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Evidence for Ecuadorian Firms

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The Impact of ICT Capital on Firm Output and Productivity

(Evidence for Ecuadorian firms)*

Jose Israel Campoverde, Maria Luisa Granda, Jose Luis Saboin

December, 2022

Abstract

We estimate the effects of ICT capital and ICT use on firm output and total factor productivity in Ecuador, using a capital augmented production function. We study heterogeneities across 2 dimensions: (i) economic sectors and (ii) firm characteristics (size, export orientation, age, location, technological intensity, and knowledge intensity). Using a novel and comprehensive data set of 27,489 Ecuadorian formal firms and using 2 identification strategies, we find positive and statistically significant effects of ICT capital and ICT use on output and TFP across economic sectors, controlling for firm characteristics. For robustness, we use four alternative measures of (i) ICT capital intensity and (ii) ICT use by the firm, finding, for the former, interesting industry differences on the effect of ICT capital and, for the latter, a positive effect of digital training on firms' TFP.

Keywords: ICT, digitalization, productivity, TFP, Ecuador

JEL classification: D24, E22, O33.

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1 Introduction

The digital transformation has a great potential to increase productivity and well-being in all economies. The new tools and opportunities that are emerging continuously nowadays are creating business model and consumption innovations, transforming production systems and value chains, generating new dynamics in the workplace, and introducing new conditions for competitiveness (OECD *et al.* (2021a)). The use of digital technologies and the development of employees' digital skills could improve the contribution of capital and labor to total factor productivity (TFP).

There is a clear need to understand the evolution of the digital transformation in developing economies and the effects of firms' investments in inputs that help them catch up in the digitalization challenge.[1] In this paper, we provide firm-level evidence on the impact of information and communication technologies (ICT) capital on output and TFP in Ecuador.

Ecuador and the Latin American region more broadly have characterized by persistent low levels of productivity due to low diversification of products, scarce value added, export specialization based on the abundance of natural resources, and low qualification of labor. Whereas there is little doubt that investment in ICT equipment has had a significant impact on TFP in developed economies, the evidence on emerging and developing countries is less abundant.

In Ecuador, conditions in recent years seem to have favored the creation of digital capabilities and an environment that fosters e-commerce. However, the country's performance in facilitating digital innovation has been marked by unequal results and other indicators are below the region average OECD *et al.* (2021b); in turn, the impacts on productivity and economic growth for the country are unknown. Internet use and access have improved and e-commerce has attracted more firms, especially following the COVID-19 crisis. That said, digital maturity in Ecuadorian firms is still incipient. In a recent report, Campoverde & Granda (2021) noted that 69% of firms in Ecuador have low levels of digitalization, though there is variation related to firm size and across industries. Firms show good attitude toward digital technologies; however, low knowledge about them doesn't help the firms advance in this matter. According to Microsoft (2021), 9 out of 10 small- and medium-sized enterprises (SMEs) accelerated their digital transformation process and 92% of SMEs invested in technology in the past year. The technologies most commonly prioritized were those that facilitate remote work: laptops (77%), cloud storage/computing (58%), communication platforms (31%), and collaborative work software (31%).

In this paper, we use a control function approach that estimates production over fixed (e.g., capital) and variable (e.g., labor) inputs, controlling for the unobserved productivity by the econometrician. In our framework, capital is disaggregated (or augmented) into ICT and non-ICT capital, where the former measures computers and software as firm assets; this is an approach that has been growing in favor in recent years (Biagi (2013)). We use this variable as a proxy for firm investment and adoption of digital technologies. Digital

[1] According to Gartner's glossary, digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business.

technologies have been argued to have a positive impact on productivity (Gal *et al.* (2019)); however, it is unclear how these might be affecting firms that are far from the productivity frontier (Harkushenko & Kniaziev (2019); Borowiecki *et al.* (2021)).

Several methodological challenges arise using the control function approach. Among the most common of these are selection bias, multicollinearity, functional form misspecification, and endogeneity. Our empirical approach follows conventional methods to correct for these biases (Olley & Pakes (1996); Levinsohn & Petrin (2003); Wooldridge (2009); Mollisi & Rovigatti (2018)). Previous studies have used the ICT capital measure to understand ICT capital's effects on different performance measures such as output, sales, and productivity (O'Mahony & Vecchi (2005); Mosiashvili & Pareliussen (2020); Smeets & Warzynski (2020); Hagsten (2022); Liu & Saam (2022)), finding a positive and significant effect that varies across industries. Others have studied this relationship using industry and cross country data (Spiezia (2012); Strauss & Samkharadze (2012)). In Latin America, Garcia-Carpio (2022) estimates the effect of ICT use and R&D investment on TFP in the manufacturing sector in Peru and finds that the latter has a significant effect on TFP of larger firms, but mixed results regarding ICT usage. In contrast, Seclen-Luna *et al.* (2022) find a positive effect of utilization of digital technologies with differences according to firm size, the type of digital technology, and the share of women in management. In Colombia, Gallego *et al.* (in press) also find positive effects of ICT capital on output and TFP in a panel of manufacturing firms for the period 2013–2018, controlling for different firm heterogeneities.

To the best of our knowledge, this is the first paper to build this type of analysis in Ecuador, with the added value of the introduction of information on firm perception of ICT *use*, measured by a tool that captures the level of ICT adoption and therefore complements the analysis of the ICT capital variable. Previous studies have found effects at the *industry* level of firm size, export orientation, and age on productivity in Ecuador, such as for the construction sector (Camino-Mogro & Bermudez (2021)), the service sector (Simbaña & Carrion (2021)), and the manufacturing sector (Ho *et al.* (2019); Camino (2021)). This paper, in contrast, provides an estimation of the production function for *all* formal firms in Ecuador that considers four inputs: labor, ICT capital, non-ICT capital, and intermediates. The estimation is then used to analyze the contribution of ICT capital to output and assess whether there are differences across the following firm characteristics: industry, size, geographic location, export orientation, technological intensity, and knowledge intensity. Moreover, we estimate a model to identify TFP determinants across these heterogeneities.

We present evidence based on a novel database we built for 27,489 firms using administrative records data provided by Superintendencia de Compañias, Valores y Seguros del Ecuador (SCVS) and the Directory of Companies (DoC). We also integrate to the analysis firms' responses to the Chequeo Digital survey[2]. Firms in Latin America (mostly SMEs) use this web-based tool to self-diagnose their level of "digital maturity" and obtain guidance in terms of the actions to take in order to improve their "digitalization maturity level". Chequeo Digital, however, was implemented in the country for the first time *during* the pandemic and the majority of responses were obtained in 2021.

[2]This was developed by Fundacion Pais Digital and financed by the Inter-American Development Bank (IDB) to support SMEs, by generating evidence on the state of their digital transformation in the region.

Because data on the use of ICT technologies are available only for one year, our study is divided into two moments. First, we study only the role of ICT capital on output and TFP during the pre-pandemic period (2010–2018); second, in a smaller sample (just for 2021), we again explore the role of ICT capital, here in tandem with qualitative measures on the *use* of digitalization technologies from the Chequeo Digital survey. This way, we intend to add value by studying the impact not only of the ICT capital variable but also its use, incorporating variables related to four key aspects of firms' use of digitalization technologies: (i) digital skills (by the workforce), (ii) organizational capacity, (iii) digital communication (i.e., with customers and providers, as well as online presence), and (iv) processes.

We obtain robust and consistent results in the estimation of the production function in the pre-pandemic period. The findings show that ICT capital has a positive and statistically significant effect on output, comparable to non-ICT capital. Larger effects are found for firms in the oil and mining and service sectors and smaller ones for those in manufacturing and agriculture sectors.

Regarding TFP determinants, our results provide empirical evidence of a positive effect of a larger share of capital devoted to ICT on the estimated TFP measure of Ecuadorian firms over the period of study. Firms above the median value of ICT capital, however, show lower productivity levels, suggesting that large ICT investments don't pay off. Moreover, while our results suggest that the effect accelerates as more ICT capital investment is made, it shows decreasing returns in some instances, particularly at very high levels. This intuitively makes sense: as with any capital variable, the law of diminishing marginal returns applies. In sum, increasing the share of ICT capital over total capital, has sizeable effects, suggesting that making strategic decisions about the distribution of capital investment with regard to ICT might yield sizable returns on firms' productivity.

Regardless of the ICT capital measure used, several firm characteristics also matter for productivity: younger, larger, and export-oriented firms seem to be more productive. Location differences are also found, as firms established in big cities seem to be on average more productive than firms outside them.

Our results also show that there are industrial differences in productivity. Agriculture is the most productive sector in the sample, followed by oil and mining; this is an expected result, because these are the sectors in which the country is internationally competitive.

Our results also show that increases in ICT capital share raise productivity in the manufacturing sector. In the same way, a larger firm size, exporting, and being a young firm increases TFP. For the manufacturing sector, our results show the possibility of a convex relationship between firm age and TFP. This is certainly possible, because more time in the market increases TFP, most often due to learning by doing and experience (De Kok et al. (2006)). A "big city" effect that is negative and significant suggests that being in a big city lowers productivity for a manufacturing firm. Put other way, firms located outside of big cities are the most productive firms. This can be explained by an industrial policy in Ecuador that has motivated firms to locate their plants on the periphery of cities and not inside them. Moreover, firms that are high/medium-high technology intensive are *less* productive than those low/medium-low technology intensive. These results contradict those

of Khanna and Sharma (2021), who show that firms in high-technology industries are more productive than those in low-technology industries in India. For Ecuadorian firms, Camino (2021) estimates the production function in subsamples by technological intensity of firms and finds that the output elasticity of capital declines as technological intensity of the firms increases. Furthermore, this author shows that firm age and international linkages are key determinants of productivity and that firms in low-tech industries in Ecuador benefit more from international trade activities than firms in industries that are more technology intensive. We believe our results derive from the fact that the core of the Ecuadorian economy is not manufacturing in technology-intensive industries, but is instead associated to primary production.

In the service sector –the largest sector in the Ecuadorian economy– investing in ICT capital increases TFP up to a point, especially if a firm is below the median in terms of ICT capital, in which case increasing the share of total capital always increases TFP. This suggests that the most productive services firms in Ecuador do not benefit from large investments in ICT capital, although devoting some of their capital investment toward ICT would be beneficial. This is expected for this sector, as it is dominated by small firms that are less knowledge intensive and do not require large ICT capital investments to be productive. For instance, much of the software these companies use is free or can be acquired at very low cost, which will result in lower values of ICT capital investment. Moreover, beyond investment in it, ICT capital impacts TFP according to how a firm *uses* it, particularly in this sector; therefore, variables such as the ICT skills of the labor force and digital marketing strategies would certainly contribute to TFP in this sector.

As with technological intensity in the manufacturing sector, the intensity of knowledge in the service sector shows a negative relationship with productivity. In Ecuador, Simbaña & Carrion (2021) estimate the effect of being in a knowledge-intensive sector and its interaction with firm size. They find results that contradict ours, for example that the coefficient on knowledge intensive is positive and significant and that there is a premium for larger firms. Their model defers from ours in that the covariates include return on assets, foreign direct investment, long term debt, marketing expenditures, and income tax payment, among others. However, when analyzing the sector by the degree of knowledge intensity, we observe that most of the firms in the service sector in our sample have a low intensity of knowledge. Thus, although the service sector in Ecuador is important in terms of number of firms, its contribution to productivity is limited and its level of sophistication is incipient. This result therefore raises the question of what is dragging down the productivity of the high-knowledge sector below its low-knowledge counterpart, a quite interesting avenue for further research.

The results regarding the effect of the use of digital technologies and their complementarities with ICT capital (using the small sample of firms that responded to the Chequeo Digital survey) only show (out of 4 aspects of a firm's use of digital technologies) a positive effect of digital training (a variable that indicates whether firm employees received education or training on digital issues). This result adds to the evidence in the literature that highlights the relevance of digital skills for productivity (Bloom et al. (2010), Konings and Vanormelingen (2015), Branco *et al.* (2018), Sorbe *et al.* (2019)), favoring the thesis that beyond ICT

capital investment, what really drives TFP is the associated human capital investment that enables firms to use this type of capital more effectively.

The paper is organized as follows: Section 2 explains our empirical strategy. Section 3 describes the data used in the study and its treatment. Lastly, section 4 provides a discussion of the main results, and section 5 offers some concluding remarks.

2 Methodology

The purpose of this paper is to estimate the effect of the use of ICT capital on output and TFP of Ecuadorian firms. To do so, we construct a panel using (i) balance sheets and financial statements presented annually by formal firms to the SCVS and DoC for the period 2010–2018 and (ii) survey data on the level of digitalization of Ecuadorian firms since the pandemic period. Our empirical analysis proceeds as follows:

(1) As do Gallego *et al.* (in press) and others, we estimate a capital-augmented production function (on ICT capital) using the different "control function" approaches that are standard in the literature on firm productivity estimation.

(2) From this production function estimation, for each firm and year we obtain (i) estimates of the participation of ICT capital on output as well as (ii) TFP estimates.

(3) Exploiting the comprehensiveness of the data, we decompose the sample into the main economic sectors of the Ecuadorian economy (Agriculture, Oil and Mining, Manufacturing, Commerce, and Services) and obtain ICT output elasticities as well as TFP residuals for each sector. We select the specification that is more suitable to the data.

(4.) To estimate the effect of ICT intensity on the TFP of the Ecuadorian firms, we carry out 2 types of analysis:

  (4.1) Using the traditional Kolmogorov (1933) - Smirnov (1939) (K-S) tests of equality of distributions, we estimate the stochastic dominance of the TFP distribution of ICT-intensive firms versus firms that are less ICT intensive. The analysis is done for all Ecuadorian firms as well as for different sectors and different sources of heterogeneity across firms that are traditionally analyzed in the literature, namely, size, age, external linkages, geographic location, technological intensity (for manufacturing), and knowledge intensity (for services).

  (4.2) Using regression analysis, we parameterize and provide statistical relevance for the previous findings by estimating the effect of ICT intensity on TFP for the full sample and sectors, controlling for size, age, external linkages, geographic location, and unobserved heterogeneity at the firm level.

(5) Because our ICT variable does not account for *how* it is used, we match a subsample of firms that responded to Chequeo Digital Survey in 2021.

We now turn to the explanation of each of the empirical specifications used in the study. First, we present the standard empirical production function and describe the different problems for its proper estimation that might arise. Then, we review how each of these problems has been dealt with in the existing literature. After laying out the different approaches, we present the variation of the specification used in this study: a production function that splits the capital variable into (i) ICT capital and (ii) non-ICT capital. We end the section by presenting the two methods that we use for identification: (i) the K-S test and (ii) the TFP regressions.

2.1 The control function approach and total factor productivity (TFP)

Production is the transformation of inputs (i.e., production factors) into outputs (i.e., goods or services) through the use of a technology. Generally, production factors are capital, labor, and materials. Productivity is understood as an efficiency measure of the use of the different factors to generate one unit of output and is usually measured as the ratio between the total production volume and the volume of one of the inputs used during the production process.

Following Mollisi & Rovigatti (2018), assuming Cobb-Douglas technology and after taking logs, production for a given firm i at time t can be empirically estimated as follows:

$$y_{it} = \alpha + \beta \mathbf{w}_{it} + \gamma \mathbf{x}_{it} + \upsilon_{it} \tag{1}$$

where y_{it} is the log of gross (or value added) output, $\mathbf{w}_{it}$ is a $1 \times J$ vector of log free variables (i.e., variables that can be adjusted by the firm, such as labor and materials), β represents the elasticity of output with respect to the free factors, $\mathbf{x}_{it}$ is a $1 \times K$ vector of log state variables (i.e., variables that cannot be adjusted by the firm, generally capital),[3] γ is the output elasticity with respect to the state factors, and the residual υ_{it} is decomposed as follows:

$$\upsilon_{it} = \omega_{it} + \varepsilon_{it} \tag{2}$$

where ω_{it} is unobservable productivity or technical efficiency. This represents productivity shocks that are potentially observable for the firm i at any time t when production decisions are taken; it has been associated to the skills and experience of firm managers, expected shocks to production, and the technological level of the firm, among other factors. ε_{it}, on the other hand, is an idiosyncratic output shock distributed as white noise that is neither observable nor predictable by the firm before it makes its production decisions (e.g., output levels and input uses).[4] Thus, the residual υ_{it} represents the log of TFP, a measure of the

[3] This assumption classification is commonly used in microeconomics, as firms can fix labor in both the short and long run, but capital only in the long run.

[4] When subject to productivity shocks, firms respond by expanding their level of output and by demanding more input. Negative shocks, on the other hand, lead to a decline in both output and demand for input.

productivity not explained by the production factors identified or observed by the econometrician. The TFP resumes all the externalities that contribute to the increase of production by the firm.

The decomposition of υ_{it} is due to different sources of bias previously identified in the literature in the parametric estimation of the production function. Among them are

- Selection problems that arise from the relationship between the unobserved productivity and a firm's decision to enter and exit the market (which is often associated to smaller, less-productive firms that have a greater probability of exiting the market than bigger, more-productive firms).
- Measurement errors on both the production variable and production factors.
- Endogeneity by simultaneity generated by the relationship between productivity and input demands.
- Multicollinearity among production factors.
- The functional form of the specification (e.g., the interrelationship of production factors).

To solve these problems, different methods have been proposed based on expressing unobservable productivity as a function of observable variables by using a "control function" approach. These methods have their origins in the proposals of Olley & Pakes (1996) and Levinsohn & Petrin (2003), which were later enriched in Ackerberg *et al.* (2015), Wooldridge (2009), and Mollisi & Rovigatti (2018). We now briefly discuss each methodology; a more detailed description is available in Appendix B. A key assumption common to all of these models is related to the dynamics of ω_{it}:

$$\omega_{it} = E(\omega_{it} \mid \Omega_{it-1}) + \xi_{it} = E(\omega_{it} \mid \omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \tag{3}$$

where Ω_{it-1} is the information set at $t-1$ and ξ_{it} is the productivity shock, which is uncorrelated with ω_{it} and state variables $\mathbf{x}_{it}$. This implies that a firm's productivity evolves according to a first-order Markov process.

Olley and Pakes (1996). These authors develop a two-step estimation procedure (hereafter OP) that proposes a deterministic relationship between productivity, ω_{it}, and investment, i_{it}. The latter is used as a proxy for the former. They assume that capital, a state variable, evolves according to an investment policy function, i_{it}, which is decided at time $t-1$. This investment policy function, $i_{it} = f(\mathbf{x}_{it}, \omega_{it})$, is monotonically increasing and also invertible in ω_{it}. Free variables, on the other hand, are chosen at time t, after the firm productivity shock occurs.

Such assumptions enable the identification of a model only in the vector of free variables, $\mathbf{w}_{it}$, yielding consistent β estimates (the first stage). Then, from the Markov process assumption of the productivity variable, ω_{it}, it is possible to estimate the γ parameters by

rewriting the model for $y_{it} - \mathbf{w}_{it}\beta$, conditional on $\mathbf{x}_{it}$. The residuals of this model are used to build a generalized method of moments (GMM) estimator (the second stage) for γ, exploiting residual orthogonality with state variables $E\left[e_{it}x_{it}^{k}\right] = 0$, $\forall k$, where x^k are the single elements of vector $\mathbf{x}$.

Levisohn and Petrin (2003). Because the investment variable could be truncated towards zero, the OP has proven to be inefficient in many empirical applications, as it violates the monotonicity assumption of the investment demand function. Although one possibility is to exclude all firms for which the investment is zero, doing so entails the cost of a significant loss of observations, which would affect the asymptotic properties of the estimator. Levinsohn & Petrin (2003) propose to overcome this issue by using intermediate input levels as a proxy for ω_{it} (hereafter LP).

The assumptions are the same as in OP, that is, the LP estimation assumes that inputs depend on productivity and capital and monotonicity is assumed in the relationship between inputs and productivity. This method estimates the parameters of interest through the GMM estimator. The moment conditions are stated in terms of the idiosyncratic errors of the production function and the stochastic process of productivity orthogonal to the instruments (capital and inputs lagged one period).

