities capture correlation rather than causation. Second, although robust PF estimation techniques are applied, unobserved firm characteristics and potential measurement errors (e.g., in categorizing ICT capital) could influence the results. Finally, this study focuses on estimating the output elasticity of ICT capital, rather than its direct effects on productivity. Further research could investigate how ICT adoption influences efficiency improvements beyond its contribution to output.

This paper's contributions emphasize the importance of understanding the conditions under which ICT capital contributes most significantly to output growth. These results underscore the need to address firm-level and sectoral heterogeneities to maximize the returns from ICT investments. While output elasticity is not synonymous with productivity, the results offer new insights on ICT's role in firm performance and provide the basis for further research on ICT investments in firms and more broadly on the concept of digital transformation.

References

Aboal, D., & Tacsir, E. (2018). Innovation and productivity in services and manufacturing: the role of ICT. *Industrial and Corporate Change*, 221-241.

Ackerberg, D., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*.

Alderete, M., & Gutiérrez, L. (2012). ICT and productivity in service industries in Colombia. *Lecturas de Economía*.

Alvarez, R. (2016). *The Impact of R&D and ICT Investment on Innovation and Productivity in Chilean Firms*. https://doi.org/10.18235/0009293

Acharya, R. C. (2016). ICT use and total factor productivity growth: intangible capital or productive externalities? *Oxford Economic Papers*, *68*(1), 16–39. https://doi.org/10.1093/oep/gpv058

Badescu, M., & Garcés-Ayerbe, C. (2009). The impact of information technologies on firm productivity: Empirical evidence from Spain. *Technovation*, *29*(2), 122–129. https://doi.org/10.1016/j.technovation.2008.07.005

Black, S. E., & Lynch, L. M. (2001). How to Compete: The Impact of Workplace Practices and Information Technology on Productivity. *Review of Economics and Statistics*, *83*(3), 434–445. https://doi.org/10.1162/00346530152480081

Brambilla, I., & Tortarolo, D. (2018). *Investment in ICT, Productivity, and Labor Demand: The Case of Argentina.* (8325; Policy Research Working Paper).

Bloom, N., Sadun, R., & Reenen, J. Van. (2012). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review*, *102*(1), 167–201. https://doi.org/10.1257/aer.102.1.167

BID. (2020). LAKLEMS: Crecimiento económico y productividad en América Latina – Metodología. *Banco Interamericano de Desarrollo*.

Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, *25*(3), 109–125.

Commander, S., Harrison, R., & Menezes-Filho, N. (2011). ICT and productivity in developing countries: New firm-level evidence from Brazil and India. *Review of Economics and Statistics*, 528–541.

Crespi, G., Criscuolo, C., & Haskel, J. (2007). *Information technology, organisational change and productivity growth: Evidence from UK firms.* Centre for Economic Performance, LSE.

Colecchia, A., & Schreyer, P. (2002). ICT Investment and Economic Growth in the 1990s: Is the United States a Unique Case? *Review of Economic Dynamics*, *5*(2), 408–442. https://doi.org/10.1006/redy.2002.0170

Díaz-Chao, Á., & Sainz-González, J. T.-S. (2015). ICT, innovation, and firm productivity: New evidence from small local firms. *Journal of Business Research*, 1439–1444.

Doraszelski, U., & Jaumandreau, J. (2013). R&D and productivity: Estimating endogenous productivity. *Business Economics and Public Policy Papers*.

Duryea, S., & Pages-Serra, C. (2002). *Human capital policies: What they can and cannot do for productivity and poverty reduction in Latin America.* Washington, DC: Inter-American Development Bank. doi:http://dx.doi.org/10.2139/ssrn.1817264

Fernández-Arias, E. (2014). *Productivity and Factor Accumulation in Latin America and the Caribbean: A Database (2014 Update).* http://www.iadb.org/research/pub_desc.cfm?pub_id=DBA-015.

Fulgenzi, R., Gitto, S., & Mancuso, P. (2024). Information and communication technology and labour productivity growth: a production-frontier approach. *Annals of Operations Research*, *333*(1), 123–156. https://doi.org/10.1007/s10479-024-05818-8

Gallego, J. M., Gutierrez, L. H., & Lee, S. H. (2015). A firm-level analysis of ICT adoption in an emerging economy: evidence from the Colombian manufacturing industries. *Industrial and Corporate Change*, *24*(1), 191–221. https://doi.org/10.1093/icc/dtu009

Garone, L. F., Villalba, P. A., Maffioli, A., & Ruzzier, C. A. (2020). Firm-level productivity in Latin America and the Caribbean. *Research in Economics, 74(2)*, 186–192.