Ackerberg *et al.* (2015). These authors tackle a conditional dependency issue in OP and LP. This conditional dependency is implied by the possibility of collinearity among the free factors, that is, that labor and intermediate inputs can be also determined by the state variables (capital and productivity). Thus, to the extent that labor is a dynamic variable or is associated to investment or intermediate inputs, the parameter associated with the labor factor cannot be accurately identified.

In order to resolve the problem of conditional dependency, Ackerberg *et al.* (2015) propose an adjustment (hereafter ACF), which consists of assuming that productivity also depends on the labor factor and that through the moment conditions of orthogonal errors with capital and labor, it is possible to properly identify the parameters of both factors.

Wooldridge (2009). This author proposes to address the problems of OP and LP by replacing the two-step estimation with a GMM setting that estimates all model parameters simultaneously (hereafter WDRG). This is done by estimating two equations that have the same dependent variable (y_{it}), but that are characterized by a different set of instruments. That is, contemporary state (capital) and proxy (investment or intermediate inputs) variables can be instrumented with their lags (generally of order 1), as well as by functions of these variables.

WDRG overcomes the conditional dependency issue targeted by ACF, is easier to estimate due to its linearity, and enables the obtaining of robust standard errors (i.e., accounting for both serial correlation and heteroskedasticity).[5] Moreover, it is important to highlight that,

[5]In OP and LP the standard errors are bootstrapped, as in any two-step estimation process.

although more efficient than the previous two-step procedures (such as OP, LP, and ACF), both methods are consistent.

Mollisi and Rovigatti (2018). These authors propose a modification to the Wooldridge estimator based on a matrix of dynamic panel instruments (hereafter MR) to avoid losing degrees of freedom in the estimation of the parameters when using lagged values as instrumental variables. Thus, following the proposal of dynamic panel instruments of Blundell and Bond (1998), by using as values of the instruments only the lagged data available at each moment, information from the first years is not lost.

MR allows the increasing of moment restrictions without the loss of information, something that is useful when using "large N, small T" data sets, often common in practical applications of firm-level data. According to these authors, their estimator outperforms WDRG in simulated data and produces more-stable results, particularly in overidentified models (thanks to the increase in sample size).

2.2 A capital-augmented control function

To account for the impact of ICT capital on output and productivity, in this paper we estimate a capital-augmented control function:

$$y_{it} = \alpha + \mathbf{w}_{it}\beta + k_{nonictit}\gamma + k_{ictit}\delta + \omega_{it} + \varepsilon_{it} \tag{4}$$

where δ measures the contribution of ICT capital (k_{ictit}) to output, γ measures the contribution of non-ICT capital ($k_{nonictit}$), the vector β measures the contribution of other free variables ($\mathbf{w}$; e.g., labor and materials), ω measures TFP, and ε is the productivity shock.

As before, ω_{it} evolves according to a first-order Markov process.

$$\omega_{it} = E(\omega_{it} \mid \omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \tag{5}$$

where ω_{it-1} is the information set at $t-1$ and ξ_{it} is the productivity shock, which is uncorrelated with ω_{it} and capital variables k_{ictit} and $k_{nonictit}$.

We estimate this general model using the five procedures explained above.

2.3 Test of equality of distributions

To assess whether the intensity of ICT is associated to higher TFP, we perform K-S tests of equality of distributions. The idea is to evaluate the hypothesis that high-ICT-intensity firms' TFP distribution stochastically dominates low-ICT-intensity firms' TFP distribution.

The procedure consists of three steps. The first evaluates the hypothesis that, for a given variable x (in our case $\widehat{tfp}$), one sample, which we call group 1, contains *smaller* values than

another sample, which we call group 2. The second step tests the hypothesis that x for group 1 contains *larger* values than for group 2. This is done by estimating the largest differences between these samples' distributions.

More concretely, these "directional hypotheses" are evaluated with the following statistics:

$$D^{+} = \max_{x}\{F(x) - G(x)\}$$
$$D^{-} = \min_{x}\{F(x) - G(x)\}$$

where $F(x)$ and $G(x)$ are the empirical distribution functions of the samples being compared. The final step is the calculation of a combined statistic in the following way:

$$D = \max\left(\left|D^{+}\right|, \left|D^{-}\right|\right)$$

The p-value for this statistic may be obtained by evaluating the asymptotic limiting distribution. Let m be the sample size for the first sample and n be the sample size for the second sample. Smirnov (1939) shows that

$$\lim_{m,n\to\infty} \Pr\left\{\sqrt{mn/(m+n)}D_{m,n} \leq d\right\} = 1 - 2\sum_{i=1}^{\infty}(-1)^{i-1}\exp\left(-2i^2d^2\right)$$

where d is the observed value of $\max|F(x) - G(x)|$.

The Stata command *ksmirnov* test these p-values using the first 5 terms from the approximation and also provides an "exact" p-value, which is calculated by the counting algorithm in Gibbons & Chakraborti (2011). K-S test results will be accompanied to visual inspection of cumulative distribution functions (CDFs) plots in order to compare high-ICT vs. low-ICT TFPs across firm characteristics.

2.4 TFP determinants

To estimate TFP determinants, we use the TFP estimated by WDRG and MR with two data sets. First, we estimate the determinants of TFP using the SCVS. In this estimation, our goal is to estimate the effect of ICT capital on the TFP, controlling for sector, export status, age, and geographic location of the firm. Second, we match data of the SCVS with the survey Chequeo Digital. In this case, our goal is to estimate the effect of the use of specific ICTs and complementarities for ICT adoption on firms' TFP.

Using (pooled) ordinary least squares (OLS), we estimate the following baseline model:

$$\widehat{tfp}_{it} = \alpha + ict_{it}\beta + \mathbf{x}_{it}\gamma + u_{it} \tag{6}$$

where ict is the ICT capital intensity variable, β is the effect of this variable on the $\widehat{tfp}$, $\mathbf{x}$ is a $1 \times j$ vector of controls, γ is a j x 1 vector of coefficients, and u_{it} is the error term.

The previous model, however, does not allow for the possibility of unobserved individual heterogeneity and therefore could be considered a naive model. To control for the possibility that the coefficients of the explanatory variables in the previous pooled model are driven by either (a) firm specific characteristics or (b) nationwide changes in productivity, our baseline specification is augmented by including firm and time fixed effects:

$$\widehat{tfp}_{it} = ict_{it}\beta + \mathbf{x}_{it}\gamma + \alpha_i + \delta_t + u_{it} \tag{7}$$

where α and τ represent unobserved firm specific and time specific effects, respectively. The model does not impose restrictions on the relations between the covariate vector and the unobserved effects. In our setting, conditioning on the unobserved effects also serves to control for endogeneity, as the firm and time effects capture unobserved heterogeneity that can be related to the covariates.

3 Data

3.1 Data sources

We use 2010–2018 balance sheets and financial statements submitted annually by formal firms to the Superintendencia de Compañías, Valores y Seguros (SCVS) to construct the variables of the production function. Additionally, we use the Directory of Companies, a data set that contains firms' geographical, industry, creation, and legal status information, to construct control variables used in the heterogeneity and determinant analysis.

We also take advantage of firm information in the database of Chequeo Digital in Ecuador. Chequeo Digital is a tool used by firms in Latin America to self-diagnose their level of digital maturity and guide them along the digital adoption path. It was developed by Fundacion Pais Digital and financed by IDB to support the digital transformation of micro-, small-, and medium-sized enterprises (MSMEs). The tool has been available in Ecuador since October 2020, and from that point until early August 2022, 977 firms completed the questionnaire and received a report with their digital maturity level and recommendations to advance their digitalization. From the beginning, the tool could be used by every firm in the country, and oriented primarily to SMEs; hence the results are not representative of the universe of firms, as these are overrepresented in this group.

The Chequeo Digital survey database provides information generated by 62 questions intended to measure the overall digital maturity level of the firm and the specific levels of digital maturity across 8 dimensions and 3 conditions. The reported dimensions are technologies and digital skills, products and innovation, strategy and digital transformation, people and organization, culture and leadership, communications, processes, and data and analytics. The conditions are attitude, preparation, and knowledge.

The tool provides MSMEs firms with a report that details their level of adoption of digital technologies. From this questionnaire, we extracted a set of specific questions related to the use of digital technology in the productive process. The questions were classified into 4 categories or aspects, which we named digital skills, organizational capacity, digital communication, and processes. A detailed explanation of these categories is provided in the next section.

3.1.1 Main variables

We estimate the control function explained in section 2.2 with the following variables:

Output. In this paper, the output variable is defined as operational income.

Capital. We divide firm's capital into ICT capital and non-ICT capital. The former is the book value of computer equipment and software and the latter is defined as the values of property, plant, and equipment other than computers and software.

Investment. In section 2.1, we explained that OP uses investment as a proxy for ω_{it}. Because our data do not have an explicit variable for investment for the two capital accounts (ICT and non-ICT), we construct it as follows:

$$i_{it} = K_{it+1} - (1 - \delta)K_{it} \tag{8}$$

where i_{it} is the investment at time t, K_{it} and K_{it+1} are the stock variables of ICT and non-ICT capital accounts, at time t and $t+1$, respectively; and δ is the depreciation rate for each sector and capital type, extracted from the LAKLEMS methodology (Gu and Hofman (2021)).

Labor. Because the data set does not provide reliable information on number of employees, our measure for labor is the value of wages and benefits for all employees reported by the firm.

Intermediate inputs. This variable is defined as the sum of sales cost and other expenses used in the production process, as in Camino *et al.* (2020).

ICT capital intensity. To robustly estimate ICT capital's effect on firms' productivity, we use four different measures of ICT capital: (i) an indicator variable that takes the value of 1 if the firm's ICT capital is above the median and 0 otherwise, (ii) ICT capital's share of total capital, (iii) the log of ICT capital value, and (iv) the ICT capital value plus its square. All of these are measures of intensity. The first investigates whether "being to the

right of the median" in the ICT capital distribution contributes positively to productivity. The second tries to verify whether the effect of devoting more ICT capital –in detriment to non-ICT capital– increases firm productivity. The third evaluates the effect of the (log) level of ICT capital on TFP, whereas the fourth, while also evaluating this possibility, accounts for nonlinearities, that is, it introduces a quadratic term of the firm's value of ICT capital. See Table 1 for detailed definitions of the variables.

Firm digital capabilities. We used the framework developed by Van Laar *et al.* (2017), for the "21st-century digital skills" that organizations and the workforce need to drive organizations' competitiveness, performance, innovation, and productivity. To define the categories within the characteristics analyzed by Chequeo Digital, questions are selected and grouped in the following way:

- Digital skills: (i) Digital training and (ii) ease of use of digital technology. In this category, firms respond about their workers' skills to use digital technologies and their (the firms') support for the development of these skills.
- Organizational capacity: (i) Digital technology importance, (ii) work flexibility, and (iii) teleworking. Firms respond about organizational and workers' abilities to adapt their practices using digital technologies, specifically collaborative work platforms and tools.
- Digital communication: (i) Online presence, (ii) digital communication in the workplace, (iii) digital communication with clients, and (iv) providers. Firms respond about their workers' ability to use digital technologies to send information and communicate with stakeholders effectively.
- Processes: (i) Digital technology on processes and (ii) process automation. In this category, the firms respond about the degree of implementation of digital technologies in their production processes and evaluate the possible automation of these processes where it has not yet taken place.

For a detailed explanation of the survey questions, see Appendix C.

3.1.2 Control variables

This section explains the introduction of control variables for the identification of the effect of ICT capital on TFP. These variables are firm size, external linkages (proxied by exports), age, location, technological intensity (in manufacturing), and knowledge intensity (in services).

Size. Various studies have found a positive relationship between firm size and productivity (Lundvall & Battese (2000); Van Biesebroeck (2005); Oh *et al.* (2014)). Among the explanations for this are that large firms are more productive because they are more capital

intensive (Leung et al. (2008)) and have easy access to credit markets, and because there is a difference in the quality of R&D and human capital investments that such companies have carried out (Castany *et al.* (2005)). Because we do not have data on the number of employees of firms, we use the income size classification of the SCVS [6]. Therefore, the size variable is defined as a dummy that takes the value of 1 if the firm is an MSME and 0 if it is a large firm.

External linkages. According to the literature (Casiman *et al.* (2010); Bravo-Ortega et al. (2014)), exporting firms have higher productivity than non-exporting firms and this productivity can increase over time (De Loecker (2007)). This can be explained by the learning by exporting effect (Martins & Yang (2009)), where a firm increases its productivity by entering international markets, learning about effective buy-sell relationships, and competing with foreign companies (De Loecker (2013)). To take this into account, we have a dummy variable that takes the value of 1 whether the firm is exporting at time t and 0 otherwise.

Age. We use firm's age at time t and firm age squared to account for a possible non-linearity in this variable. There is not a consensus in the literature about the effect of firm age on productivity. It has been suggested that this effect could be positive: when a firm enters the market its productivity is low, but in the following years productivity increases (De Kok et al. (2006)), thanks to learning by doing and experience. Conversely, if the firm has established a successful process or model (Cucculelli et al. (2014)), which leads to the company's becoming rigid and ignoring innovations and technological progress (Leonard-Barton (1992)), productivity might decrease over time.

Location. We use the concept of agglomeration economies, that is, the benefits firms obtain by being located close to each other and to certain resources. According to Marshall (1890), there are two types of agglomeration economies: localization and urbanization. The former refers to efficiency gains within an industry in domains such as transportation, research collaboration, or input access of firms due to proximity. The latter relates to the access to public services and infrastructure provided in big and diverse cities and to the presence of other industries that could supply specialized inputs.

For the purposes of this study we define the "big cities effect", considering Guayaquil and Quito as the chief cities in the country that provide firms with advantages of both types of agglomeration economies. The relevance of this variable is highlighted by Fabiani *et al.* (2005) "*Local conditions can affect the speed of diffusion: in particular, among the industrial districts, those organized around a number of large firms might be faster in adopting ICT.*"

Hence, we use a dummy variable that takes the value of 1 if the firm is located in Guayaquil or Quito and 0 otherwise. This is particularly important, given that the location of firms matters for productivity (Aiello *et al.* (2014)) and varies by sector. For instance, it seems that

[6] Micro: firms with operational income less than or equal to US$100,000; small: firms with operational income between US$100,001 and US$1,000,000; medium: firms with operational income between US$1,000,001 and US$5,000,000; large: firms with operational income above US$5,000,001.

for agriculture it is more favorable to be located in rural areas, whereas for manufacturing firms somewhere in between works better, while for services it is better to be in cities.

Technological intensity. We use the EUROSTAT classification for manufacturing and service firms, based on their technology and knowledge intensity, respectively. For manufacturing firms, we have a dummy variable that takes the value of 1 if the firm is high/medium-high technology intensive and 0 if it is low/medium-low technology intensive.

Knowledge intensity. For service firms, the dummy variable takes the value of 1 if the firm is considered knowledge intensive and 0 if the firm is less knowledge intensive. See Tables 2, 3, and 4 for details.

3.2 Data treatment

To filtrate the data, several criteria were used:

First, we keep firms with active legal status and drop "ghost" firms listed by the Servicio de Rentas Internas (SRI, the fiscal authority), and public sector companies listed by the Ministry of Economics and Finance.

Second, firms with complete information during the study period were kept. Firms established before 2011 must have submitted their financial statements during the following 9 years; for companies established from 2011 on, they must have submitted their statements through the end of the study period (see Table 35). With this criterion, we do not control for attrition in our panel. While we acknowledge that this could be a source of bias to our estimates, our aim in this study is to assess the productivity of the most productive firms in the country, that is, the firms that consistently (i.e., over the years) contributed to the country's *trend* GDP and TFP.

Third, given the legal and minimum capital constitution requirement of US$800, firms with average total assets less or equal to US$800 were dropped, as well as firms with zero operational income in all periods. For firms with these issues for a maximum of two consecutive periods, we substituted zeroes with the value of the closest periods (see Appendix A for detailed information). We thereby ensure that firms effectively have participated in the market.

Finally, a similar approach was used for the variables of the production function (wages, ICT capital, and non-ICT capital).

After cleaning the data, we obtained an unbalanced panel with 167,649 observations and 27,489 firms from all sectors of the Ecuadorian economy. In this study, we will emphasize the Agriculture, Manufacturing, Oil and Mining, Commerce, and Service sectors, which are the sectors that contain the vast majority of the firms in the sample.

Regarding Chequeo Digital data, we only consider results for firms that completed the questionnaire for the year 2021. Out of the 977 firms that obtained their self-diagnosis, only

212 reported their financial statements to the SCVS in 2021. Because the platform received the majority of responses in that year, we use the available financial information for 2021 to develop the function production estimation and the determinant analysis.

3.3 Summary statistics

In Figure 1, we show the characteristics of firms in the sample. As can be seen, the majority belong to the Services and Commerce sectors, while less than 1% are Oil and Mining firms. Regarding the size, we have mainly MSMEs. Also, it is not common to be an exporter firm (less than 7% of the sample were). About 67% of the companies are located in big cities (Guayaquil and Quito).

Table 5 displays descriptive statistics of production factors divided by the sectors of interest. We can see that Oil and Mining and Manufacturing are the biggest sectors in terms of average operational income; the highest-income firms are from the Commerce and Service sectors.

Concerning production factors, Table 5 shows that in all sectors, on average the intermediate inputs (or materials) are the most relevant factor, followed by wages. ICT capital has the lowest relative importance; across the sample, firms spend 23 times more on non-ICT than on ICT capital. In the Agriculture sector, firms spend 90 times more. Although the Oil and Mining sector has the highest average ICT capital, it is in Commerce and Services that the discrepancies are the smallest, with 12 and 16 times more spent on non-ICT capital, respectively, suggesting that for these sectors ICT capital is more important.

Statistics for the sample that responded to Chequeo Digital are presented in Table 6. As with the previously discussed sample, in Figure 2 we show the characteristics of these firms: about 74% are MSMEs; the majority belong to the Manufacturing, Commerce, and Service sectors; 18.5% of these firms export, and approximately 82% are located in big cities. As can be seen in Figure 3, approximately 50% of the firms are in the initial and rookie levels. This means that the majority of firms do not have the capacity and knowledge necessary to begin the process of digital development and if a firm does have these, their level is considered basic. More detailed results on Chequeo Digital Ecuador are found in the report published by Campoverde & Granda (2021). Regarding the statistics for the production function variables, Table 6 displays the same picture as for the entire sample: ICT capital is still the less-used factor, and intermediate inputs and non-ICT capital are the factors on which firms spend much more.

Table 7 displays the summary statistics for the variables of the Chequeo Digital questionnaire. In this table, a larger value indicates a higher level in the variable analyzed. For the digital skills category, we have 2 different pictures: on the one hand, company workers, on average, seem to handle digital technology with relative ease (mean and median of 5). On the other, the development of digital skills through digital training has not been carried out frequently –the mean and median of 5 indicate that this type of training has been carried out, but skills acquisition remains incomplete.

The organizational capacity category indicates that the average firm that responds to Chequeo Digital considers digital technologies to be very important (mean of 6.39 out of 7). Analyzing the next variables, it can be seen that digital technologies have brought flexibility to work practices:the mean of 5 and the median of 4 indicate that firms have already started to use different collaborative work platforms. In addition, the teleworking variable indicates that, on average, firms allow some teleworking, but this practice has not been fully adopted.

Regarding digital communication, firms that respond to Chequeo Digital have demonstrated a high level of this communication with other stakeholders. It can be seen that the variables of communication with workers and providers have means of 5.92 and 5.27, respectively, indicating that both types are made regularly through digital channels. Furthermore, the median of 6 of the online presence variables indicates that 50% of the firms have a strong presence in the forms of websites and social media. Also, the variable of digital communication with clients indicates that firms frequently communicate with their clients through digital channels.

Finally, the implementation of digital technology in processes seems to be a problem for these firms. The variables of this category show relatively low means, which indicates that digital technology has been integrated into some processes and that the automation of these is in the early stages of planning.

4 Results

4.1 Control function

This section describes the main results obtained from the estimation of the control function for the whole sample, industry groups, and the firms that answered Chequeo Digital.

4.1.1 Whole sample

Table 8 shows the coefficients of the capital-augmented specification with the inputs of labor, materials, ICT capital, and non-ICT capital. Each column represents a different specification. Column (1) is a naive OLS model; columns (2) and (3) refer to the random and fixed effects models, respectively; columns (4) and (5) are the OP and OP with ACF correction, respectively; columns (6) and (7) represent the LP and LP with ACF correction, respectively; lastly, columns (8) and (9) show the results of the WDRG and MR specifications, respectively. While all the models are meaningful and consistent, following the advances in the literature, our preferred specifications are those of WDRG (column 8) and MR (column 9). This empirical analysis enables an interpretation of the extent to which the different inputs –particularly the one of interest in this study, ICT capital– relate to output.

All coefficients are positive and statistically significant. Columns 8 and 9 in Table 8 show that a 10% increase in computers and software is associated to a 0.85%–0.9% increase in

output, holding all other inputs fixed. Moreover, all the methods provide similar effects for this output elasticity with respect to ICT capital in the range of 0.070 to 0.156.

We find a share of labor with a high dispersion, in the range of 0.236—0.586. The difference in magnitude between the largest value (0.586) estimated by OP and the rest of the coefficients (0.236–0.391) is attributed to the non-inclusion of the intermediate inputs variable as a factor of production in OP. It is also worth highlighting that because unobserved productivity (ω_{it}) is proxied by the investment variable, which in turn is estimated by calculating the yearly differences in the stock of capital (adjusting for each sector's and type of capital's depreciation rates), the loss of the first sample year is necessarily implied, thereby reducing the number of observations.

The coefficients of ICT and non-ICT capital for the LP estimator are much higher compared to OLS, a result that is consistent with the finding of Levinsohn & Petrin (2003) that the OLS estimator for capital is biased downward, while the estimator for labor is biased upward.

With regard to output, we find a similar effect of ICT capital vs. non-ICT capital. Notably, the effect of labor on output is on average 2 to 3 times higher than separate capital effects. The intermediate inputs coefficient also shows a fair dispersion across approaches, ranging from 0.272 to 0.406. Overall, these results show the relevance of the labor factor in the output of the Ecuadorian economy, followed by intermediate inputs.

4.1.2 Sectors

ICT capital use varies across different sectors of economic activity. Thus it is vital to understand how the output's share of ICT capital differs across the main sectors of the Ecuadorian economy. Tables 9–13 show separate estimations by industry based on ISIC Rev. 4 for Agriculture, Oil and Mining, Manufacturing, Commerce, and Services. We estimate the same 9 models detailed in section 4.1.1. As expected, the production function estimates show relevant heterogeneity in the output share across industries.

Agriculture. In Table 9, the specific results for the Agriculture sector are presented. The estimated coefficients for the four inputs are all positive and significant at the 1% level. We find that the coefficient of ICT capital is relatively low for Agriculture (0.055-–0.190), as the coefficients of labor, non-ICT capital, and especially intermediate inputs significantly exceed that of ICT capital in most cases. Also, while it seems that Agriculture seems to be the least labor intensive of all sectors in the Ecuadorian economy, because the coefficients' sum is less than 1, it seems that an important part of output could be attributed to productivity.

Oil and Mining. Our results show a high and significant effect of ICT capital on firm output for the Ecuadorian extractive sector firms (Table 10). The coefficient on ICT capital ranges from 0.095 to 0.359, the highest across all the sectors. Moreover, in our preferred specifications (columns 8 and 9) the share of ICT capital matches that of the non-ICT capital; for an industry that is intensive in terms of non-ICT capital, this result might seem

unintuitive. However, we attribute this result to the increase in the degree of automation the sector has seen over the last decade (Carbon Trust & IDB (In press)). Additionally, our interpretation of these two results of (i) a high ICT capital share and (ii) comparability of that share with that of non-ICT capital is that an export-oriented industry with substantial organizational capabilities creates complementarities that enable it to take advantage of ICT capital. Previous studies (e.g., Bloom et al. (2010)) have found that elasticities of ICT capital tend to be higher in industries that use intangibles more intensively.

Manufacturing. As shown in Table 11, the Manufacturing sector estimates for ICT capital share are relatively lower than the extractive sector, in the range of 0.044 to 0.153, and as such being the lowest share of all inputs. However, this result is expected by us for two reasons: (i) the share of intermediate inputs is higher for the Manufacturing sector in general and (ii) because Ecuador's economy is one of low-technology sectors for the most part, it is expected that the share of non-ICT capital to be greater than that of ICT capital.

There is substantial international evidence on the relationship between ICTs in relation to the Manufacturing sector, for instance, in the United States and Europe (Bloom et al. (2010)), Germany (Kaus *et al.* (2020)), India (Khanna and Sharma (2021)), and Peru (Garcia-Carpio (2022)). Although no previous study estimates the augmented production function for ICT capital in Ecuador, similar results for the coefficient estimates are found using the production function approach in Camino *et al.* (2020) and Camino (2021).

Commerce. The results for the commercial sector show that the effect of ICT capital is comparable to that of non-ICT capital (see Table 12). As expected, the intermediate inputs coefficient is larger for this group of firms (0.402—0.543), because they have a large share of goods for trade. Several studies (e.g., Rybalka (2009) and Hempell *et al.* (2004)) include the Commerce sector as a subsector of the Service sector, but provide separate results. They concede that the industries of the Commerce sector are less ICT capital intensive than other services industries analyzed, such as electronic processing, technical services, and telecommunications. Nonetheless, the impact of ICT capital on productivity is much higher than that of non–ICT capital.

Services. In our study, the Service sector is associated to an output share of ICT capital of between 0.099 and 0.158 (see Table 13). This is the sector with the largest output share, second only to Oil and Mining. Moreover, the ICT capital share is double that of non-ICT capital. As expected, in this sector labor matters the most for output. Due to its relevance in the Ecuadorian economy (it is the biggest sector in the sample, representing 46.7% of firms) and the large positive impacts ICTs have been found to have, this sector is of special interest for the role of ICTs as an output (and productivity) booster.

The Service sector has received a fair amount of attention in the literature. Rybalka (2009) studies the ICT impact on labor productivity and finds the impact to be much higher in Services than in Manufacturing, while the opposite holds for human capital. The findings of Hempell *et al.* (2004) are similar. In both Germany and the Netherlands, ICT capital

deepening raised labor productivity in services firms. Alvarez (2016) provides evidence of a positive association between ICTs and TFP in Chilean firms in the service sector. Using a data set of firms for Uruguay, Aboal and Tacsir (2018) discuss the relevance of ICT for the service sector, finding a greater impact of ICT on productivity in services than in manufacturing. In Ecuador, Simbaña & Carrion (2021) estimate a production function for the service sector that yields similar results and coefficients of comparable magnitudes of labor, intermediate inputs, and capital.

4.1.3 Chequeo Digital

As explained in sections 3.1 and 3.2, we only consider firms in the sample that completed the questionnaire provided by the tool Chequeo Digital and combine these responses with the SCVS information in 2021.

Some explanation of the nature of this sample is in order. Chequeo Digital became available in October 2020, and since that time continuous efforts have been made to encourage usage through social media campaigns, webinars, and alliances with local organizations related to the development of MSMEs. We believe that firms that chose to register and complete the questionnaire had a pre-existing interest in measuring their digital maturity level and receiving recommendations to improve their adoption of digital technologies – in other words, the sample is self-selected. Hence, estimates may reflect this bias.

Although the sample size (212 firms) is small, estimates remain significant for labor and ICT capital, and the coefficients are similar to those for the full sample estimates (see Table 14). The share of ICT capital is 0.105 (vs. 0.109 for the full sample), whereas non-ICT capital is not significant in this case. The magnitude of the coefficient for labor is 0.471, higher than the full sample value of 0.347.

4.2 Heterogeneity analysis

In this section, we test for the stochastic dominance of the TFP distribution of ICT-intensive firms as compared to that of less-ICT-intensive firms (median value cutoff). First, we present the analysis for the whole sample across different sources of heterogeneities and then we present the analysis for the sectors. We use the K-S tests for equality of distributions explained in section 2.3, together with visual inspection of CDF plots to compare high-ICT vs. low-ICT TFPs across firm characteristics.

4.2.1 Whole sample

Figure 5 shows the dominance of the TFP distribution of the firms with higher ICT capital across all the firm characteristics considered in this study: international linkages, firm age, and big cities. That is, firms with high ICT capital have on average a higher TFP than their counterparts with low ICT (The K-S tests in Table 15 support these results).

Size. Firm size shows a different picture: for larger firms, those with lower ICT capital have the highest TFP, and for MSMEs, we do not find differences in TFP. This could be explained by the fact that large firms with low ICT capital are in primary sectors (Agriculture, Oil and Mining, etc.), and their higher productivity mainly depends on other factors (labor and non-ICT capital), and not on high ICT capital in the form of software and computers.

International linkages. In the literature it has been suggested that ICT can facilitate the internationalization and export process of firms because of the different capacities that this type of technology provides, such as online presence and transactions (Hagsten & Kotnik (2016); Pickernell *et al.* (2016)), the possibility of promoting the firm and its products (Eduardsen (2018)), and flexibility in the implementation of internationalization strategies through social networking (Cassetta *et al.* (2019)). This logic is consistent with our results in which higher TFP is associated to high ICT firms in the exporters group.

Age. Analyzing the results in terms of firms' age, it can be seen that both younger and older firms with high ICT intensity have higher TFP than their counterparts with low ICT intensity. Regarding older firms, they may have a large amount of accumulated technical knowledge (know-how), which leads them to efficiently exploit advanced technologies (Arvanitis & Hollenstein (2001); DeStefano *et al.* (2017)) and therefore achieve higher productivity than other old firms that have not started to apply such technologies. Young firms for their part are more likely to use multiple new generation digital technologies (NGDTs) such as artificial intelligence and the internet of things (Cho *et al.* (2022)), because they have newer assets that could be more compatible with these new technologies (Baldwin & Rafiquzzaman (1998)). Moreover, stable credit environments induce young firms to invest in computers and servers (DeStefano *et al.* (2017)).

Location. The location analysis yields similar results in the sense that ICT-intensive firms show an average higher TFP than less-ICT-intensive ones, when firms in big cities are compared to firms in the rest of the country.

4.2.2 Sectors

Figure 4 presents the CDF in each of the five sectors of the Ecuadorian economy analyzed in this study, compared to the rest of the economy. As can be seen in Figures 4a and 4b, firms in Agriculture and Oil and Mining are on average more productive, as their TFP distributions dominate those of others, as expected for the Ecuadorian economy. This is consistent with the results of the K-S equality of distributions test in Table 21.

The TFP distributions for the remaining of sectors are not distinguishable from their complement. In other words, the TFP distribution of Manufacturing, Commerce, and Services is on average equal when we compare them to their complement, and the K-S test results in Table 21 confirms this.

To understand the role of ICT capital intensity in this industry differences, we perform the previous analysis for each of the sectors in the sample. We find interesting differences, which we briefly describe here.

Agriculture. Figure 6 and the K-S tests in Table 16 together present the heterogeneity analysis for the Agricultural sector. Similar results to the analysis for the full sample are found – that is, in general the empirical TFP distribution of firms with higher ICT capital dominates the TFP distribution of firms with lower ICT capital.

- *Size.* In Figure 6a, a particularity is shown: although MSMEs with high ICT intensity show higher productivity than their counterparts with low intensity, for larger firms we find that low-ICT firms are more productive.
- *International linkages.* Analyzing Figure 6b, it can be seen that exporting firms with high-ICT-capital intensity have the highest TFP within this group. Although being a high-ICT firm made non-exporter firms more productive, the external linkages seem to give a larger impulse to productivity.
- *Age.* Figure 6c shows that having high ICT capital is associated to higher productivity for both younger and older firms.
- *Location.* When considering location, it can be seen that firms with high ICT capital are also the most productive. However, due to the special characteristics of this sector, such as the need for a greater amount of space to carry out business activities, firms located outside big cities (but with high ICT intensity), show the highest TFP.

Oil and Mining. The effect on productivity of ICT capital significantly differs across heterogeneities in this sector. It's worth noting that the extractive industry in Ecuador is dominated by large corporations in the oil sector, with large external linkages.

- *Size.* Figure 7a shows that large oil and mining firms have higher productivity. Regarding ICT use, Table 17 suggests an inverse relationship with productivity. For both sizes, firms with low ICT capital intensity are more productive than firms with high ICT.
- *International linkages.* Figure 7b shows that the TFP distribution for oil exporters with low ICT intensity stochastically dominates all non-exporters and high ICT exporters. Among non-exporters, high ICT firms exhibit higher productivity.
- *Age.* Figure 7c shows that, among the older firms, experience effects seem to be present, as higher TFPs are observed for high ICT capital firms.
- *Location.* Figure 7d shows that firm location in a big city seems to be a determinant of higher productivity.

Manufacturing. The heterogeneities of the Manufacturing sector are presented in Figure 8 and Table 18. We can see patterns similar to those in the previous results: here, again, higher ICT capital intensity is related to higher TFP.

- *Size.* Regarding firm size, we observe two different patterns. In the case of large firms, ICT intensity seems to have a negative impact on productivity, as firms with high ICT intensity have lower productivity. For MSMEs on the other hand, the results of K-S tests shown in Table 18 suggest that ICT use promotes productivity. In other words, high ICT capital firms have higher productivity than low ICT capital firms.

- *International linkages.* Figure 8b shows that manufacturing firms with high ICT intensity have higher productivity than other firms with low ICT intensity. However, exporter firms (with either high or low ICT intensity) surpass non-exporter firms, suggesting that in this sector, the export feature increases productivity and that ICT capital intensity provides an additional boost.

- *Age.* Figure 8c shows that ICT capital makes a big difference with respect to the time a firm has been in the market. This occurs since firms with low ICT capital intensity are less productive. Thus, discriminating by age, Figure 8c shows that older firms with high ICT capital are the firms with the distribution that shows the highest TFP.

- *Location.* In Figure 8d, a clear message can be distinguished: manufacturing firms with high ICT intensity show higher productivity and, among these, firms located outside of big cities are the most productive firms. This can be explained by industrial policy in Ecuador, which has motivated firm plants to locate on the periphery of cities and not inside them.

- *Technological intensity.* In Figure 8e, we use the EUROSTAT technological intensity classification. It can be seen that firms with higher intensity in ICT capital have higher productivity. However, among these, firms considered to be low technological intensive are slightly more productive than those with high technological intensity. A possible explanation for this result is that, because Ecuador has historically specialized in the production and transformation of goods with lower added value (such as food, textiles, and petroleum), coupled with the accumulation of experience and scale economies, production of these goods has become more efficient.

Commerce. In line with the previous sectors, the results presented in Figure 9 show that high intensity in ICT capital seems to be related to higher productivity.

- *Size.* Figure 9a and Table 19 show that large commerce firms have higher productivity. Analyzing the impact of ICT capital, it can be seen that for MSMEs, using ICT capital does not give differential benefits in productivity. However, in the case of large firms, firms with low ICT intensity have higher productivity than high ICT firms.

- *International linkages.* For international linkages, Figure 9b shows that ICT capital positively influences the productivity of exporters and non-exporter firms. Furthermore, exporter firms with high ICT capital benefit from higher productivity, probably because of their relationship and competition with foreign firms.

- *Age.* Regarding firm age heterogeneity, Figure 9c shows that young and old firms with high ICT capital have higher TFP than their counterparts with low ICT intensity.

- *Location.* When analyzing firm location, from Figure 9d it can be seen that ICT capital has a positive relationship with TFP. However, firms with high ICT capital located in other cities are slightly more productive than other firms located in big cities.

Services. In the Service sector, no clear pattern can be distinguished about the influence of ICT capital on TFP. We discuss the results for firms in this sector next.

- *Size.* Regarding firm size, Figure 10a shows that large firms dominate and have higher productivity. Among this group, it can be seen that low ICT intensity firms have higher productivity than firms with high ICT. With regard to MSMEs, the K-S tests presented in Table 20FF show no significant differences in productivity and ICT intensity.

- *International linkages.* In the case of exporting firms, Figure 10b shows that those with high ICT capital intensity have higher productivity than firms with low ICT capital intensity. However, for non-exporter firms, there is no significant difference between firms with high and low ICT capital intensity.

- *Age.* Figure 10c shows that, among old firms, there is a relationship between a high intensity of ICT capital and firm productivity. However, younger firms do not show any difference.

- *Location.* Figure 10d shows that service firms located in big cities and with high ICT capital intensity have higher TFP than their counterparts with low ICT capital intensity. On the other hand, firms located outside big cities do not show significant differences.

  Knowledge intensity. In Figure 10e we present the CDF of the EUROSTAT knowledge intensity classification (see Tables 2–4 for definitions). From the chart, it can be seen that there are little differences in the distributions. However, the results of the K-S tests in Table 20 show that in the two types of firms (Knowledge and less knowledge intensive), the distribution of the high ICT intensive firms dominates that of low ICT firms, indicating a positive relationship between TFP and ICT intensity.

4.3 TFP determinants

In this section, we try to answer the following research questions: (i) What is the effect of ICT capital on TFP in Ecuador? and (ii) How does the effect on TFP vary across different

firm characteristics? We use the TFP estimation based on the WDRG method for the endogeneity correction and the stability of results.[7] To answer these questions, we estimate the models explained in section 2.

To robustly estimate ICT capital's effect on firms' productivity, we use four different measures of ICT capital: (i) an indicator variable that takes the value of 1 if the firm's ICT capital is above the median and 0 otherwise, (ii) ICT capital's share of total capital, (iii) the log of ICT capital value, and (iv) the ICT capital value plus its square. All of these measures are measures of intensity. The first measure seeks to investigate whether "being to the right of the median" in the ICT capital distribution contributes positively to productivity. The second tries to verify that the effect of devoting more ICT capital –in detriment to non-ICT capital– is an increase in firm productivity. The third evaluates the effect of the (log) level of ICT capital on TFP; the fourth also evaluates this possibility, but accounts for nonlinearities by introducing a quadratic term of the firm's value of ICT capital.

While the literature provides plenty of evidence for the relationship between productivity and ICT for developed countries, it offers less for developing economies. For such economies, recent studies have found interesting results that are in line with ours. In Argentina, Brambilla and Tortarolo (2018), who study the effect of ICT change on several outcomes (productivity, wages, and employment) find that at the firm level, adoption of ICTs leads to a rise in firm productivity; for Colombia, Gallego *et al.* (2015) use firm characteristics as determinants of ICT adoption and find that the positive association of key determinants and ICT adoption is more pronounced for SMEs; and for Turkey, Taştan & Gönel (2020) use a labor-augmented ICT and non-ICT in the production function, instead of capital, and find significant effects of ICT labor in manufacturing and services. Finally, there is recent work in the context of Ecuador about productivity, notably Ho *et al.* (2019), who provide evidence based on Ecuadorian firm-level data on reallocation and productivity, and Camino-Mogro & Bermudez (2021), who analyze the determinants of productivity in construction firms and find that firms that are larger, older, or located in large cities exhibit a higher TFP.

As in sections 4.1 and 4.2, we provide the results for the sample that encompasses all the sectors first; then, we do the same for the main sectors; and we conclude section 4.3 by providing model results for the sample that consider digital capabilities and ICT capital as determinants of productivity.

4.3.1 Entire sample

Table 22 shows the results for the four measures of ICT capital intensity described above from using the pooled OLS model of equation 6. They are presented in the order that we introduced them. In this sense, column (1) shows that, in Ecuador, a representative firm with an ICT capital level above the median of the distribution (around US$4,000) is characterized by higher productivity than those below it. At the same time, column (2) shows that a 10% increase in the share of ICT capital over total capital is associated to a 1% increase in TFP. While the natural log of the ICT capital value does show a positive effect,

[7] Because results from the MR method follow those of WDRG closely, TFP estimates from this model can also be used in this analysis of TFP determinants.

it is not statistically significant. Interestingly, the results of the model shown in column (4), the model that evaluates the possibility of a nonlinearity in the effect of ICT capital on TFP, point to the possibility of a concave relationship, that is, productivity increases with ICT capital until the latter reaches some threshold, at which point the former starts to decrease. However, both coefficients are quite close to 0, suggesting that, this effect will have an order of magnitude, if any, only at very high levels of ICT capital.