Gërguri-Rashiti, S., Ramadani, V., Abazi-Alili, H., Dana, L. P., & Ratten, V. (2017). ICT, innovation and firm performance: The transition economies context. *Thunderbird International Business Review*, 93–102.

Grazzi, M., & Pietrobelli, C. (2016). Firm innovation and productivity in Latin America and the Caribbean: The engine of economic development. *Springer Nature*.

Grazzi, M., & Jung, J. (2016). Information and Communication Technologies, Innovation, and Productivity: Evidence from Firms in Latin America and the Caribbean. In *Firm Innovation and Productivity in Latin America and the Caribbean* (pp. 103–135). Palgrave Macmillan US. https://doi.org/10.1057/978-1-349-58151-1_4

Gómez, M., Posada E., & Rhenals, R. (2018). Determinants of Total Factor Productivity: The cases of the main Latin American and emerging economies of Asia (1960 - 2015)," Documentos de Trabajo de Valor Público 17081, Universidad EAFIT.

Gutiérrez, L. H. (2011). ICT and labor productivity in Colombian manufacturing industry. In *ICT in Latin America: Microdata analysis.* (pp. 121–144). Santiago: ECLAC.

Hall, B., Lotti, F., & Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*, 300–328.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*.

Matteucci, N., O'Mahony, M., Robinson, C., & Zwick, T. (2005). Productivity, workplace performance and ICT: Industry and firm-level evidence for Europe and the US. *Scottish Journal of Political Economy*, 359–386.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica, 71(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Mohnen, P., Polder, M., & van Leeuwen, G. (2018). *ICT, R&D and organizational innovation: Exploring complementarities in investment and production.* National Bureau of Economic Research.

OECD. (2019). *Latin American Economic Outlook 2019: Development in Transition.* París: OECD Publishing, https://doi.org/10.1787/g2g9ff18-en.

Olarte-Delgado, M. A. (2017). Heterogeneidad de la demanda de trabajo en el sector manufacturero de Colombia. *Reportes del Mercado Laboral-Julio de 2017. No. 2*.

Olley, S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*.

Piget, P., & Kossaï, M. (2013). The relationship between information and communication technology use and firm performance in developing countries: A case study of electrical and electronic goods manufacturing SMEs in Tunisia. *African Development Review, 25*(3), 330–343.

Pilat, D. (2004). The ICT productivity paradox: Insights from micro data. *OECD Economic Studies*, 37–65.

Robinson, P. M. (1988). Root-n-consistent semiparametric regression. *Econometrica, 56*, 931–954.

Rovigatti, G., & Mollisi, V. (2018). Theory and practice of total-factor productivity estimation: The control function approach. *Stata Journal*.

Stiglitz, J. E. (2009). *Report by the commission on the measurement of economic performance and social progress.*

Wooldridge, J. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*.

World Bank. (2006). *Information and communications for development: Global trends and policies.* Washington, DC.

World Bank. (2021). *World Development Indicators Online database*. Retrieved from https //data.worldbank.org/data-catalog/world-development-indicators

Appendix I

To calculate capital through the KLEMS method, we use the following steps:

- **STOCK:** $ki = \left(\frac{k_{it-1}}{ppi_i}\right) * 100$
- **INVESTMENT:** $I_i = c_{iut} + c_{int} + c_{ipt} - v_{ivt} + i$it
- **CAPITAL (STOCK + INVESTMENT):** $K_i = (1 - depreciation_{klems,i})k_i + I_i$

Where

ppi: Producer price index

c_{iut}: Purchase value of used assets

c_{int}: Purchase value of new assets

c_{ipt}: Purchase value of produced assets

v_{ivt}: Value of assets sold

And *i* refers to the following types of capital: (1) buildings and structures, (2) machinery and equipment, (3) transportation equipment, (4) technology and communications equipment, (5) office equipment, and (6) land.

Table 13 EDIT-EAM: ICT Questions

EAM	EDIT
Fixed assets and Investnents: Value on books	Indicate the value invested by your company in the years 2017 and 2018, in each of the following scientific, technological and innovation activities, for the introduction of new or significantly improved goods, services, and/or implementation of new or significantly improved processes, new organizational methods, or new marketing techniques.
Computer and communication equipment	Information technology and telecommunications
DANE clarification: For the EAM, it is clarified that the EAM assets module includes all the assets that the source has at the plant location for each of the variables requested in this module.	Acquisition, generation, outsourcing or leasing of hardware, software and/ or services for information handling or processing, specifically for the production or introduction of new and significantly improved services, goods or processes. (Do not include information and telecommunications technologies for R&D registered under item 1, or those purchased simply for the replacement or expansion of installed capacity, i.e., those dedicated to traditional production).