Taken together, these results provide empirical evidence of a positive effect of ICT capital on the TFP of Ecuadorian firms over the period of study. Such an effect is small for firms above the median value of ICT capital. However, while the results suggest that the effect accelerates as more ICT capital investment is made, it has decreasing returns, particularly at very high levels. This intuitively makes sense: as happens with any capital variable, the law of diminishing marginal returns applies. Nevertheless, because the magnitude of the coefficient is quite low, the implication is that the relationship is almost linear. Moreover, increasing the share of ICT capital over total capital has sizeable effects, suggesting that making strategic decisions about the type of capital investment might yield sizable returns on firms' productivity.

According to Bloom et al. (2010), there is not a single effect of ICT capital on TFP, but rather an heterogeneous one, which depends on other firm-level factors. Hence, we include in the specification other variables as firm size, export status, age, location in a big city, technology intensity (manufacturing), and knowledge intensity (services).

In this sense, Table 22 shows, unsurprisingly, that size effects are consistent with the general literature: the larger the firm, the higher the productivity. Similarly, the exporting status of the firm positively affects TFP. Such a result is in line with that of Khanna and Sharma (2021) who find, for Indian firms, that TFP gains associated with ICT investments are higher for exporting firms than non-exporting firms. Younger firms are more productive, a result consistent with the literature for Ecuadorian firms that finds that age is positively related to TFP (Camino-Mogro & Bermudez (2021)); this result is consistent with the findings of the international literature as well Ding *et al.* (2016)). We also introduced the variable age squared in the specification to account for nonlinearities; however, the lack of significance of the coefficient tells us that the age effect is mostly linear in Ecuador.

We decided to include a measure of location in big cities to examine its impact on TFP and how it interacts with ICT capital and thereby explore possible agglomeration economy effects. Most of the firms in the sample are located in the two largest cities in Ecuador, Quito and Guayaquil. Table 22 shows that this "big cities effect" is positive and statistically significant. We interpret this result as pointing to the influence of interactions among firms and the local industry structure on technology adoption. In general, areas with a high concentration of firms provide access to others to information about new technologies, stimulating their adoption. This adds to the network aspects of location, such as access to communication services and to network externalities that influence firms' decisions to adopt technologies that others are adopting as well. Fabiani *et al.* (2005) also controls for location of the firm in order to understand the effect of interactions among firms on ICT adoption, finding that, for a group of Italian firms, the presence of large firms in the local environment affects ICT adoption. It is worth noting that our results may be affected by the fact that some firms

may be legally registered in a big city but operating in other places; hence correcting for this source of bias is needed to confirm our result.

We acknowledge that other controls can be incorporated in the regression. Garcia-Carpio (2022), for instance, in estimating the effect of digital adoption on Peruvian firms' TFP, controls for the role of innovation, which is a variable that has consistently shown a positive effect on firms' productivity (Hempell *et al.* (2004), Taştan & Gönel (2020)), as well as for the impact of the firm's mark-up, in order to consider the role of differences in market power and demand characteristics for each firm. This author finds sizable, positive, and statistically significant effects for the innovation variable. Incorporating this and other variables is certainly the next step in the agenda of our research on the role of ICTs on Ecuadorian firms' TFP. This also leads us to the issue of endogeneity between the estimated TFP variable and the ICT capital variable. While we try to address it by using the two-way fixed effects model, we acknowledge that we can improve our results by controlling further for this possibility, for instance, through the use of an instrumental variable model. Again, this is part of our future research agenda. Nevertheless, the R-squared values presented in Table 22 imply that our specifications explain the data variation quite well, suggesting that our results could be a good approximation of the *true* parameters.

Table 22 shows that there are industrial differences in productivity. Agriculture is the most productive sector in the sample, followed by Oil and Mining; this is an expected result, because these are the sectors in which Ecuador is internationally competitive. These results are consistent with the analysis in section 4.2.2.

Table 28 shows the results of the TWFE model of equation 7, that is, we look for the effect of ICT capital on firms' TFP, controlling for unobserved heterogeneity at the firm and year levels. As can be noticed from the table, some of the control variables are dropped for collinearity reasons. Column (1) shows that having an ICT capital level above the sector median decreases TFP, whereas increasing ICT capital's share of total capital increases TFP, both with significance. Taken together, these results indicate that, on the one hand, investing in ICT capital increases TFP up to a point, especially if a firm is below the median and, on the other, increasing the share of ICT capital always increases TFP. Thus, while high investments in ICT capital seem not to be a guarantee of increased TFP in Ecuador, devoting an increasing share of capital investments to ICT capital seems to generate large TFP gains for Ecuadorian firms.

Moreover, the possibility that this result is driven by sector characteristics seems to be ruled out by the firm fixed effect. Our application of equation 7 to our sectors of interest in the next section confirms this for all our analyzed sectors, further validating the notion that firms that are ICT capital intensive cannot translate their investments into higher TFP. Of the many potential reasons for this result, we suggest the use of this factor by firms is responsible. If workers and managers do not use their resources effectively, productivity gains from such resources might be missed. In this paper, we take into account this possibility by specifically looking at firms' use of digital technologies from Chequeo Digital survey. The results of that analysis are discussed in the last part of this section.

A more in-depth discussion of the effect of ICT capital (and the control variables) on the TFP of each of the economic sectors is provided next.

4.3.2 Sectors

We also estimate our specification for TFP determinants using subsamples based on the type of economic activity of the firm. Our results suggest that the association between ICT and productivity may differ across sectors.

Agriculture. Columns (1) and (2) of Table 23 show the results of the model using equation 6. These results indicate that having ICT capital above the sector median, as well as increasing share of total capital, increases productivity with significance for agricultural firms. Moreover, the results in columns (3) and (4) rule out the possibility of a nonlinear relationship between ICT capital and TFP in this sector.

As with the full sample, however, the results in Table 29 (i.e., from the TWFE model) show that these variables operate in opposite directions: an ICT capital level above the sector median decreases TFP, whereas increasing ICT capital's share of total capital increases TFP, with both results being significant. Nevertheless, the results in column (5) of Table 29 suggest that higher ICT investment might result in larger TFP after a threshold –but for this effect to occur the investment has to be substantial.

The coefficients for control variables for the four specifications show that increasing firm size and exporting increase TFP. As expected for this sector, being in a big city reduces productivity. This is due to the special characteristics of this sector, such as the need for a bigger space to carry out agricultural activities. Thus firms located outside the big cities are the ones that see an increase in their TFP.

Oil and Mining. The results presented in columns (1) and (2) of Table 24 have contrasting implications. Column (1) shows that having ICT capital above the sector median decreases TFP, whereas column (2) shows that increasing ICT capital's share of total capital increases TFP, with both results being significant. Moreover, the results in column (4) suggest the possibility of a concave relationship between ICT capital and TFP in this sector, although the levels of each must be extremely high for this to be meaningful.

These results suggest that the most productive oil and mining firms in Ecuador do not benefit from large investments in ICT capital, although directing some of their capital investment toward ICT would be beneficial. When contrasted with the results from the TWFE shown in Table 30, however, we notice that the share of ICT capital variable loses its statistical significance.

We interpret this result as an expected one, considering that the sector relies more on non-ICT capital (e.g., specialized machinery such as drills). However, if we take into account the results from the production function (see Section 4.1 and Table 10), we notice that the

output share associated to ICT capital is almost the same as that associated to non-ICT capital, implying the latter's relevance in the productive process.

We offer a possible explanation for this result, which is worthy of investigation: in section 4.2 we noted that the TFP distribution of young firms with high ICT capital intensity dominated that of old firms of the same type. This suggests that a sprout of innovation might be occurring in this sector and that young firms, which tend to use ICT capital more intensively, might be starting to be more productive than old firms.

As with the full sample, the coefficients for control variables for the four specifications show that increasing firm size, exporting, being a young firm, and being located in a big city increase TFP.

Manufacturing. All the results in Table 25 show that increases in ICT capital raise productivity with significance in the Manufacturing sector. Moreover, the results in column (4) suggest the possibility of a concave relationship between ICT capital and TFP in this sector, but as with other samples, this will only occur at really high levels of both.

As with the full sample, and in line with the literature for the manufacturing sector (Tambe and Hitt (2012), Aboal and Tacsir (2018), Fabiani *et al.* (2005), Rybalka (2009)), coefficients for control variables show that increasing firm size, exporting, and being a young firm increase TFP. The squared age coefficient, however, is positive and statistically significant in some regressions, suggesting the possibility of a convex relationship between firm age and TFP in the Manufacturing sector. This is certainly possible, because more time in the market increases TFP, most often due to learning by doing and experience (De Kok et al. (2006)).

The coefficient for the "big city" effect is negative and significant, implying that being in a big city lowers productivity for a manufacturing firm. Put another way, firms located outside of big cities are the most productive firms. This can be explained by industrial policy in Ecuador, which has motivated firms to locate their plants on the peripheries of cities, not inside them. This is certainly a good hypothesis to be tested empirically in further research.

The coefficient of technology intensity is negative and significant across all specifications, implying that firms that are high/medium-high technology intensive are *less* productive than those that are low/medium-low technology intensive. These results contradict those of Khanna and Sharma (2021), who show that firms in high-technology industries are more productive than those in low-technology industries in India. For Ecuadorian firms, Camino (2021) estimates the production function in subsamples by technological intensity of firms and finds that the output elasticity of capital declines as technological intensity of the firms increases. Also, firm age and international linkages matter are key determinants of productivity, and firms in low-tech industries benefit more from international trade activities than firms in more technologically intense industries. We believe our results rely on the fact that the core of the Ecuadorian economy is not manufacturing in technology-intensive industries, but instead associated to primary production. This is certainly another hypothesis to be tested in further research.

The results from the TWFE model shown in Table 31 only confirm the positive effects regarding the share of ICT capital. They also indicate that being a high ICT firm reduces TFP.

Moreover, in this model, the possibility of a convex relationship between the level of ICT capital and productivity exists, this might be true for very large firms in the Manufacturing sector.

Commerce. The results presented in column (1) of Table 26 show that having ICT capital above the sector median increases productivity with significance in the Commerce sector. Moreover, in this sector, increasing ICT capital's share of total capital does not have an effect on TFP. The results in columns (3) and (4) suggest the possibility of a concave relationship between ICT capital and TFP in this sector, although both must be at extremely high levels for this possibility to be meaningful.

As with the full sample, however, the results in Table 32 (i.e., from the TWFE model) show that an ICT capital level above the sector median decreases TFP, whereas increasing ICT capital's share of total capital increases TFP, both with significance.

The coefficients for control variables for the four specifications show that increasing firm size and exporting increase TFP. The squared age coefficient is positive and statistically significant in all regressions, implying a robust convex relationship between firm age and TFP in the Commerce sector. This is certainly possible, because more time in the market increases TFP, most often due to learning by doing and experience.

Unexpectedly for this sector, the location in a big city reduces productivity with significance. We offer a possible cause for this: being a low value added sector, the regulations imposed by the authorities in big cities regarding business operations may be imposing additional transaction costs and constraining the possibilities for development and productivity, particularly for MSMEs.

Services. The results presented in columns (1) and (2)of Table 27 point to different conclusions. Column (1) shows that having ICT capital above the sector median decreases TFP, whereas column (2) shows that increasing ICT capital's share of total capital increases TFP, with both sets of results being significant. Moreover, the results in column (3) suggest the possibility of a negative relationship between ICT capital and TFP in this sector.

Taken together, these results indicate on the one hand that investing in ICT capital increases TFP up to a point, especially if a firm is below the median and, on the other, that increasing the share of ICT capital always increases TFP. This suggests that the most productive services firms in Ecuador do not benefit from large investments in ICT capital, although devoting some of their capital investments toward ICT would be beneficial. This is expected for this sector, as it is dominated by small firms that are less knowledge intensive and do not require large ICT capital investments to be productive. For instance, most of the software these companies use is free or can be acquired at very low cost, thereby causing ICT capital investment to be associated to lower coefficients. Moreover, beyond capital investment, the effect of ICT on TFP is more related to how a firm *uses* it, particularly in this sector; therefore, variables such as the ICT skills of the labor force, digital marketing strategies, etc., would certainly contribute to TFP. Not surprisingly, the low R-squared of

the specifications suggests there are other factors that explain TFP in the sector. We explore the use of ICT in the smaller sample at the end of this section.

As with the full sample, the coefficients for control variables for the four specifications show that increasing firm size, exporting, being a young firm, and being located in a big city increase TFP.

The dummy that accounts for the intensity of knowledge in the service offered to consumers provides evidence of a negative relationship with productivity. In Ecuador, Simbaña & Carrion (2021) estimate the effect of being in a knowledge-intensive sector and its interaction with firm size. Their results contradict ours: the coefficient of knowledge intensive is positive and significant, with a premium for larger firms. It should be noted that their model differs from ours in that the covariates include return on assets, foreign direct investment, long term debt, marketing expenditures, and income tax payment, among others. However, when we analyze the Service sector, we observe that most of the firms have a low intensity of knowledge. This implies that firms operating in higher knowledge sectors are less productive than their low knowledge counterparts. Thus, although the Service sector in Ecuador is important in terms of the number of firms, its contribution to productivity is limited and its level of sophistication is incipient. This result therefore raises the research question: What is dragging down the productivity of the high knowledge sectors below that of low knowledge sectors? This presents a quite interesting avenue for further research.

In line with the result from the pooled OLS model, Table 33 shows the results of the TWFE model of equation 7. Column (1) shows that having an ICT capital level above the sector median decreases TFP, whereas increasing ICT capital's share of total capital, increases TFP, both with significance. The occurrence of such result with the two models suggest a robust result for the Service sector. Thus, as with the full sample, high investments on ICT capital are detrimental in the Service sector to increase TFP. On the other hand, however, devoting an increasing share of capital investments to ICT capital seems to generate large TFP gains. Moreover, in this model, the possibility of a convex relationship between the level of ICT capital and productivity is statistically significant, something that might be true for very large service firms.

4.3.3 Chequeo Digital

In this section, we report the results on TFP determinants for the sample of 190 firms with complete information on the relevant variables for 2021, using the Chequeo Digital data set. We argue that digital technology adoption matters for firm performance and productivity and that it involves not only ICT capital, but also other complementary factors that lead to firm performance and productivity.

Preliminary results on the data collected for Latin American countries through Chequeo Digital presented in IDB (2022) indicate that there is a bias toward firms' technology acquisition, while they lack development of digital abilities. Specifically, over 90% of the firms in Latin America that completed the questionnaire report greater technological equipment availability than digital abilities.

As discussed in Bloom et al. (2010) and Spiezia (2012), strong complementarities between ICT capital and certain "intangibles" such as management practices and organizational structures are relevant for firm productivity. Moreover, microeconomic studies need to focus on the complexity of the relationship of technology and productivity, specifically that to take advantage of ICT capital and investments, firms must make significant investments in digital capabilities for business organization, practices, and human capital.

Cusolito et al. (2020) estimate TFP of manufacturing firms, adopting digital technology in 82 developing economies for the period 2002 to 2019. Email adoption, website adoption, managerial experience, and exporting status are the key variables that they use in the analysis. They find that changes in digital technology adoption are labor and capital augmenting. Dutz *et al.* (2018) confirm that digital technology adoption offers a pathway to higher productivity in a group of Latin American economies.

Following this literature and in order to add to the analysis, we explore the role of several proxies for these variables regarding firm digital capabilities using firm responses to the Chequeo Digital questionnaire. We select 11 questions that may well be related to productivity and organize them according to four dimensions: digital skills, organizational capacity, digital communication, and processes. More details on the questions are presented in Appendix C.

The specification includes these 11 variables and results for estimates are shown in Table 34. It shows 6 columns with different measures of ICT capital: (1) ICT capital intensity, (2) the share of ICT capital, (3) the log of ICT capital, (4) a quadratic function of the level of ICT capital, (5) ICT capital intensity and the share of ICT capital jointly, and (6) no ICT capital measures. We also include in the estimation control variables for firm size, export status, age and age squared, big city location, and sector indicator variables.

The first panel of the table shows ICT capital variables, the next displays firm digital capabilities variables, and the last one shows control variables results for this sample of firms. In contrast with the full sample results, there is no evidence of an effect of ICT capital measures on TFP.

Regarding firm digital capabilities, the results related to which can be seen in the second panel, the coefficient of digital training, a variable that indicates whether firm employees received education or training on digital issues, is significant at the 10% level with an average value of 0.07, providing evidence of a positive impact on TFP. This might be in accordance with the literature that highlights the relevance of digital skills for productivity (Bloom et al. (2010), Konings and Vanormelingen (2015), Branco *et al.* (2018), Sorbe *et al.* (2019)).

There is no conclusive evidence that other firm digital capabilities have any effect on TFP. Our results might be limited by the variables' measurement approach. Those variables are perception-based measures of digital adoption and behaviors in the firm that may be capturing several different views and understandings of how advanced the firm is regarding digital maturity and of the firm's skills, organizational capacity, and communication practices and processes.

To sum up, there are two findings that we intend to interpret: (i) the lack of statistical significance of the ICT capital variable and (ii) the statistical relevance of just one variable

related to the use of digital technologies. Although these might be driven by the small number of formal firms that answered the survey, we suggest one possible explanation that has to do with how the firms use their ICT capital. The logic is that if workers and managers do not use their resources effectively, productivity gains from such resources can be missed. Thus, the results of this section suggest that this is the case for this sample, as the only variable related to digital capabilities showing a statistically significant effect is workers' training in them. Therefore, our results seem to favor the thesis that beyond ICT capital investment, what really drives TFP from ICTs is the human capital investment that enables firms to use ICT more effectively.

The last panel shows results for the control variables. The coefficients for export status and age remain significant and with the same sign reported before, but show much larger effects on productivity for this sample. Similarly, the indicator variable for location in a big city in this sample is significant and provides evidence of a much larger productivity for firms located in the two main cities of the country.

5 Concluding Remarks

The role of ICT adoption of firms in order to meet the digitalization challenge is fundamental and ICT's contribution to productivity is well established in the literature for both developed and developing economies. However, while the latter need to catch up in several aspects, evidence is needed to support specific interventions. We contribute to the understanding of productivity and its determinants across different economic sectors and specifically the impact of ICT capital. This is of particular interest because the benefits of ICTs may differ among sectors, with diverse economic implications.

We study this issue in a developing economy setting, building a novel data set that merges three different public sources of information. Our approach is also novel, in the sense that we use a capital augmented production function, splitting ICT and non-ICT capital of firms to identify specific effects on output and productivity. We estimate our models using a combined comprehensive micro data set that includes data on Ecuadorian firms' characteristics and financial information and data on a smaller sample of firms collected using qualitative firm digital capability measures on digital technology use and organizational variables by means of the web-based tool Chequeo Digital.

Our results provide empirical evidence of a positive effect of ICT capital share on TFP, except for Ecuadorian firms with ICT capital above the median value, meaning that though higher ICT investment is good for productivity it shows decreasing returns. In the full sample analysis, age, size, firm location, and export-orientation matter for Ecuadorian firms' productivity: firms that are younger, larger, located in big cities, and export oriented seem to be more productive. Sector differences in productivity are also evident: agriculture is the most productive sector in the sample, consistent with the country's exporting tradition and orientation.

We are able to relate ICT capital intensity and the benefits in productivity of several heterogeneities. Also, for manufacturing firms, we find a negative and significant effect of

technology intensity, that is, technology intensive firms display a lower productivity than less technology intensive firms. Because they are exporters, firms in low-tech industries are more productive than firms in more technologically intense industries. Again, we believe this is driven by the fact that the Ecuadorian manufacturing industry is mainly associated to primary production and exports.

The service industry has significant relevance in the literature and in the Ecuadorian economy for being the sector with the largest number of firms; such firms, however, are mostly MSMEs and have little knowledge intensity. They could only obtain limited ICT capital productivity gains inherent to their activity's scope. Our takeaway from this analysis is that the role of ICT capital for this group of firms depends on the particular choice of combination of ICT investments and resources such as management abilities, digital skills, and other intangibles.

Overall, our results point out several opportunities for policy making. Providing firms with an environment that fosters the strategic decision-making process regarding ICT investments can create benefits for both firms and the industry as a whole. The rise in TFP could be even more significant in the Agricultural and Manufacturing sectors of Ecuador. The positive effect of digital training at the firm level (found for the sample of Chequeo Digital firms) could potentially enhance this productivity effect. That is, combining smart ICT investment policy with the development of adequate human skills for the adoption and use of digital technologies could bring powerful results in terms of the TFP of Ecuadorian firms.

We acknowledge as a limitation the fact that our measure of ICT capital includes only computer equipment and software, because we are not able to measure and include other resources as other hardware, communications equipment, and other software that may be reported as office materials. Also, the small sample size of Chequeo Digital firms leads to results that diverge to some extent from those of the full sample, specifically for ICT impacts on productivity. It would help to have Chequeo Digital-type data from a considerable number of firms to match with the SCVS data set; this would be possible by further promoting the use of tools such as Chequeo Digital among firms in Ecuador.

These results raise a few questions that point to interesting avenues for further research. The significant effect of digital training as shown by our smaller sample opens up an opportunity to explore more broadly the role of digital skills on firms' TFP. Also, the lower productivity of the high knowledge (services) and high technology (manufacturing) sectors in contrast with their counterparts in Ecuador is puzzling and it could be beneficial to understand the dynamics behind this phenomenon.

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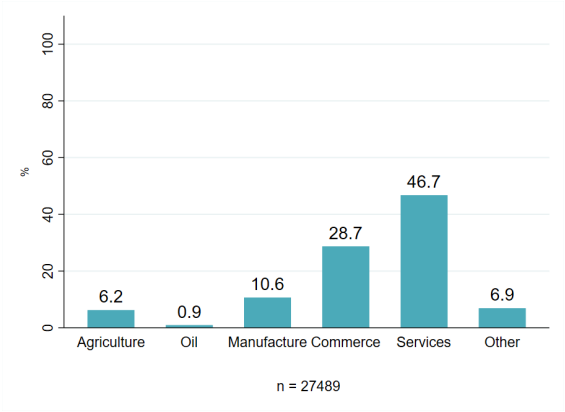
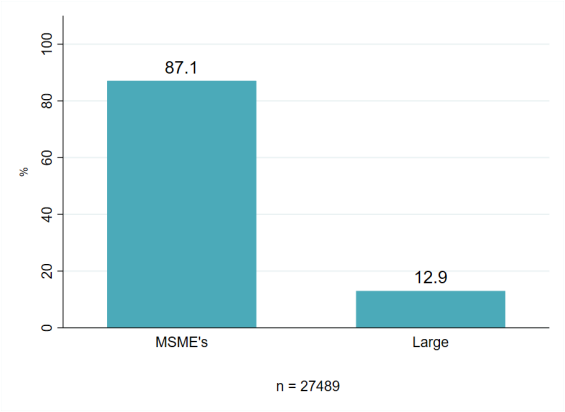
Figures and Tables

Figure 1: Firms' characteristics – Entire sample



(a) Sector



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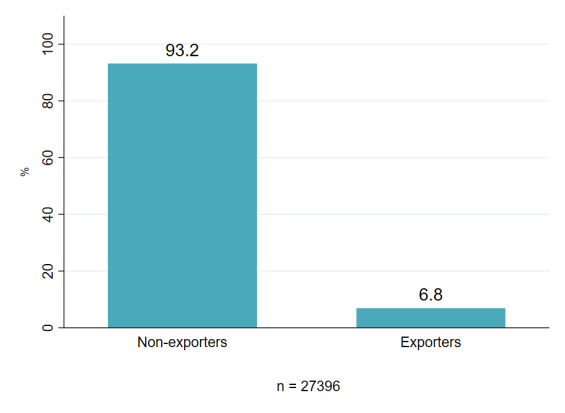

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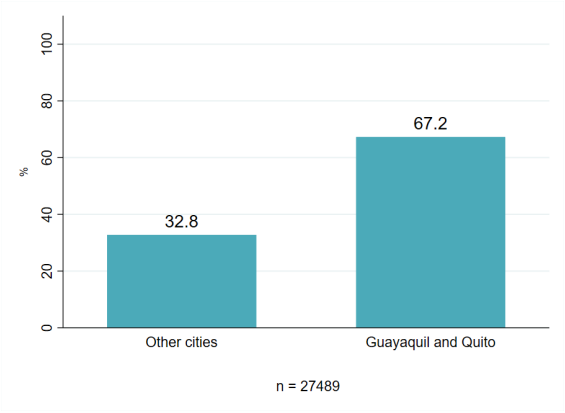
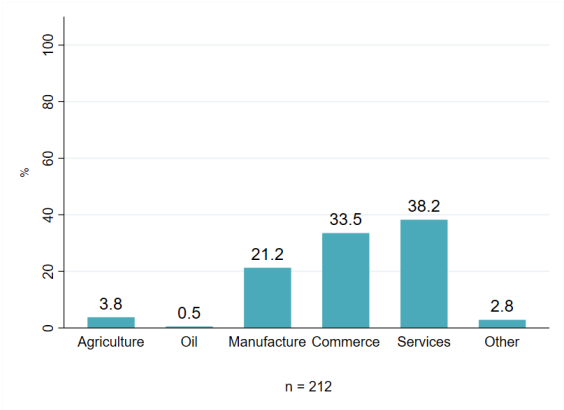


(d) Location – Cities

Figure 2: Firms' characteristics – Chequeo Digital



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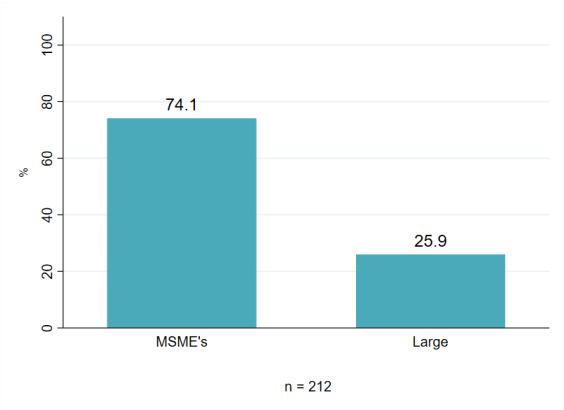

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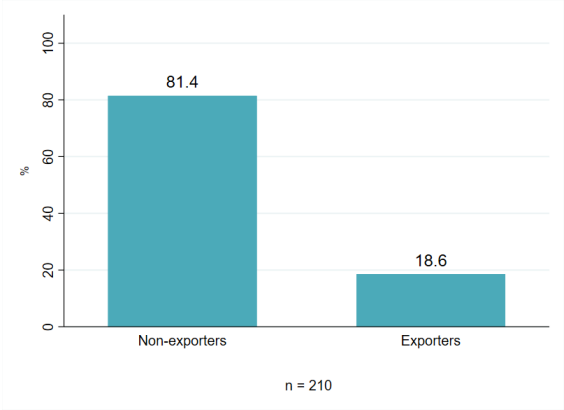


(c) Export status

(d) Location – Cities

Figure 3: Digital maturity level – Chequeo Digital

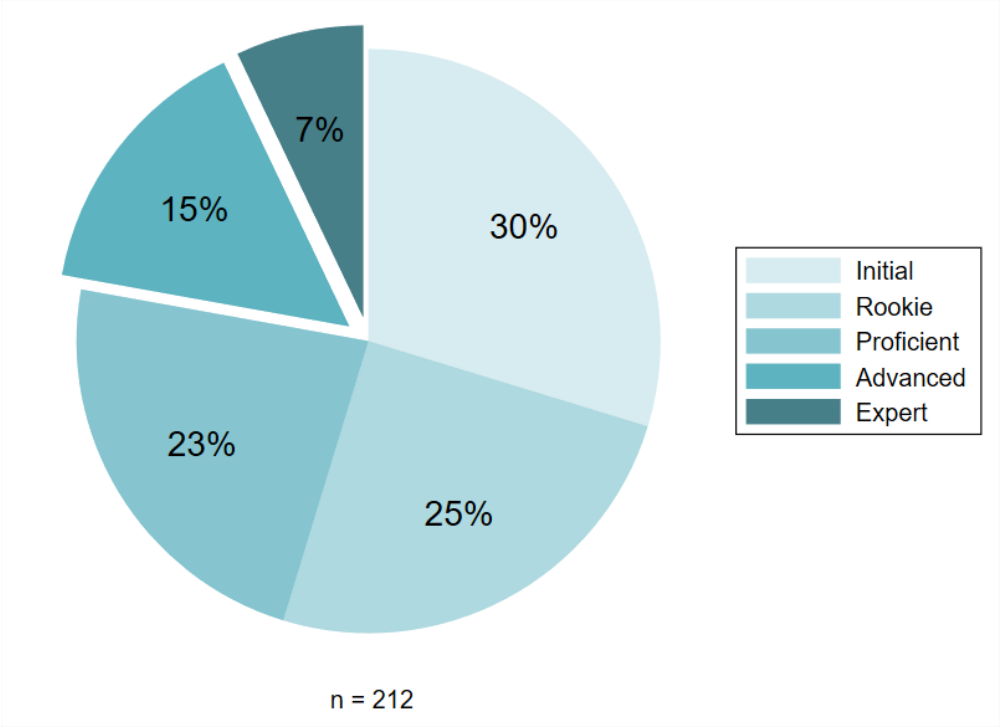
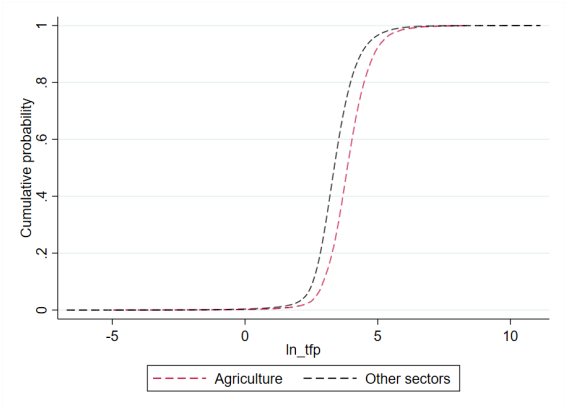


Figure 4: TFP kernel density – Sector comparison



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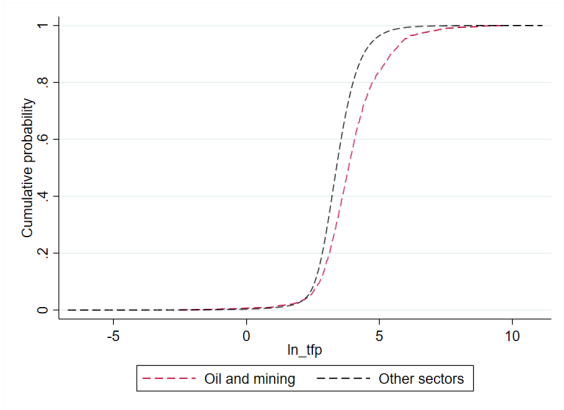

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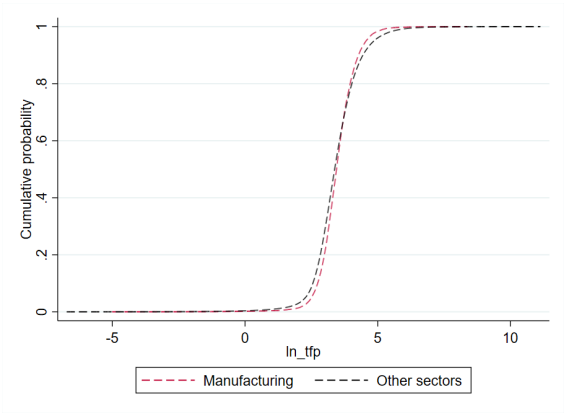

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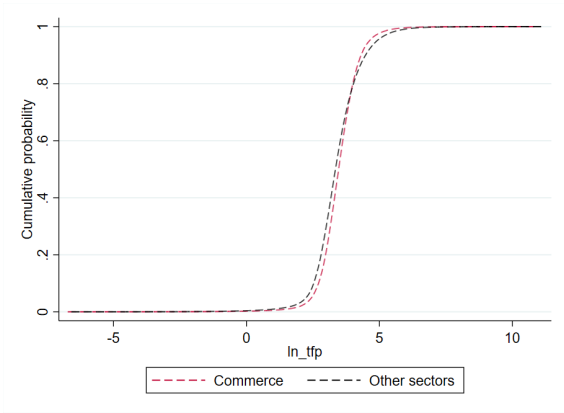

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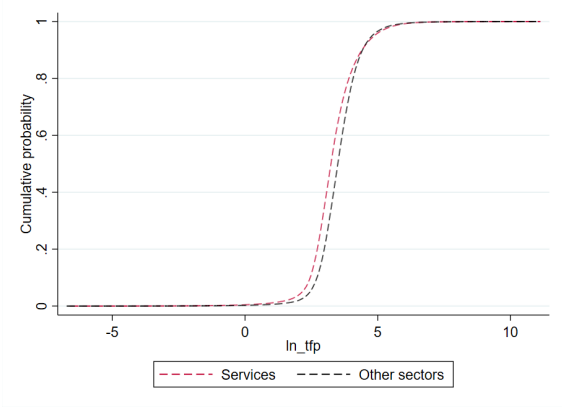
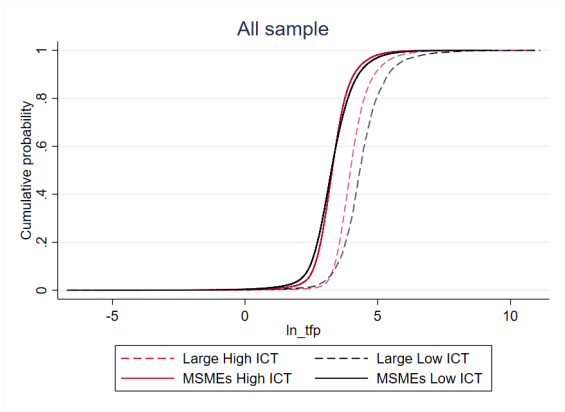


(e) Services

Figure 5: Cumulative distribution function – Heterogeneities – Entire sample



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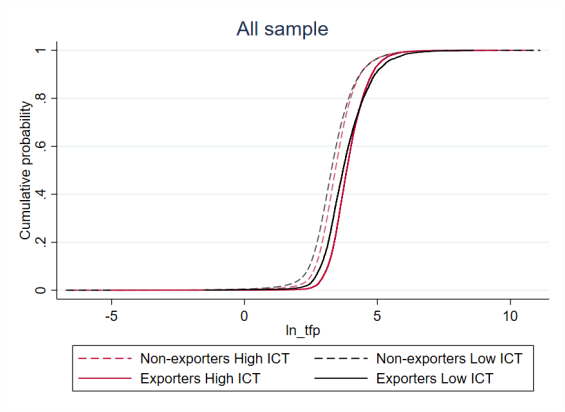
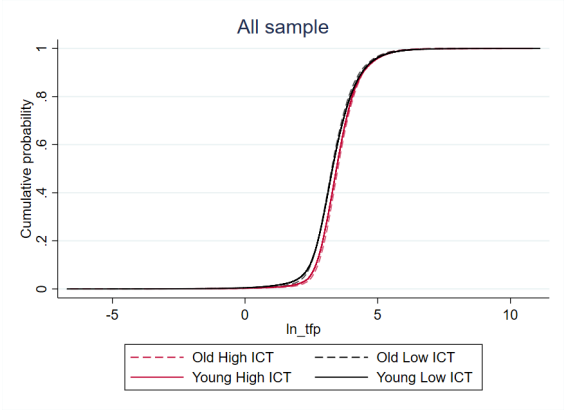


(b) International linkages



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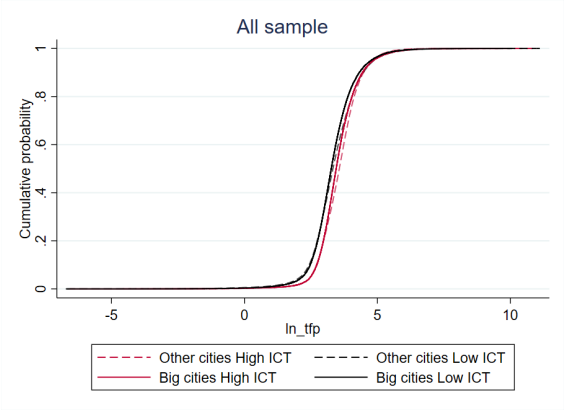
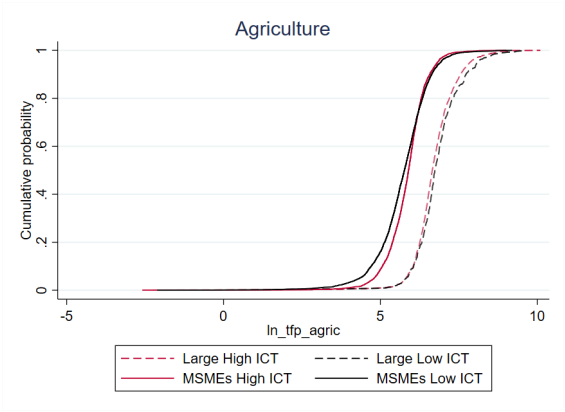


(d) Big cities

Figure 6: Cumulative distribution function – Heterogeneities – Agriculture



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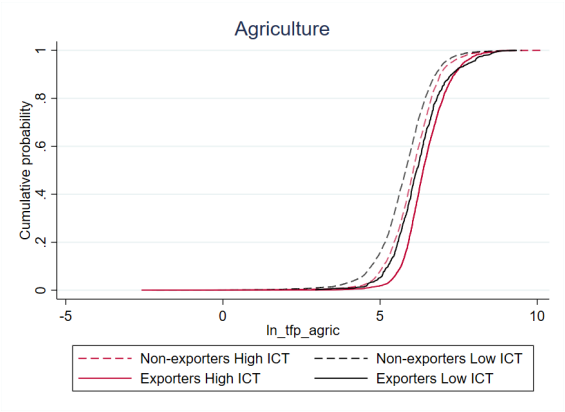

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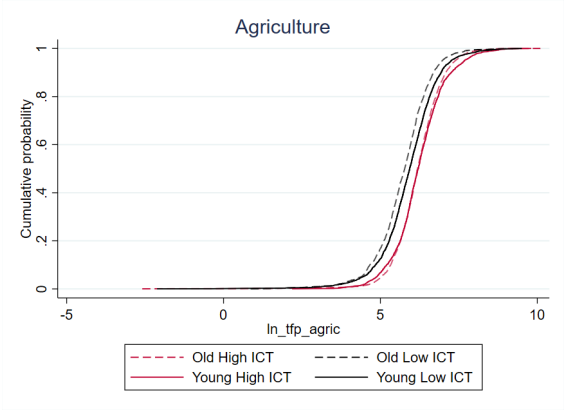

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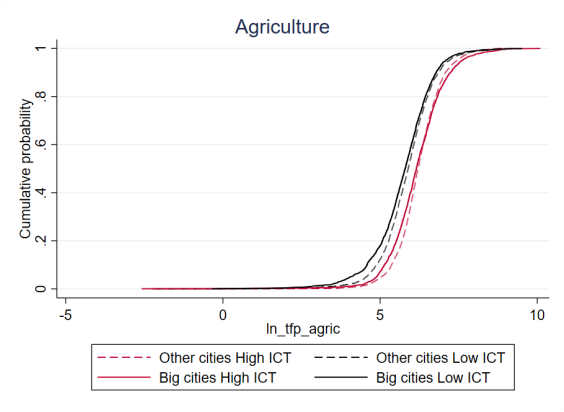