Table 14 Extractive Industries

191	Manufacture of coke ovens products
192	Manufacture of refining products
222	Manufacture of plastic products
231	Manufacture of glass and glass products
239	Manufacture of non-metallic mineral products n.e.c.
241	Manufacture of basic iron and steel products
242	Manufacture of precious metals and non-ferrous metals
243	Foundry of metals
251	Manufacture of structural metal products, tanks, reservoirs, tanks and steam generators
259	Manufacture of other fabricated metal products and service activities incidental to metal working

Appendix II Densities According to Heterogeneities

Figure 1 Workers by top 25% and bottom 25% of ICT capital

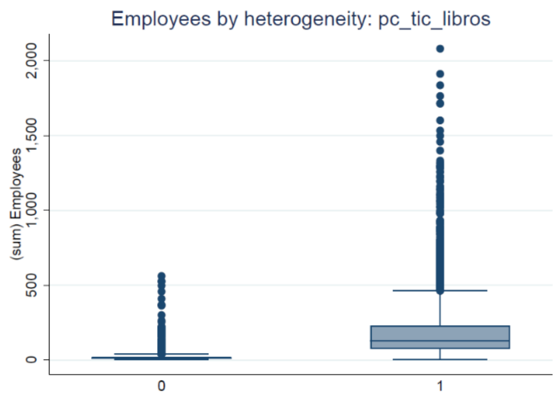


Figure 2 Workers by exporting and non-exporting firms

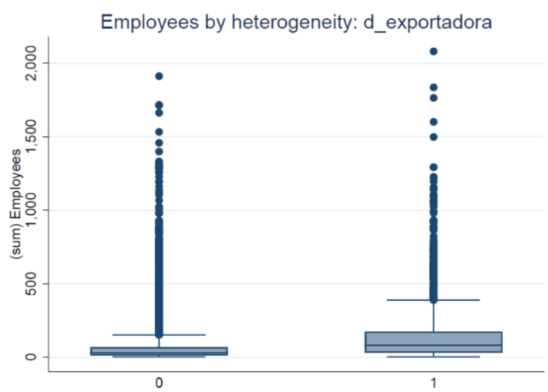


Figure 3 Workers by extractive and nonextractive firms

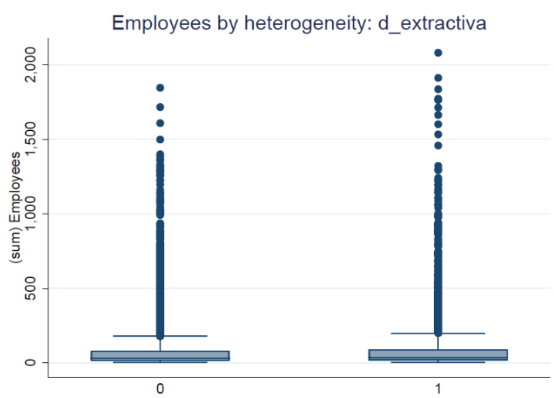


Figure 4 Workers by top 25% and bottom 25% of ICT capital

Figure 5 Logarithm of ICT capital by exporting and nonexporting firms

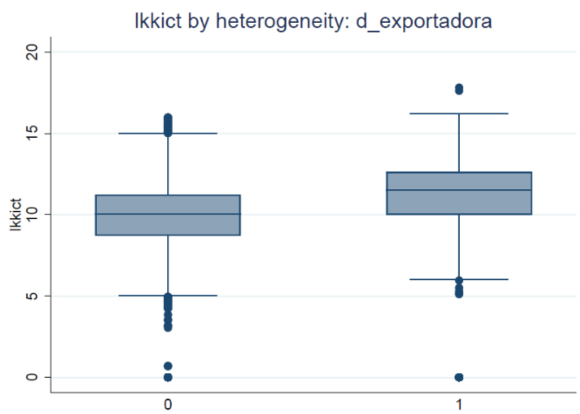


Figure 6 Logarithm of ICT capital by innovative and noninnovative firms

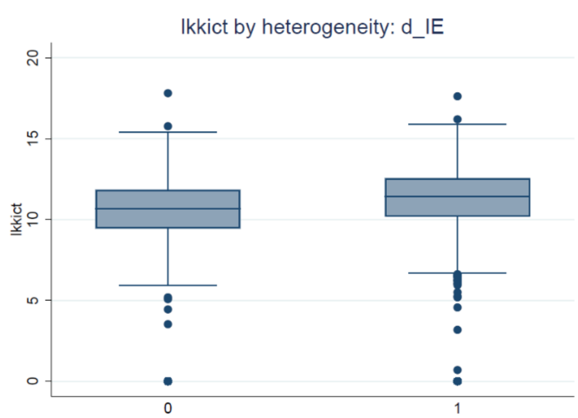
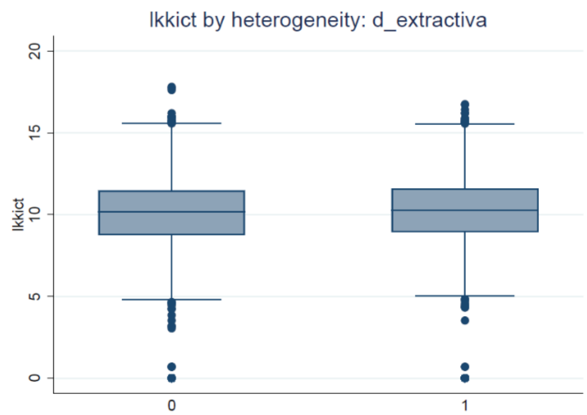


Figure 7 Logarithm of ICT capital by extractive and nonextractive firms



Graph 8 Logarithm of ICT capital by SMEs and big firms

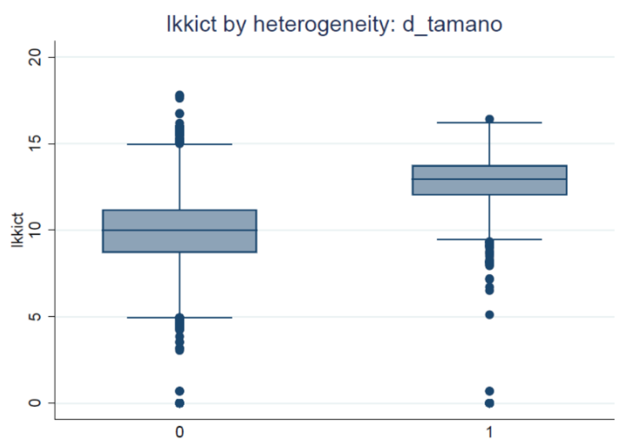
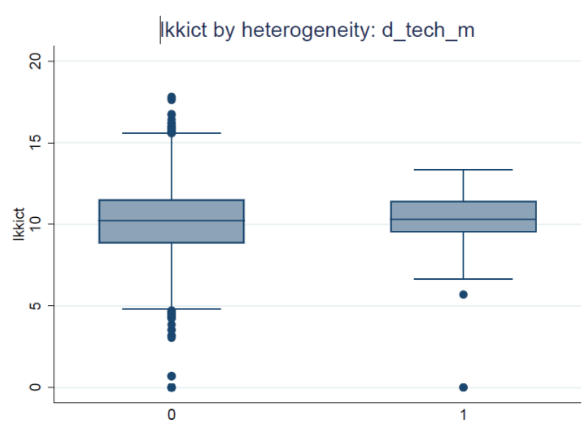


Figure 9 Logarithm of ICT capital by low-and medium-tech firms vs. high-tech firms



Appendix III Stochastic Dominance

When subsampling according to heterogeneity, each production factor has a different share, particularly ICT capital. We previously observed that big, exporting, innovative, nonextractive firms have a higher output elasticity of ICT capital compared to their counterparts; ultimately, these varying elasticities affect TFP, since TFP is the residual of the PF. Therefore, the performance of a stochastic dominance test should allow us to show that, in addition to a higher use and returns of ICT capital, the associated TFP is also higher. A summary of these tests is presented in Table 15.

The table's results are to be interpreted as follows: using one group as reference (e.g., SMEs), we first compute the probability of that group presenting lower values than the other group (Big firms). The corresponding *p*-value (0.000) rejects the null hypothesis and for this reason, SMEs are dominated by big firms, because the latter have bigger values of TFP. The second row tests the opposite statement, that is, SMEs have higher values of TFP. The corresponding *p*-value (0.964) does not reject the null hypothesis. Therefore, SMEs do not have higher PTF values compared to big firms. The same analysis is conducted subsequently for all heterogeneities, which gives us the following results: big, exporting, innovative, and nonextractive firms dominate their counterparts since they have higher TPF values across all distributions. This pattern is also observed comparing the top 25 and top 50 percent (using both KLEMS and book value estimations). The results of these estimations are also presented in Figure 10 at the end of this appendix.