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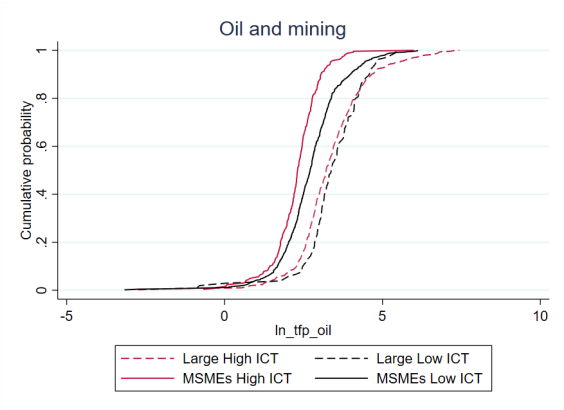
Figure 7: Cumulative distribution function – Heterogeneities – Oil and mining



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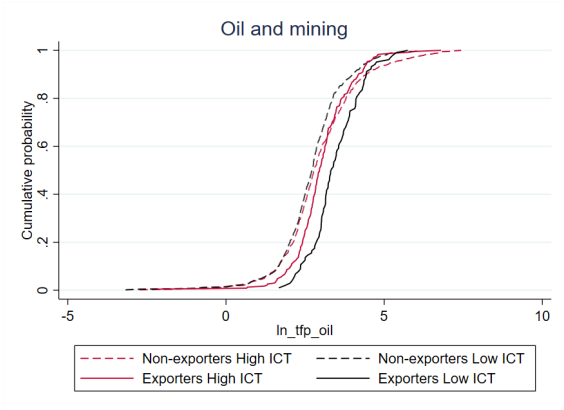

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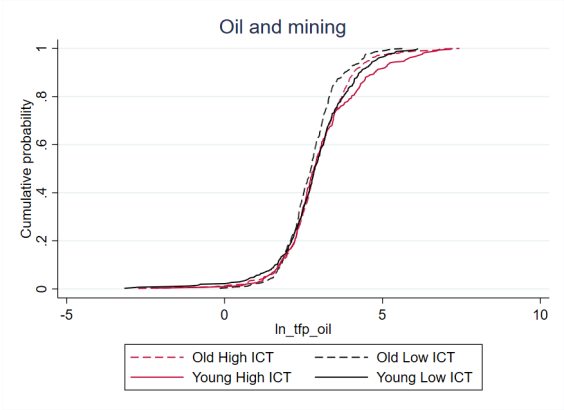

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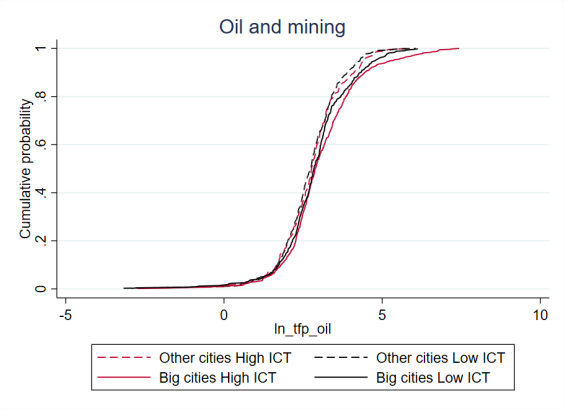

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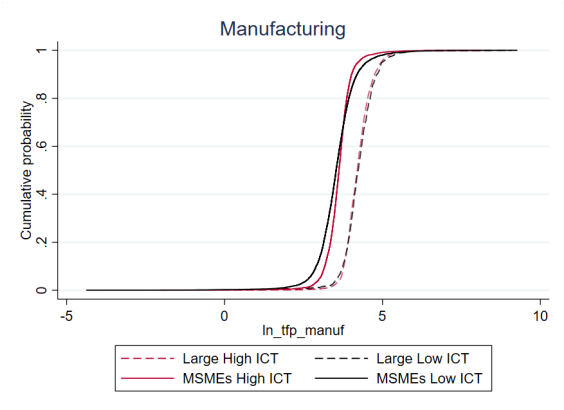
Figure 8: Cumulative distribution function – Heterogeneities – Manufacturing



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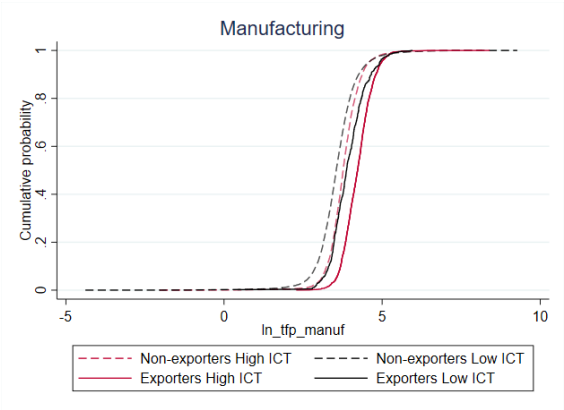

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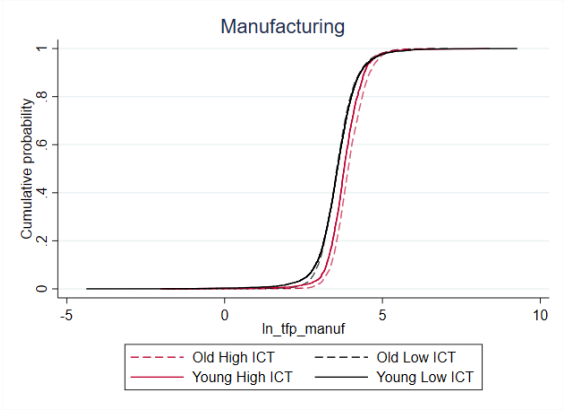

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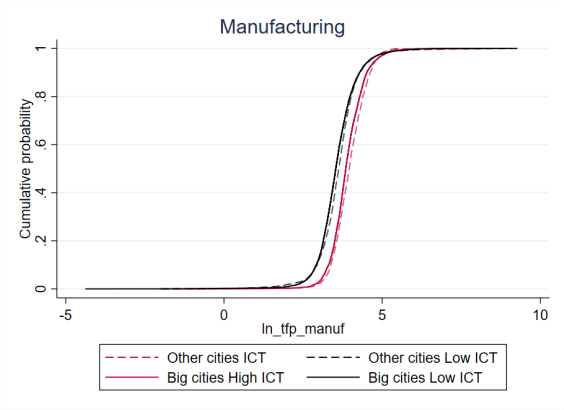

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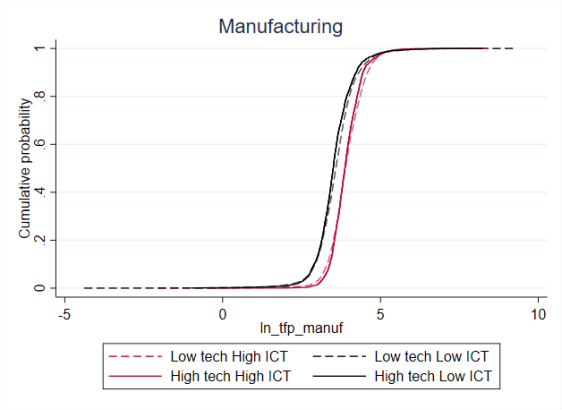

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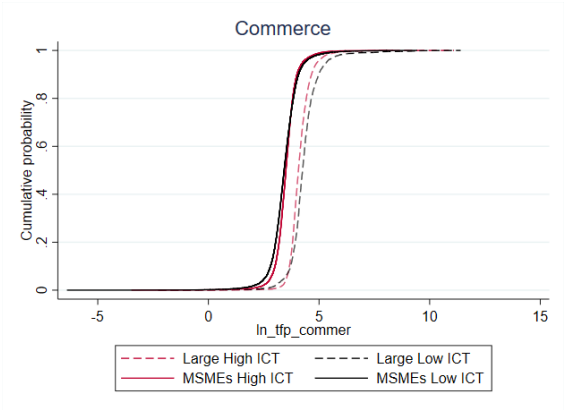
Figure 9: Cumulative distribution function – Heterogeneities – Commerce



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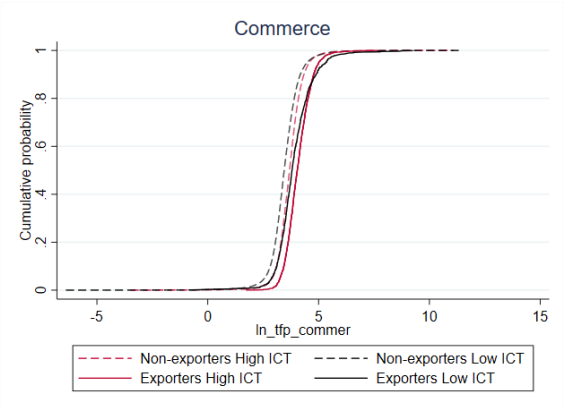

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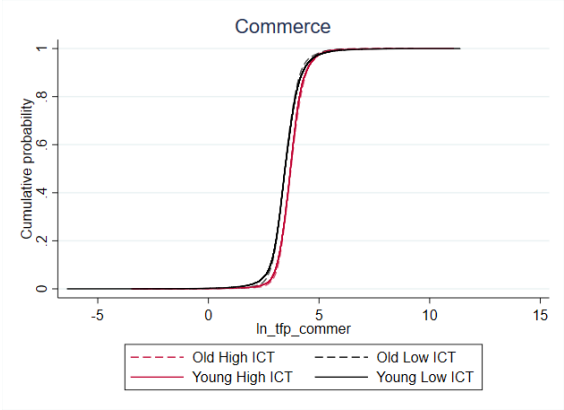
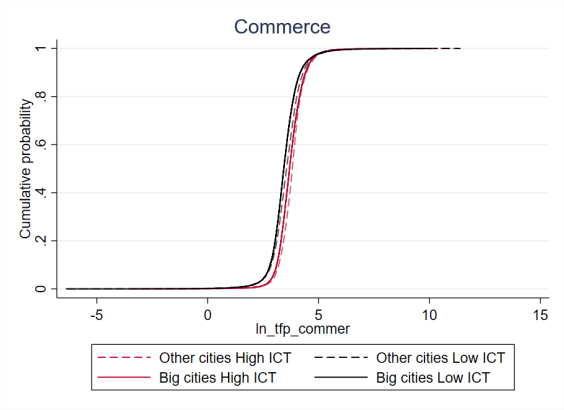
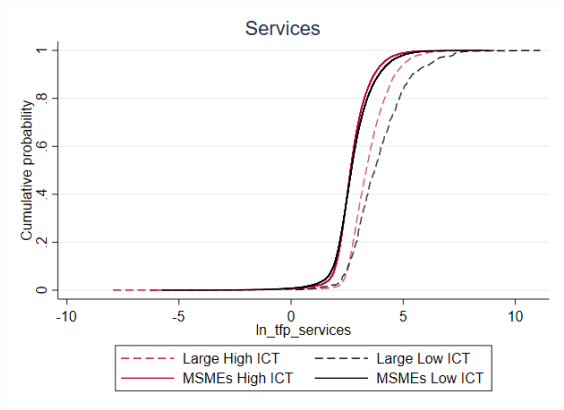


(c) Firm age

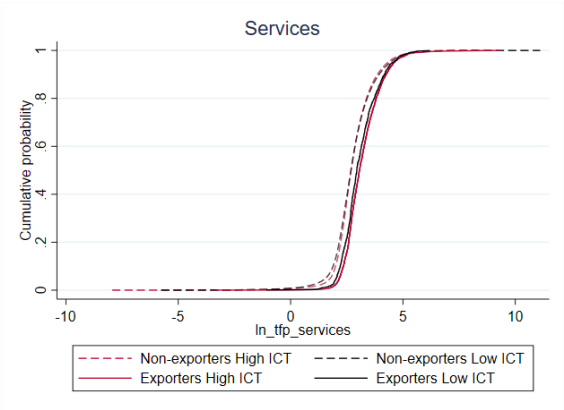


(d) Big cities

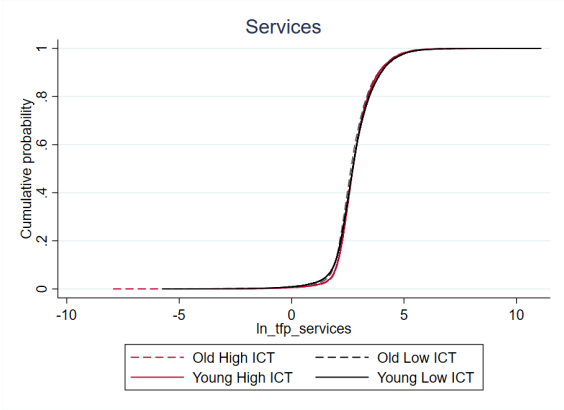
Figure 10: Cumulative distribution function – Heterogeneities – Services



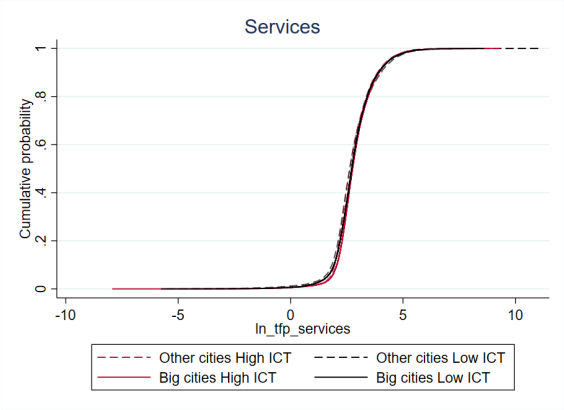
(a) Size



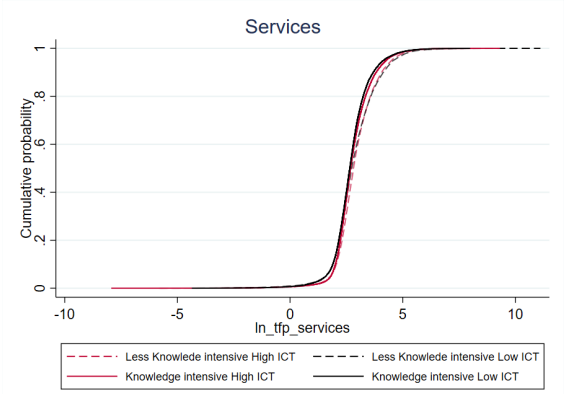
(b) International linkages



(c) Firm age



(d) Big cities



(e) Knowledge intensity

Table 1: Definition of variables

Variable	**Code**	**Definition**
Total assets	A	The value of total assets of each company in each year
Operational Income	Y	Revenue from ordinary activities = Local sales of goods and services, net exports, revenue from construction services, revenues from commissions and similar (agency relationship), and revenue from operating leasing.
Wages	L	Employee benefit expenses = wages expenses, social benefits and compensation, social security expenses, professional fees, professional fees to foreign employees, retirement expenses, employee eviction, and others.
ICT capital	ICT	Computer equipment and software
Non-ICT capital	NICT	The value of buildings, motor vehicles, machinery, construction in progress, office furniture, other property, plant, and equipment.
Intermediate inputs	M	Initial intermediate inventory + Initial inventory of products not produced by the firm + Initial inventory of products in process + Initial inventory of finished products + imports of intermediates + imports of products not produced by the firm + local net purchases of intermediates + local net purchases of products not produced by the firm + transport expenses + fuel expenses + office supplies expenses + maintenance and reparation expenses + basic service expenditure - Final inventory of intermediates - Final inventory of products in process - Final inventory of finished products - Final inventory of products not produced by the firm.

Table 2: Manufacturing – technology intensity aggregation

Technology intensity	**ISIC Rev 4**	**Description**
High	21	Pharmaceuticals, medicinal chemical and botanical products
	26	Computer, electronic and optical products
Medium-high	20	Chemical and chemical products
	27	Electrical equipment
	28	Machinery and equipment n.e.c.
	29	Motor vehicles, trailers and semitrailers
	30	Other transport equipment
Medium-low	19	Coke and refined petroleum products
	22	Rubber and plastics products
	23	Other nonmetallic mineral products
	24	Basic metals
	25	Fabricated metal products, except machinery and equipment
	33	Repair and installation of machinery and equipment
Low	10	Food products
	11	Beverages
	12	Tobacco products
	13	Textiles
	14	Wearing apparel
	15	Leather and related products
	16	Wood and wood products
	17	Paper and paper products
	18	Printing and reproduction of recorded media
	31	Furniture
	32	Other manufacturing products

Table 3: Services – knowledge intensive aggregation

Knowledge intensity	**ISIC Rev 4**	**Description**
	H50	Water transport
	H51	Air transport
	J58	Publishing activities
	J59	Motion picture, video and television program production, sound recording and music publishing activities
	J60	Programming and broadcasting activities
	J61	Telecommunications
	J62	Computer programming, consultancy and related activities
	J63	Information service activities
	K64	Financial service activities, except insurance and pension funding
	K65	Insurance, reinsurance and pension funding, except compulsory social security
	K66	Activities auxiliary to financial service and insurance activities
Knowledge intensive	M69	Legal and accounting activities
	M70	Activities of head offices; management consultancy activities
	M71	Architectural and engineering activities, technical testing and analysis
	M72	Scientific research and development
	M73	Advertising and market research
	M74	Other professional, scientific, and technical activities
	M75	Veterinary activities
	N78	Employment activities
	N80	Security and investigation activities
	O84	Public administration and defence;=, compulsory social security
	P85	Education
	Q86	Human health activities
	Q87	Residential care activities
	Q88	Social work activities without accommodation
	R90	Creative, arts, and entertainment activities
	R91	Libraries, archives, museums, and other cultural activities
	R92	Gambling and betting activities
	R93	Sports activities and amusement and recreation activities

Table 4: Services – less knowledge intensive aggregation

Knowledge intensity	**ISIC Rev 4**	**Description**
	H49	Land transport and transport via pipelines
	H52	Warehousing and support activities for transportation
	H53	Postal and courier activities
	I55	Accommodation
	I56	Food and beverage activities
	L68	Real estate activities
	N77	Rental and leasing activities
Less knowledge	N79	Travel agency, tour operator, reservation service and related activities
intensive	N81	Services to buildings and landscape activities
	N82	Office administrative, office support, and other business support activities
	S94	Activities of membership organizations
	S95	Repair of computers and personal and household goods
	S96	Other personal service activities
	T97	Activities of households as employers of domestic personnel
	T98	Undifferentiated goods and services-producing activities of private households for own use
	U99	Activities of extraterritorial organizations and bodies

Table 5: Summary statistics – Production function variables

	Mean	sd	min	max	N
Panel A: Entire sample					
Operating income	3,409	25,587	0	2,149,390	167,649
Wages	292	1,646	0	124,461	167,649
Intermediate inputs	1,866	14,368	0	1,165,630	167,649
ICT capital	46	768	0	128,303	167,649
Non-ICT capital	1,058	13,640	0	1,745,944	167,649
Panel B: Agriculture					
Operating income	3,635	13,713	0	359,840	10,283
Wages	184	620	0	14,191	10,283
Intermediate inputs	2,126	9,586	0	224,663	10,283
ICT capital	19	100	0	3,261	10,283
Non-ICT capital	1,647	8,168	0	280,250	10,283
Panel C: Oil and mining					
Operating income	17,787	74,832	0	1,122,029	1,550
Wages	1,191	5,307	0	73,821	1,550
Intermediate inputs	2,822	13,307	0	222,338	1,550
ICT capital	196	1,346	0	25,449	1,550
Non-ICT capital	6,794	29,739	0	510,802	1,550
Panel D: Manufacturing					
Operating income	6,557	28,439	0	781,084	20,039
Wages	431	1,818	0	62,562	20,039
Intermediate inputs	3,845	17,678	0	570,611	20,039
ICT capital	66	336	0	15,527	20,039
Non-ICT capital	2,721	12,427	0	310,187	20,039
Panel E: Commerce					
Operating income	4,732	28,869	0	1,571,267	50,783
Wages	337	1,908	0	108,053	50,783
Intermediate inputs	3,492	22,435	0	1,165,630	50,783
ICT capital	47	545	0	39,962	50,783
Non-ICT capital	573	5,457	0	420,089	50,783
Panel D: Services					
Operating income	1,501	22,695	0	2,149,390	74,181
Wages	238	1,397	0	124,461	74,181
Intermediate inputs	338	3,749	0	308,035	74,181
ICT capital	45	1,029	0	128,303	74,181
Non-ICT capital	732	17,918	0	1,745,944	74,181

Note: Variables in thousands of 2007 USD.