Table 15 Stochastic Dominance Estimates for Each Heterogeneity

Heterogeneity	Corresponding comparison	Smaller group	D	*p*-value
Size	SMEs < Big firms	0	0.3259	0
	SMEs > Big firms	1	-0.0032	0.964
	Combined	Combined K-S	0.3259	0
Exporting firms	Nonexporting firms < Exporting firms	0	0.1113	0
	Nonexporting firms > Exporting firms	1	-0.0046	0.912
	Combined	Combined K-S	0.1113	0
Innovative firms	Noninnovative firms < Innovative firms	0	0.0887	0
	Noninnovative firms > Innovative firms	1	-0.0011	0.998
	Combined	Combined K-S	0.0887	0
Extractive firms	Nonextractive firms < Extractive firms	0	0.0063	0.653
	Nonextractive firms > Extractive firms	1	-0.0817	0
	Combined	Combined K-S	0.0817	0
Tech requirements	Low- and medium-tech < High-tech	0	0.0656	0.215
	Low- and medium-tech > High-tech	1	-0.1234	0.004
	Combined	Combined K-S	0.1234	0.009
Bottom 50%-Top 50% ICT capital – Book value	Bottom 50% < Top 50%	0	0.1935	0
	Bottom 50% > Top 50%	1	-0.0028	0.916
	Combined	Combined K-S	0.1935	0
Bottom 25%-Top 25% ICT capital – Book value	Bottom 25% < Top 25%	0	0.1785	0
	Bottom 25% > Top 25%	1	-0.0016	0.971
	Combined	Combined K-S	0.1785	0
Bottom 50%-Top 50% ICT capital - KLEMS	Bottom 50% < Top 50%	0	0.296	0
	Bottom 50% > Top 50%	1	-0.0017	0.984
	Combined	Combined K-S	0.296	0
Bottom 25%-Top 25% ICT capital - KLEMS	Bottom 25% < Top 25%	0	0.2684	0
	Bottom 25% > Top 25%	1	-0.0014	0.988
	Combined	Combined K-S	0.2684	0

Table 16 Production Estimates Subsampling. by Export Orientation of Firms

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (ROB)*	*Wooldridge (ROB)*	*Wooldridge*
Capital method	*Book value*	*Book value*	*Book value*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*
Labor variable	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*
Heterogeneity	**Nonexporting firms**						**Exporting firms**
Estimation	(1)	(2)	(3)	(7)	(9)	(12)	(10)
Labor, White collar	0.129***	0.115***	0.129***	0.119***	0.118***	0.209***	0.196***
	(0.00560)	(0.00640)	(0.0132)	(0.00564)	(0.0130)	(0.0331)	(0.0270)
Labor, Blue collar	0.0988***	0.0978***	0.101***	0.0943***	0.0951***	0.403***	0.121***
	(0.00676)	(0.00966)	(0.0216)	(0.00650)	(0.0209)	(0.0370)	(0.0309)
Capital, without ICT	0.0365***	0.0192*	0.0395***	0.0234*	0.0235*	0.0202*	0.0703**
	(0.0127)	(0.0114)	(0.0137)	(0.0138)	(0.0126)	(0.0121)	(0.0322)
Capital, ICT	0.0227***	0.0333***	0.0238***	0.0679***	0.0707***	0.0564***	0.0851**
	(0.00718)	(0.00626)	(0.00779)	(0.0149)	(0.0152)	(0.0149)	(0.0331)
Materials	0.431***	0.530***	0.441***	0.402***	0.411***	0.343***	0.272***
	(0.0295)	(0.104)	(0.0404)	(0.0297)	(0.0395)	(0.0387)	(0.0707)
Observations	11,369	11,369	11,369	11,343	11,343	11,343	1,767
Number of groups	3,117	3,117	3,117	3,109	3,109	3,109	694

Table 17 Production Function Estimates, Nonextractive Firms

Production function method	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*	*Wooldridge*
Capital method	*Book value*	*Book value*	*Book value*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*
Labor variable	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*	*Wages*
Heterogeneity	*Nonextractive firms*								*Extractive firms*
Estimation	(1)	(2)	(3)	(7)	(9)	(10)	(11)	(12)	(9)
Labor, White collar	0.148***	0.132***	0.149***	0.137***	0.137***	0.172***	0.174***	0.172***	0.107***
	(0.00590)	(0.00725)	(0.0168)	(0.00598)	(0.0166)	(0.0123)	(0.0148)	(0.0352)	(0.0197)
Labor, Blue collar	0.0771***	0.0818***	0.0792***	0.0756***	0.0764***	0.395***	0.416***	0.399***	0.0803*
	(0.00571)	(0.00788)	(0.0196)	(0.00549)	(0.0182)	(0.0130)	(0.0173)	(0.0395)	(0.0417)
Capital, without ICT	0.0391***	0.0236**	0.0403***	0.0340***	0.0345***	0.0322**	0.0201**	0.0327***	0.549***
	(0.0117)	(0.0113)	(0.0121)	(0.0130)	(0.0121)	(0.0128)	(0.00883)	(0.0117)	(0.0545)
Capital, ICT	0.0155**	0.0248***	0.0162**	0.0604***	0.0634***	0.0489***	0.0762***	0.0519***	0.0250*
	(0.00727)	(0.00610)	(0.00729)	(0.0141)	(0.0142)	(0.0139)	(0.0105)	(0.0141)	(0.0149)
Materials	0.471***	0.643***	0.482***	0.439***	0.448***	0.380***	0.340***	0.388***	0.0497***
	(0.0303)	(0.108)	(0.0416)	(0.0303)	(0.0411)	(0.0299)	(0.0744)	(0.0404)	(0.0184)
Observations	11,407	11,407	11,407	11,382	11,382	11,382	11,382	11,382	7,417
Number of groups	2,117	2,117	2,117	2,106	2,106	2,106	2,106	2,106	1,416

Table 18 Production Function Estimates for Innovative Firms

Production function method	*Wooldridge*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (ROB)*
Capital method	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*
Labor variable	*Wages*	*Wages*	*# of workers*	*# of workers*
Heterogeneity	**Innovative firms**			
Estimation	(7)	(9)	(10)	(12)
Labor, White collar	0.269***	0.259***	0.212***	0.205***
	(0.0251)	(0.0629)	(0.0300)	(0.0569)
Labor, Blue collar	0.0553***	0.0539*	0.295***	0.291***
	(0.0130)	(0.0286)	(0.0346)	(0.0822)
Materials	0.190**	0.187**	0.165**	0.158**
	(0.0758)	(0.0736)	(0.0757)	(0.0758)
			(0.0346)	(0.0822)
Capital, without ICT	0.0763**	0.0858***	0.0746**	0.0810***
	(0.0319)	(0.0279)	(0.0319)	(0.0282)
Capital, ICT	0.0875**	0.0873**	0.0854**	0.0836**
	(0.0385)	(0.0414)	(0.0384)	(0.0411)
Observations	1,467	1,467	1,467	1,467
Number of groups	1,132	1,132	1,132	1,132

Table 19 Production Function Estimates for Small and Medium Firms

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge (GMM)*
Capital method	*Book value*	*Book value*	*Book value*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*
Labor variable	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*	*Wages*
Heterogeneity				**SMEs**			**Big firms**
Estimation	(1)	(2)	(3)	(7)	(8)	(9)	(8)
Labor, White collar	0.131***	0.117***	0.132***	0.120***	0.108***	0.120***	0.172***
	(0.00467)	(0.00557)	(0.0127)	(0.00470)	(0.00550)	(0.0125)	(0.0342)
Labor, Blue collar	0.0660***	0.0708***	0.0682***	0.0637***	0.0672***	0.0659***	0.0919**
	(0.00524)	(0.00723)	(0.0185)	(0.00510)	(0.00678)	(0.0174)	(0.0371)
Capital, without ICT	0.0268***	0.00533	0.0283***	0.0268**	-0.00157	0.0274***	0.0417*
	(0.00972)	(0.00873)	(0.00994)	(0.0108)	(0.00772)	(0.0103)	(0.0238)
Capital, ICT	0.0190***	0.0275***	0.0199***	0.0510***	0.0719***	0.0539***	0.108***
	(0.00593)	(0.00484)	(0.00591)	(0.0119)	(0.00978)	(0.0116)	(0.0267)
Materials	0.512***	0.683***	0.524***	0.494***	0.641***	0.503***	0.220**
	(0.0246)	(0.0965)	(0.0341)	(0.0247)	(0.0874)	(0.0339)	(0.0969)
Observations	16,988	16,988	16,988	16,957	16,957	16,957	1,571
Number of groups	3,355	3,355	3,355	3,340	3,340	3,340	354

Table 20 Production Function Estimates by ICT Median Investment

Production function method	**Wooldridge**	**Wooldridge (GMM)**	**Wooldridge (ROB)**	**Wooldridge**	**Wooldridge (ROB)**
Capital method	KLEMS	KLEMS	KLEMS	KLEMS	KLEMS
Labor variable	Wages	Wages	Wages	Wages	Wages
Heterogeneity	**Bottom 50%**			**Top 50%**	
Estimation	(7)	(8)	(9)	(7)	(9)
Labor, White collar – wages	0.0920***	0.0843***	0.0926***	0.191***	0.190***
	(0.00528)	(0.00584)	(0.0124)	(0.00933)	(0.0385)
Labor, Blue collar – wages	0.113***	0.114***	0.116***	0.0458***	0.0480***
	(0.00838)	(0.0118)	(0.0298)	(0.00614)	(0.0180)
Materials	0.478***	0.579***	0.499***	0.525***	0.528***
	(0.0340)	(0.109)	(0.0475)	(0.0336)	(0.0523)
Capital, without ICT	0.0214	0.00119	0.0209	0.0797***	0.0795***
	(0.0145)	(0.0103)	(0.0140)	(0.0191)	(0.0175)
Capital, ICT	0.0337**	0.0454***	0.0345**	0.137***	0.142***
	(0.0154)	(0.0121)	(0.0157)	(0.0327)	(0.0305)
Observations	8,464	8,464	8,464	8,922	8,922
Number of groups	2,464	2,464	2,464	1,933	1,933