Table 6: Summary statistics – Chequeo Digital

	Mean	**SD**	**Min**	**Max**	***N***
Operating income	13,311	77,926	0	924,521	212
Wages	1,031	6,018	4	82,504	212
Intermediate inputs	7,286	52,120	0	733,244	212
ICT capital	362	3,401	0	48,918	212
Non-ICT capital	4,074	21,969	0	252,692	212

Note: Variables in thousands of 2007 USD.

Table 7: Summary statistics – Chequeo Digital questionnaire variables

Variable	**Mean**	**Median**	**sd**	**Min**	**Max**	**N**
Digital skills						
Digital training	3.93	4	1.986876	1	7	190
Ease of use of digital technologies	5.10	5	1.990852	1	7	190
Organizational capacity						
Digital technology importance	6.39	7	1.067011	3	7	190
Work flexibility	5.03	4	1.527297	1	7	190
Teleworking	2.02	2	0.712384	1	3	190
Digital communication						
Online presence	5.16	6	2.06157	1	7	190
Digital communication in the workplace	5.92	7	1.569915	1	7	190
Digital communication with clients	2.94	3	0.946288	1	4	190
Digital communication with providers	5.27	5	1.745392	1	7	190
Processes						
Digital technology on processes	4.30	4	1.79048	1	7	190
Proccess automation	4.08	4	1.645606	1	7	190

Table 8: Production function estimation – Entire sample

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP - ACF	(8) WDRG	(9) MR
Wages	0.347***	0.273***	0.236***	0.538***	0.586***	0.342***	0.338***	0.391***	0.382***
	(0.002)	(0.004)	(0.004)	(0.005)	(0.006)	(0.003)	(0.009)	(0.002)	(0.005)
Non-ICT capital	0.114***	0.114***	0.082***	0.070***	0.214***	0.145***	0.079***	0.096***	0.102***
	(0.001)	(0.002)	(0.003)	(0.008)	(0.003)	(0.001)	(0.006)	(0.003)	(0.003)
ICT capital	0.109***	0.112***	0.070***	0.156***	0.144***	0.144***	0.103***	0.085***	0.090***
	(0.002)	(0.003)	(0.004)	(0.021)	(0.011)	(0.001)	(0.013)	(0.004)	(0.005)
Intermediate inputs	0.396***	0.358***	0.325***			0.304***	0.406***	0.296***	0.272***
	(0.001)	(0.003)	(0.004)			(0.004)	(0.005)	(0.002)	(0.007)
Constant	2.378***	3.557***	5.096***						
	(0.016)	(0.034)	(0.058)						
Observations	167,649	167,649	167,649	125,570	125,570	167,649	167,649	135,670	167,649
Number of groups		27,489	27,489	25,489	25,489	27,489	27,489	27,489	27,489

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p <0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 9: Production function estimation – Agriculture

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP - ACF	(8) WDRG	(9) MR
Wages	0.191***	0.144***	0.122***	0.336***	0.414***	0.163***	0.233***	0.179***	0.183***
	(0.008)	(0.011)	(0.012)	(0.021)	(0.021)	(0.012)	(0.021)	(0.006)	(0.016)
Non-ICT capital	0.188***	0.181***	0.158***	0.088**	0.213***	0.203***	0.114***	0.162***	0.181***
	(0.006)	(0.011)	(0.014)	(0.044)	(0.053)	(0.009)	(0.031)	(0.011)	(0.016)
ICT capital	0.080***	0.087***	0.055***	0.190***	0.109***	0.132***	0.066**	0.055***	0.060***
	(0.006)	(0.010)	(0.010)	(0.046)	(0.027)	(0.018)	(0.033)	(0.012)	(0.013)
Intermediate inputs	0.419***	0.314***	0.260***			0.272***	0.462***	0.263***	0.128***
	(0.007)	(0.013)	(0.015)			(0.011)	(0.011)	(0.006)	(0.017)
Constant	3.427***	5.245***	6.737***						
	(0.080)	(0.166)	(0.242)						
Observations	10,283	10,283	10,283	7,645	7,645	10,283	10,283	8,326	10,283
Number of groups		1,701	1,701	1,559	1,559	1,701	1,701	1,701	1,701

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 10: Production function estimation – Oil and mining

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP - ACF	(8) WDRG	(9) MR
Wages	0.319***	0.290***	0.276***	0.422***	0.464***	0.304***	0.334***	0.353***	0.316***
	(0.029)	(0.038)	(0.041)	(0.035)	(0.021)	(0.041)	(0.025)	(0.027)	(0.047)
Non-ICT capital	0.186***	0.184***	0.197***	0.096	0.204***	0.192***	0.156***	0.192***	0.203***
	(0.018)	(0.035)	(0.053)	(0.091)	(0.065)	(0.039)	(0.042)	(0.039)	(0.041)
ICT capital	0.306***	0.196***	0.095**	0.359***	0.357***	0.311***	0.345***	0.193***	0.205***
	(0.023)	(0.036)	(0.043)	(0.068)	(0.045)	(0.050)	(0.062)	(0.044)	(0.050)
Intermediate inputs	0.253***	0.250***	0.240***			0.237***	0.218***	0.233***	0.239***
	(0.020)	(0.037)	(0.040)			(0.044)	(0.055)	(0.017)	(0.038)
Constant	2.095***	3.542***	4.570***						
	(0.206)	(0.371)	(0.513)						
Observations	1,550	1,550	1,550	1,167	1,167	1,550	1,550	1,266	1,550
Number of groups		249	249	238	238	249	249	249	249

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 11: Production function estimation – Manufacturing

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP-ACF	(8) WDRG	(9) MR
Wages	0.239***	0.197***	0.173***	0.519***	0.598***	0.225***	0.230***	0.248***	0.234***
	(0.007)	(0.010)	(0.011)	(0.016)	(0.018)	(0.009)	(0.008)	(0.004)	(0.011)
Non-ICT capital	0.123***	0.123***	0.085***	0.081**	0.215***	0.143***	0.087***	0.110***	0.119***
	(0.004)	(0.007)	(0.009)	(0.034)	(0.033)	(0.007)	(0.018)	(0.006)	(0.009)
ICT capital	0.073***	0.083***	0.044***	0.153***	0.123***	0.104***	0.065***	0.054***	0.062***
	(0.004)	(0.007)	(0.007)	(0.022)	(0.024)	(0.011)	(0.005)	(0.007)	(0.008)
Intermediate inputs	0.523***	0.474***	0.436***			0.432***	0.524***	0.410***	0.367***
	(0.007)	(0.013)	(0.015)			(0.019)	(0.010)	(0.004)	(0.025)
Constant	2.094***	3.073***	4.677***						
	(0.040)	(0.100)	(0.191)						
Observations	20,039	20,039	20,039	15,495	15,495	20,039	20,039	16,794	20,039
Number of groups		2,925	2,925	2,803	2,803	2,925	2,925	2,925	2,925

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 12: Production function estimation – Commerce

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP-ACF	(8) WDRG	(9) MR
Wages	0.288***	0.240***	0.208***	0.647***	0.708***	0.256***	0.303***	0.281***	0.272***
	(0.005)	(0.007)	(0.008)	(0.013)	(0.016)	(0.006)	(0.006)	(0.003)	(0.008)
Non-ICT capital	0.072***	0.067***	0.046***	0.023	0.138***	0.087***	0.038***	0.062***	0.067***
	(0.002)	(0.004)	(0.004)	(0.037)	(0.027)	(0.006)	(0.006)	(0.004)	(0.005)
ICT capital	0.068***	0.073***	0.039***	0.149***	0.119***	0.103***	0.069***	0.057***	0.062***
	(0.003)	(0.004)	(0.005)	(0.036)	(0.030)	(0.007)	(0.005)	(0.005)	(0.006)
Intermediate inputs	0.536***	0.504***	0.469***			0.463***	0.543***	0.429***	0.402***
	(0.004)	(0.008)	(0.010)			(0.010)	(0.008)	(0.003)	(0.017)
Constant	1.991***	2.929***	4.265***						
	(0.028)	(0.067)	(0.120)						
Observations	50,783	50,783	50,783	38,017	38,017	50,783	50,783	41,898	50,783
Number of groups		7,882	7,882	7,354	7,354	7,882	7,882	7,882	7,882

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 13: Production function estimation – Services

Variables	(1) OLS	(2) RE	(3) FE	(4) OP	(5) OP - ACF	(6) LP	(7) LP-ACF	(8) WDRG	(9) MR
Wages	0.389***	0.310***	0.265***	0.514***	0.583***	0.409***	0.405***	0.480***	0.467***
	(0.003)	(0.005)	(0.006)	(0.007)	(0.016)	(0.005)	(0.007)	(0.003)	(0.007)
Non-ICT capital	0.092***	0.110***	0.089***	0.060***	0.150***	0.105***	0.070***	0.085***	0.090***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.009)	(0.003)	(0.004)	(0.005)	(0.005)
ICT capital	0.143***	0.145***	0.099***	0.194***	0.124***	0.158***	0.148***	0.115***	0.120***
	(0.003)	(0.005)	(0.007)	(0.001)	(0.028)	(0.006)	(0.009)	(0.007)	(0.008)
Intermediate inputs	0.336***	0.284***	0.256***			0.249***	0.341***	0.237***	0.229***
	(0.002)	(0.004)	(0.005)			(0.004)	(0.005)	(0.003)	(0.008)
Constant	2.497***	3.639***	5.040***						
	(0.026)	(0.052)	(0.088)						
Observations	74,181	74,181	74,181	55,470	55,470	74,181	74,181	58,906	74,181
Number of groups		12,847	12,847	11,797	11,797	12,847	12,847	12,847	12,847

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income.

Table 14: Production function estimation – Chequeo Digital

Variables	(1) OLS
Wage and salaries	0.471***
	(0.088)
Non-ICT capital	0.040
	(0.044)
ICT capital	0.105**
	(0.047)
Intermediate inputs	0.421***
	(0.057)
Constant	1.373***
	(0.416)
Observations	212
R-squared	0.869

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Note: Variables in logarithms. Dependent variable: Logarithm of Operational Income. Estimation year: 2021.

Table 15: Kolmogorov-Smirnov test – Heterogeneities – Entire sample

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.014***	0.290	-0.249	0.000	0.249	0.000	Higher TFP for low ICT firms
	MSMEs	0.060	0.000	-0.042	0.000	0.060	0.000	About the same
International Linkages	Non-exporters	0.103	0.000	-0.002***	0.703	0.103	0.000	Higher TFP for high ICT firms
	Exporters	0.127	0.000	-0.028***	0.019	0.127	0.000	Higher TFP for high ICT firms
Firm age	Old	0.149	0.000	-0.001***	0.969	0.149	0.000	Higher TFP for High ICT firms
	Young	0.097	0.000	-0.001***	0.969	0.097	0.000	Higher TFP for High ICT firms
Big cities	Other cities	0.135	0.000	-0.009***	0.130	0.135	0.000	Higher TFP for high ICT firms
	Big cities	0.126	0.000	-0.001***	0.981	0.126	0.000	Higher TFP for high ICT firms

Table 16: Kolmogorov-Smirnov test – Heterogeneities – Agriculture

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.006***	0.971	-0.089	0.001	0.089	0.003	Higher TFP for low ICT firms
	MSMEs	0.119	0.000	-0.025***	0.094	0.119	0.000	Higher TFP for high ICT firms
International linkages	Non-exporters	0.146	0.000	-0.001***	0.998	0.146	0.000	Higher TFP for high ICT firms
	Exporters	0.162	0.000	-0.023***	0.619	0.162	0.000	Higher TFP for high ICT firms
Firm age	Old	0.248	0.000	-0.002***	0.993	0.248	0.000	Higher TFP for high ICT firms
	Young	0.167	0.000	-0.001***	0.996	0.167	0.000	Higher TFP for high ICT firms
Big cities	Other cities	0.211	0.000	-0.003***	0.977	0.211	0.000	Higher TFP for high ICT firms
	Big cities	0.191	0.000	-0.001***	0.999	0.191	0.000	Higher TFP for high ICT firms

Table 17: Kolmogorov-Smirnov test – Heterogeneities – Oil and mining

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.051**	0.636	-0.159	0.013	0.159	0.026	Higher TFP for low ICT firms
	MSMEs	0.009***	0.970	-0.260	0.000	0.260	0.000	Higher TFP for ow ICT firms
International linkages	Non-exporters	0.118	0.000	-0.005***	0.982	0.118	0.000	Higher TFP for high ICT firms
	exporters	0.009***	0.990	-0.278	0.000	0.278	0.000	Higher TFP for low ICT firms
Firm age	Old	0.127	0.001	-0.021***	0.839	0.127	0.003	Higher TFP for high ICT firms
	Young	0.067	0.216	-0.037	0.621	0.067	0.428	About the same
Big cities	Other cities	0.054	0.463	-0.029	0.805	0.054	0.836	About the same
	Big cities	0.090	0.020	-0.003**	0.997	0.090	0.040	Higher TFP for high ICT firms

Table 18: Kolmogorov-Smirnov test – Heterogeneities – Manufacturing

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.026**	0.492	-0.058	0.030	0.058	0.06	Higher TFP for low ICT firms
	MSMEs	0.148	0.000	-0.059***	0.000	0.148	0.000	Higher TFP for high ICT firms
International linkages	Non-exporters	0.213	0.000	-0.004***	0.856	0.213	0.000	Higher TFP for high ICT firms
	Exporters	0.283	0.000	-0.006***	0.973	0.283	0.000	Higher TFP for high ICT firms
Firm age	Old	0.310	0.000	-0.004***	0.92	0.31	0.000	Higher TFP for high ICT firms
	Young	0.199	0.000	-0.005***	0.931	0.199	0.000	Higher TFP for high ICT firms
Big cities	Other cities	0.278	0.000	-0.007***	0.826	0.278	0.000	Higher TFP for high ICT firms
	Big cities	0.290	0.000	-0.004***	0.905	0.290	0.000	Higher TFP for high ICT firms
Technology intensity	Low/medium-low tech	0.257	0.000	-0.005***	0.836	0.257	0.000	Higher TFP for high ICT firms
	High/medium-high	0.353	0.000	-0.005***	0.952	0.353	0.000	Higher TFP for high ICT firms

Table 19: Kolmogorov-Smirnov test – Heterogeneities – Commerce

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.024***	0.174	-0.196	0.000	0.196	0.000	Higher TFP for low ICT firms
	MSMEs	0.111	0.000	-0.025	0.000	0.111	0.000	About the same
International linkages	Non-exporters	0.198	0.000	-0.003***	0.817	0.198	0.000	Higher TFP for high ICT firms
	Exporters	0.186	0.000	-0.032***	0.172	0.186	0.000	Higher TFP for high ICT firms
Firm age	Old	0.221	0.000	-0.001***	0.990	0.221	0.000	Higher TFP for high ICT firms
	Young	0.202	0.000	-0.004***	0.817	0.202	0.000	Higher TFP for high ICT firms
Big cities	Other cities	0.219	0.000	-0.005***	0.846	0.219	0.000	Higher TFP for high ICT firms
	Big cities	0.214	0.000	-0.003***	0.850	0.214	0.000	Higher TFP for high ICT firms

Table 20: Kolmogorov-Smirnov test – Heterogeneities – Services

		Low ICT		High ICT				
Heterogeneities		**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Size	Large	0.025***	0.639	-0.179	0.000	0.179	0.000	Higher TFP for low ICT firms
	MSMEs	0.027	0.000	-0.040	0.000	0.040	0.000	About the same
International linkages	Non-exporters	0.037	0.000	-0.012	0.006	0.037	0.000	About the same
	Exporters	0.074	0.000	-0.001***	0.998	0.074	0.001	Higher TFP for high ICT firms
Firm age	Old	0.071	0.000	-0.004***	0.817	0.071	0.000	Higher TFP for high ICT firms
	Young	0.037	0.000	-0.018	0.002	0.037	0.000	About the same
Big cities	Other cities	0.039	0.000	-0.027	0.001	0.039	0.000	About the same
	Big cities	0.046	0.000	-0.003***	0.827	0.046	0.000	Higher TFP for high ICT firms
Knowledge intensity	Less knowledge intensive	0.066	0.000	-0.011***	0.130	0.066	0.000	Higher TFP for high ICT firms
	Knowledge intensive	0.042	0.000	0.000***	0.998	0.042	0.000	Higher TFP for high ICT firms

Table 21: Kolmogorov-Smirnov test – Sectors of the Ecuadorian economy

	Other sectors		**Interest sector**				
Sector	**D_1**	**p_1**	**D_2**	**p_2**	**D**	**p**	**Implication**
Agriculture	0.289	0.000	0.000***	0.999	0.289	0.000	Higher TFP for agriculture sector
Oil and mining	0.240	0.000	-0.005***	0.914	0.240	0.000	Higher TFP for manufacturing sector
Manufacturing	0.079	0.000	-0.034	0.000	0.079	0.000	About the same
Commerce	0.089	0.000	-0.033	0.000	0.089	0.000	About the same
Services	0.008	0.009	-0.161	0.000	0.161	0.000	About the same

Table 22: Total factor productivity determinants – Entire sample - OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT capital > $4019)	0.011***			
	(0.004)			
Share of ICT capital		0.101***		
		(0.010)		
ln (ICT capital)			0.001	
			(0.001)	
ICT capital				0.000***
				(0.000)
ICT capital^2				-0.000***
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.745***	-0.754***	-0.748***	-0.744***
	(0.006)	(0.005)	(0.006)	(0.006)
Export (1 = Exporter)	0.213***	0.212***	0.214***	0.213***
	(0.006)	(0.006)	(0.006)	(0.006)
Firm age	-0.005***	-0.004***	-0.005***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm age^2	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Big cities (1 = Guayaquil and Quito)	0.012***	0.009**	0.013***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Sector variables				
Sector (1 = Agriculture)	4.440***	4.438***	4.437***	4.442***
	(0.011)	(0.011)	(0.016)	(0.011)
Sector (1 = Oil and mining)	4.401***	4.398***	4.399***	4.399***
	(0.029)	(0.029)	(0.031)	(0.029)
Sector (1 = Manufacturing)	4.037***	4.033***	4.035***	4.039***
	(0.009)	(0.008)	(0.015)	(0.008)
Sector (1 = Commerce)	4.083***	4.072***	4.082***	4.085***
	(0.008)	(0.007)	(0.015)	(0.007)
Sector (1 = Services)	4.031***	4.016***	4.029***	4.032***
	(0.008)	(0.008)	(0.016)	(0.008)
Sector (1 = Other)	4.122***	4.115***	4.119***	4.123***
	(0.011)	(0.011)	(0.017)	(0.011)
Observations	167,649	167,649	167,649	167,649
R-squared	0.951	0.951	0.951	0.951

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 23: Total factor productivity determinants – Agriculture – OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT capital > $2658)	0.048***			
	(0.016)			
Share of ICT capital		0.320***		
		(0.082)		
ln (ICT capital)			-0.001	
			(0.006)	
ICT capital				0.000**
				(0.000)
ICT capital^2				-0.000
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.893***	-0.912***	-0.909***	-0.895***
	(0.018)	(0.017)	(0.019)	(0.018)
Export (1 = Exporter)	0.231***	0.240***	0.245***	0.237***
	(0.017)	(0.016)	(0.017)	(0.016)
Firm age	-0.003	-0.001	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Firm age^2	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Big cities (1 = Guayaquil and Quito)	-0.062***	-0.071***	-0.063***	-0.065***
	(0.016)	(0.016)	(0.016)	(0.016)
Constant	6.656***	6.657***	6.688***	6.674***
	(0.029)	(0.028)	(0.053)	(0.027)
Observations	10,283	10,283	10,283	10,283
R-squared	0.247	0.249	0.247	0.247