Table 21 Production Function Estimates by ICT Investment Quartiles

Production function method	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*	*Wooldridge*	*Wooldridge (GMM)*	*Wooldridge (ROB)*
Capital method	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*	*KLEMS*
Labor variable	*Wages*	*Wages*	*Wages*	*# of workers*	*# of workers*	*# of workers*
Heterogeneity	**Top 25%**					
Estimation	(7)	(8)	(9)	(10)	(11)	(12)
Labor, White collar	0.231***	0.251***	0.234**	0.108***	0.121***	0.111**
	(0.0165)	(0.0460)	(0.114)	(0.0167)	(0.0230)	(0.0525)
Labor, Blue collar	0.0281***	0.0293***	0.0309	0.229***	0.252***	0.235***
	(0.00808)	(0.00986)	(0.0191)	(0.0198)	(0.0289)	(0.0573)
Materials	0.542***	0.641***	0.531***	0.531***	0.552***	0.519***
	(0.0449)	(0.127)	(0.0815)	(0.0448)	(0.123)	(0.0803)
Capital, without ICT	0.0480*	0.0266	0.0476**	0.0524**	0.0415**	0.0522**
	(0.0262)	(0.0187)	(0.0237)	(0.0261)	(0.0190)	(0.0233)
Capital, ICT	0.165***	0.235***	0.168***	0.179***	0.267***	0.183***
	(0.0495)	(0.0326)	(0.0490)	(0.0494)	(0.0298)	(0.0438)
Observations	4,304	4,304	4,304	4,304	4,304	4,304
Number of groups	1,054	1,054	1,054	1,054	1,054	1,054

Stochastic dominance

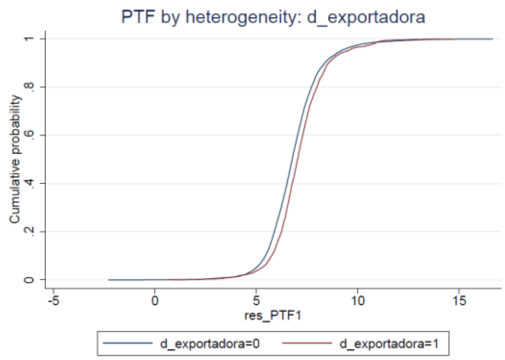


Figure 10 TPF Distribution, Exporting vs. Nonexporting Firms

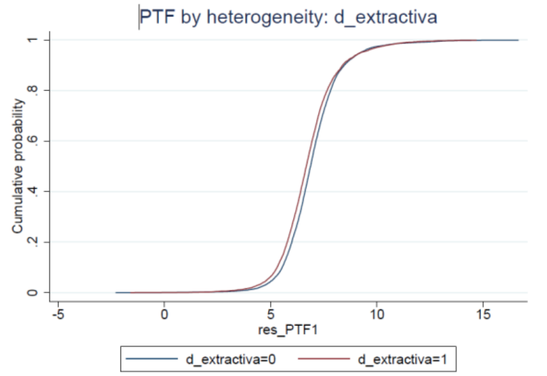


Figure 11 TPF Distribution, Extractive vs. Nonextractive Firms

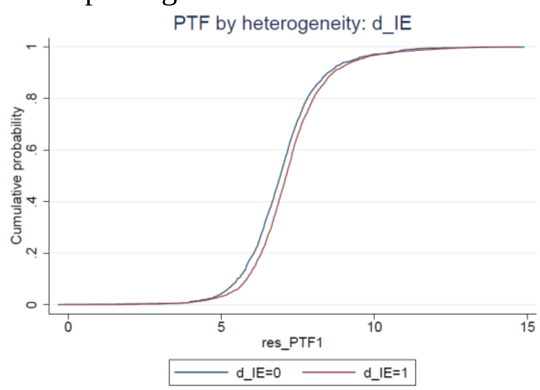


Figure 12 TPF Distribution, Innovative vs. Noninnovative Firms

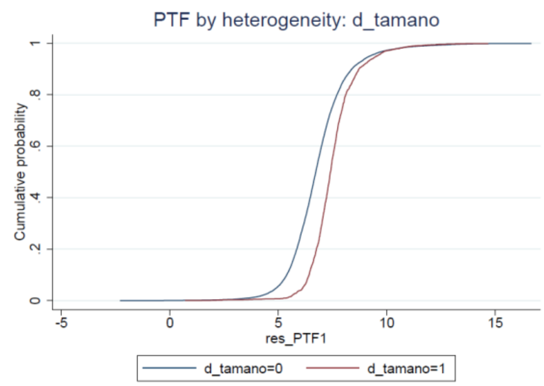


Figure 13 TPF Distribution, SMEs vs. Big Firms

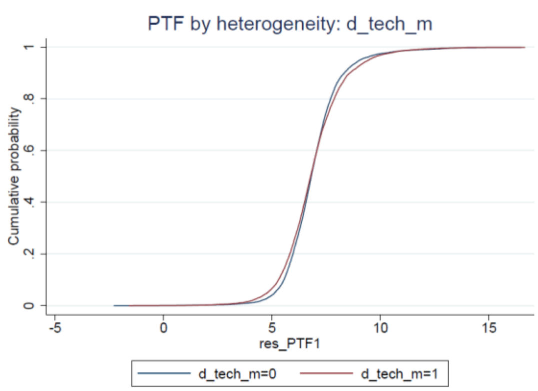


Figure 14 TPF Distribution Low- and Medium-tech Firms vss High-tech Firms

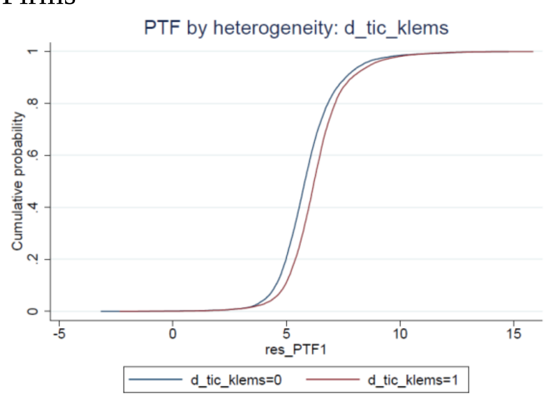


Figure 15 TPF Distribution, Bottom 50% vs. Top 50% According to ICT Capital Median—KLEMS

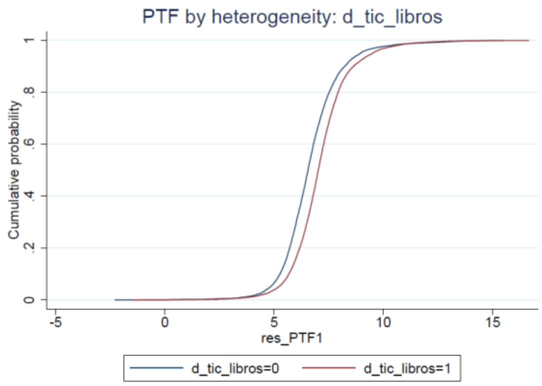


Figure 16 TPF Distribution, Bottom 50% vs. Top 50% According to ICT Capital Median—Book Value

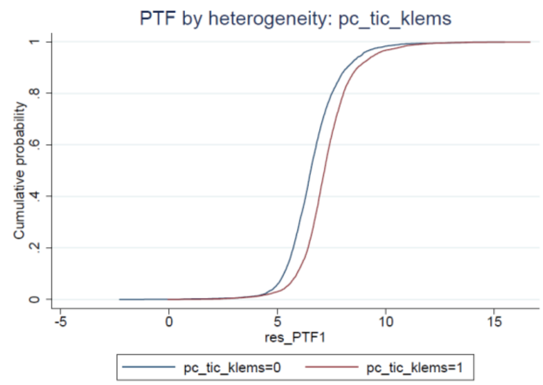


Figure 17 TPF Distribution, Bottom 25% vs. Top 25% According to ICT Capital Median—KLEMS

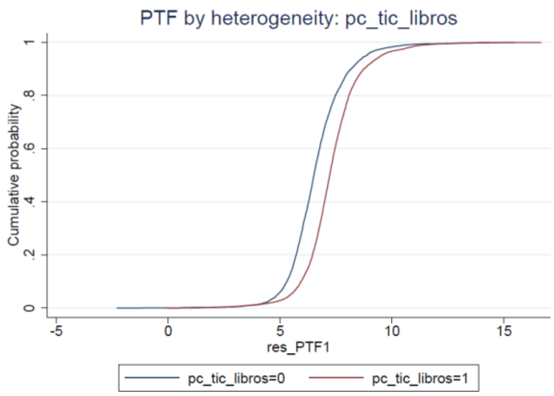


Figure 18 TPF Distribution, Bottom 25% vs. Top 25% According to ICT Capital Median—Book Value