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 24: Total factor productivity determinants – Oil and mining – OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT capital > $7783)	-0.272***			
	(0.057)			
Share of ICT capital		0.861***		
		(0.184)		
ln (ICT capital)			0.009	
			(0.018)	
ICT capital				0.000***
				(0.000)
ICT capital^2				-0.000**
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.883***	-0.735***	-0.728***	-0.691***
	(0.066)	(0.063)	(0.070)	(0.063)
Export (1 = Exporter)	0.109	0.140**	0.091	0.097
	(0.067)	(0.067)	(0.068)	(0.068)
Firm age	-0.019**	-0.021**	-0.024***	-0.025***
	(0.008)	(0.008)	(0.008)	(0.008)
Firm age^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Big cities (1 = Guayaquil and Quito)	0.126**	0.066	0.098*	0.082
	(0.053)	(0.053)	(0.053)	(0.053)
Constant	3.653***	3.398***	3.409***	3.464***
	(0.103)	(0.099)	(0.197)	(0.098)
Observations	1,550	1,550	1,550	1,550
R-squared	0.137	0.143	0.128	0.138

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 25: Total factor productivity determinants – Manufacturing – OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT Capital > $5821)	0.046***			
	(0.009)			
Share of ICT capital		0.157***		
		(0.037)		
ln (ICT capital)			0.025***	
			(0.003)	
ICT capital				0.000***
				(0.000)
ICT capital^2				-0.000***
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.565***	-0.589***	-0.535***	-0.567***
	(0.009)	(0.009)	(0.010)	(0.009)
Export (1 = Exporter)	0.214***	0.222***	0.198***	0.204***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm age	-0.003***	-0.001*	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age^2	0.000***	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tech (1 = Medium high/high tech intensity)	-0.035***	-0.039***	-0.033***	-0.032***
	(0.009)	(0.009)	(0.009)	(0.009)
Big cities (1 = Guayaquil and Quito)	-0.025***	-0.029***	-0.029***	-0.029***
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	4.154***	4.166***	3.947***	4.163***
	(0.015)	(0.014)	(0.030)	(0.014)
Observations	20,039	20,039	20,039	20,039
R-squared	0.238	0.238	0.240	0.240

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 26: Total factor productivity determinants – Commerce – OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT capital > $4556)	0.050***			
	(0.006)			
Share of ICT capital		-0.010		
		(0.015)		
ln (ICT capital)			0.025***	
			(0.002)	
ICT capital				0.000***
				(0.000)
ICT capital^2				-0.000***
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.651***	-0.670***	-0.624***	-0.656***
	(0.007)	(0.006)	(0.007)	(0.006)
Export (1 = Exporter)	0.221***	0.224***	0.214***	0.221***
	(0.010)	(0.010)	(0.010)	(0.010)
Firm age	-0.006***	-0.005***	-0.006***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age^2	0.000***	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Big cities (1 = Guayaquil and Quito)	-0.051***	-0.049***	-0.053***	-0.051***
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	4.170***	4.201***	3.974***	4.186***
	(0.010)	(0.009)	(0.022)	(0.009)
Observations	50,783	50,783	50,783	50,783
R-squared	0.199	0.198	0.200	0.200

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 27: Total factor productivity determinants – Services – OLS

Variables	(1)	(2)	(3)	(4)
ICT variables				
ICT intensity (1 = ICT capital > $3781)	-0.029***			
	(0.007)			
Share of ICT capital		0.067***		
		(0.014)		
ln (ICT capital)			-0.019***	
			(0.002)	
ICT capital				-0.000
				(0.000)
ICT capital^2				0.000*
				(0.000)
Control variables				
Size (1 = MSMEs)	-0.752***	-0.744***	-0.785***	-0.742***
	(0.014)	(0.014)	(0.015)	(0.014)
Export (1 = Exporter)	0.288***	0.278***	0.298***	0.283***
	(0.012)	(0.012)	(0.012)	(0.012)
Firm age	-0.003***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Know (1 = High knowledge intensity)	-0.152***	-0.160***	-0.145***	-0.157***
	(0.007)	(0.007)	(0.007)	(0.007)
Big cities (1 = Guayaquil and Quito)	0.079***	0.075***	0.082***	0.077***
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	3.585***	3.556***	3.746***	3.571***
	(0.017)	(0.017)	(0.028)	(0.017)
Observations	74,181	74,181	74,181	74,181
R-squared	0.063	0.064	0.064	0.063

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

Table 28: Total factor productivity determinants – Entire sample – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.056***		-0.066***		
(1 = ICT capital > $4019)	(0.008)		(0.008)		
Share of ICT capital		0.176***	0.193***		
		(0.021)	(0.021)		
ln (ICT capital)				-0.044***	
				(0.004)	
ICT capital					0.000
					(0.000)
ICT capital^2					-0.000
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.471***	-0.469***	-0.474***	-0.482***	-0.467***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Export (1 = Exporter)	0.099***	0.100***	0.101***	0.102***	0.098***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	3.874***	3.812***	3.846***	4.228***	3.842***
	(0.015)	(0.015)	(0.015)	(0.034)	(0.014)
Observations	165,378	165,378	165,378	165,378	165,378
R-squared	0.636	0.637	0.637	0.637	0.636
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 29: Total factor productivity determinants – Agriculture – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.049**		-0.057**		
(1 = ICT capital > $3781)	(0.024)		(0.024)		
Share of ICT capital		0.434***	0.449***		
		(0.149)	(0.149)		
ln (ICT capital)				-0.044***	
				(0.009)	
ICT capital					-0.000***
					(0.000)
ICT capital^2					0.000***
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.579***	-0.582***	-0.586***	-0.584***	-0.579***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Export (1 = Exporter)	0.202***	0.205***	0.210***	0.209***	0.200***
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Constant	6.461***	6.415***	6.445***	6.791***	6.447***
	(0.048)	(0.047)	(0.049)	(0.091)	(0.047)
Observations	10,129	10,129	10,129	10,129	10,129
R-squared	0.733	0.734	0.734	0.734	0.733
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 30: Total factor productivity determinants – Oil and mining – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.430***		-0.433***		
(1 = ICT capital > $7783)	(0.089)		(0.089)		
Share of ICT capital		0.264	0.330		
		(0.509)	(0.478)		
ln (ICT capital)				-0.216***	
				(0.051)	
ICT capital					0.000
					(0.000)
ICT capital^2					0.000
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.805***	-0.781***	-0.804***	-0.863***	-0.780***
	(0.154)	(0.158)	(0.154)	(0.156)	(0.157)
Export (1 = Exporter)	0.250**	0.248**	0.253**	0.266**	0.251**
	(0.114)	(0.116)	(0.113)	(0.115)	(0.117)
Constant	3.616***	3.362***	3.588***	5.437***	3.375***
	(0.110)	(0.115)	(0.116)	(0.476)	(0.112)
Observations	1,536	1,536	1,536	1,536	1,536
R-squared	0.652	0.642	0.652	0.654	0.643
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 31: Total factor productivity determinants – Manufacturing – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.012		-0.021		
(1 = ICT capital > $5821)	(0.016)		(0.016)		
Share of ICT capital		0.225***	0.233***		
		(0.071)	(0.071)		
ln (ICT capital)				-0.026***	
				(0.007)	
ICT capital					-0.000***
					(0.000)
ICT capital^2					0.000**
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.327***	-0.325***	-0.327***	-0.335***	-0.327***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Export (1 = Exporter)	0.045**	0.047**	0.047**	0.046**	0.046**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	4.008***	3.980***	3.991***	4.239***	4.006***
	(0.023)	(0.023)	(0.023)	(0.066)	(0.022)
Observations	19,892	19,892	19,892	19,892	19,892
R-squared	0.685	0.686	0.686	0.685	0.685
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 32: Total factor productivity determinants – Commerce – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.026**		-0.030***		
(1 = ICT capital > $4556)	(0.011)		(0.011)		
Share of ICT capital		0.094***	0.101***		
		(0.029)	(0.029)		
ln (ICT capital)				-0.020***	
				(0.005)	
ICT capital					0.000
					(0.000)
ICT capital^2					-0.000
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.326***	-0.326***	-0.329***	-0.331***	-0.324***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Export (1 = Exporter)	0.069***	0.070***	0.070***	0.071***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Constant	3.904***	3.874***	3.890***	4.062***	3.888***
	(0.016)	(0.016)	(0.017)	(0.046)	(0.015)
Observations	50,232	50,232	50,232	50,232	50,232
R-squared	0.635	0.635	0.635	0.635	0.634
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 33: Total factor productivity determinants – Services – TWFE

Variables	(1)	(2)	(3)	(4)	(5)
ICT variables					
ICT intensity	-0.087***		-0.095***		
(1 = ICT capital > $3781)	(0.014)		(0.014)		
Share of ICT capital		0.088***	0.115***		
		(0.032)	(0.032)		
ln (ICT capital)				-0.063***	
				(0.007)	
ICT capital					-0.000***
					(0.000)
ICT capital^2					0.000*
					(0.000)
Control variables					
Size (1 = MSMEs)	-0.578***	-0.576***	-0.579***	-0.599***	-0.576***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Export (1 = Exporter)	0.113***	0.112***	0.115***	0.118***	0.111***
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)
Constant	3.406***	3.340***	3.384***	3.914***	3.360***
	(0.039)	(0.039)	(0.039)	(0.068)	(0.038)
Observations	72,955	72,955	72,955	72,955	72,955
R-squared	0.602	0.601	0.602	0.603	0.601
Firm fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES

Robust standard errors in parentheses. Cluster SE at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: Two-way fixed effects.

Table 34: Total factor productivity determinants – Chequeo Digital – 2021

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ICT variables						
ICT intensity median (1 = ICT capital > $8276)	0.003				-0.006	
	(0.147)				(0.143)	
Share of ICT capital		0.136			0.138	
		(0.463)			(0.461)	
ln (ICT capital)			-0.020			
			(0.055)			
ICT capital				0.000		
				(0.000)		
ICT capital^2				-0.000		
				(0.000)		
Chequeo Digital variables						
Digital skills						
Digital training	0.069*	0.070*	0.071*	0.073*	0.070*	0.069*
	(0.040)	(0.040)	(0.040)	(0.041)	(0.040)	(0.040)
Ease of use of digital technology	-0.028	-0.028	-0.027	-0.038	-0.028	-0.028
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Organizational capacity						
Digital technology importance	0.151	0.152	0.153	0.164	0.152	0.151
	(0.096)	(0.096)	(0.098)	(0.100)	(0.096)	(0.096)
Work flexibility	-0.003	-0.001	-0.005	-0.006	-0.001	-0.003
	(0.042)	(0.041)	(0.042)	(0.042)	(0.042)	(0.042)
Teleworking	-0.161	-0.167	-0.158	-0.165	-0.167	-0.161
	(0.113)	(0.111)	(0.110)	(0.114)	(0.111)	(0.113)
Digital communication						
Online presence	-0.041	-0.042	-0.040	-0.043	-0.042	-0.041
	(0.050)	(0.051)	(0.051)	(0.052)	(0.050)	(0.051)
Digital communication in the workplace	-0.041	-0.039	-0.040	-0.046	-0.039	-0.041
	(0.046)	(0.048)	(0.046)	(0.048)	(0.048)	(0.047)
Digital communication with clients	-0.059	-0.059	-0.059	-0.060	-0.060	-0.059
	(0.114)	(0.117)	(0.117)	(0.118)	(0.115)	(0.117)
Digital communication with providers	0.011	0.012	0.009	0.014	0.012	0.011
	(0.026)	(0.026)	(0.026)	(0.027)	(0.026)	(0.027)
Processes						
Digital technology on processes	0.024	0.022	0.023	0.018	0.022	0.024
	(0.040)	(0.040)	(0.039)	(0.039)	(0.041)	(0.039)
Proccess automation	0.002	-0.001	0.004	0.014	-0.001	0.002
	(0.040)	(0.037)	(0.039)	(0.040)	(0.037)	(0.041)
Control variables						
Size (1 = MSMEs)	-0.223	-0.237*	-0.274	-0.219	-0.240	-0.224
	(0.166)	(0.128)	(0.211)	(0.142)	(0.151)	(0.141)
Export (1 = Exporter)	0.507**	0.497**	0.520**	0.528**	0.497**	0.508**
	(0.210)	(0.192)	(0.217)	(0.221)	(0.195)	(0.208)
Firm age	-0.029**	-0.029***	-0.028**	-0.031**	-0.028***	-0.029**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.011)
Firm age^2	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Big cities (1 = Guayaquil and Quito)	0.204**	0.201**	0.197**	0.201**	0.200**	0.203**
	(0.097)	(0.089)	(0.096)	(0.089)	(0.095)	(0.089)
Observations	190	190	190	190	190	190
R-squared	0.201	0.202	0.202	0.210	0.202	0.201
Sector dummies	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Dependent variable: Logarithm of estimated TFP. Method: OLS.

A Data Appendix

A.1 Firm filtration criteria and correction

We use two filtration criteria: total assets and operational income. In the case of total assets, we drop firms with values of 0 in all periods, and, given the minimum legal capital of constitution of $800, we also drop firms with average assets less than $800. For operational income, companies that did not report any in the study period were eliminated.

Then we counted the number of periods in which the issues persisted (assets less than $800 and operational income of 0); firms for which these conditions existed in a maximum of 1 or 2 periods were kept according to their establishment year. For example,

- For those established before 2011 (9 periods), and established between 2011–2013, we kept firms with a maximum of 2 problematic periods.
- For those established between 2014 and 2017, we kept firms with a maximum of 1 period with issues.
- For those established in 2018, we kept firms with 0 problematic periods.

Table 35: Periods in data

Establishment year	**Periods in the data**	**Number of periods with issues allowed**
Before 2011	9	2
2011	8	2
2012	7	2
2013	6	2
2014	5	1
2015	4	1
2016	3	1
2017	2	1
2018	1	0

Later, we corrected the observations of firms with issues in 1 period, per the following cases:

- Case 1: If the observation was within the periods, we replaced it with the average between the previous and the following period.
- Case 2: If the observation was the last, then we replaced it with the previous period.
- Case 3: If it was the first, then we replaced it with the following period.

B Methodological Appendix

B.1 Olley & Pakes method

Olley & Pakes (1996) develop a two-step estimation procedure that proposes a deterministic relationship between productivity (ω_{it}) and investment (i_{it}). The latter used as a proxy for the former. They prove their estimates of ω_{it} to be consistent under the following assumptions:

(i) $i_{it} = f(\mathbf{x}_{it}, \omega_{it})$ is the investment policy function, invertible in ω_{it}. i_{it} is monotonically increasing in ω_{it}.

(ii) State variables evolve according to the investment policy function (i_{it}), which is decided at time $t-1$.

(iii) Free variables $\mathbf{w}_{it}$ (i.e., labor inputs and intermediate materials) are "nondynamic", that is, a firm's decision at t does not impact future profits. Thus, $\mathbf{w}_{it}$ are chosen at time t, after the firm realizes the productivity shock.

Assumptions(i) and (ii) above imply that i_{it} is orthogonal to the state variable in t such that $E(i_{it} \mid \mathbf{x}_{it}) = 0$ and can be inverted, yielding the following proxy for productivity:

$$\omega_{it} = f^{-1}(i_{it}, \mathbf{x}_{it}) = h(i_{it}, \mathbf{x}_{it}) \tag{9}$$

This is an unknown function of observable variables. Substituting (4) into (1) yields

$$y_{it} = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + h(i_{it}, \mathbf{x}_{it}) + \varepsilon_{it} = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \Phi_{it}(i_{it}, \mathbf{x}_{it}) + \varepsilon_{it} \tag{10}$$

,

where

$$\Phi_{it}(i_{it}, \mathbf{x}_{it}) = \mathbf{x}_{it}\boldsymbol{\gamma} + h(i_{it}, \mathbf{x}_{it}) = \mathbf{x}_{it}\boldsymbol{\gamma} + \omega_{it}$$

Equation (5) is a partially linear model identified only in the free-variable vector $\mathbf{w}_{it}$. It can be estimated approximating $\Phi_{it}(i_{it}, \mathbf{x}_{it})$ by an nth-degree polynomial $\widehat{\Phi}$ or by a local linear

regression (first stage). This procedure yields a consistent estimate of the free variables' parameters $\widehat{\boldsymbol{\beta}}$. Then, by substituting equation (2) in $h(\cdot)$, it becomes possible to estimate γ by rewriting the model for $y_{it} - \mathbf{w}_{it}\widehat{\boldsymbol{\beta}}$ conditional on $\mathbf{x}_{it}$ as follows:

$$\begin{aligned} y_{it} - \mathbf{w}_{it}\widehat{\boldsymbol{\beta}} &= \alpha_0 + \mathbf{x}_{it}\boldsymbol{\gamma} + \omega_{it} + \varepsilon_{it} \\ &= \alpha_0 + \mathbf{x}_{it}\boldsymbol{\gamma} + E\left(\omega_{it} \mid \omega_{it-1}\right) + \xi_{it} + \varepsilon_{it} \\ &= \alpha_0 + \mathbf{x}_{it}\boldsymbol{\gamma} + g\left(\omega_{it-1}\right) + \epsilon_{it} \end{aligned} \tag{11}$$

where

$$e_{it} = \xi_{it} + \varepsilon_{it}$$

Because $\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \mathbf{x}_{it}\boldsymbol{\gamma}$, equation (6) above becomes

$$y_{it} - \mathbf{w}_{it}\widehat{\boldsymbol{\beta}} = \alpha_0 + \mathbf{x}_{it}\boldsymbol{\gamma} + g\left(\widehat{\Phi}_{it-1} - \mathbf{x}_{it-1}\boldsymbol{\gamma}\right) + \epsilon_{it} \tag{12}$$

where the function $g(\cdot)$ can be left unspecified and estimated nonparametrically.

Residuals e_{it} in equation (7) can be used to build a GMM estimator[8] exploiting the moment conditions $E\left(e_{it}x_{it}^k\right) = 0$, $\forall k$ (second stage), where x^k are the single elements of vector x. The γ^* vector is the vector of parameters that minimizes the criterion function:

$$\gamma^* = \text{argmax}\left\{-\sum_k \left(\sum_i \sum_t e_{it}x_{it}^k\right)^2\right\} \tag{13}$$

Olley & Pakes (1996) address the potential selection bias due to the nonrandomness in firms' dropping out of the sample. If less productive firms are forced out of the market exactly because of their low levels of productivity, only the most productive firms are left in the sample. To address this issue, the authors assume that a firm continues to operate, provided that its productivity level exceeds a lower bound: $\chi_{it} = 1 \Longleftrightarrow \omega_{it} \geq \underline{\omega}_{it}$, where χ_{it} is a survival binary variable and $\underline{\omega}_{it}$ is an industry-specific exit-triggering threshold (see Melitz (2003)).

Thus, the final step in the Olley and Pakes method accounts for this "attrition". Specifically, the bias correction consists of adding to (7) an estimate of the conditional probability of remaining active in the market:

$$\widehat{\Pr}_{it+1} \equiv \Pr\left(\chi_{it+1} = 1 \mid \mathbf{x}_{it}\right). \tag{14}$$

[8]Because ϵ_{it} is a combination of pure errors, the estimation of the second stage can be done using nonlinear least squares.

where $\widehat{\Pr}_{it}$ is the fitted surviving probability–typically estimated through a discrete choice model on a polynomial of the state-variable vector $\mathbf{x}_{it}$ and investment.

Thus, plugging (9) into (7) yields

$$y_{it} - \mathbf{w}_{it}\widehat{\boldsymbol{\beta}} = \alpha_0 + \mathbf{x}_{it}\boldsymbol{\gamma} + g\left(\widehat{\Phi}_{it-1} - \mathbf{x}_{it-1}\boldsymbol{\gamma}, \widehat{\Pr}_{it}\right) + \epsilon_{it} \tag{15}$$

B.2 Levinsohn & Petrin method

Levinsohn & Petrin (2003) propose to overcome the empirical finding of investment decisions' being postponed for a few years by many firms (which violates the assumptions of Olley and Pakes that allow investment to be used as a proxy for ω_{it}) by using intermediate input (e.g., materials) levels instead.

The three key assumptions of Olley and Pakes are kept, but investment is substituted for intermediate inputs. That is, (i) $m_{it} = f(\mathbf{x}_{it}, \omega_{it})$ is both invertible and monotonically increasing in ω_{it}; (ii) the capital variable evolves according to the investment policy function, which is decided at $t-1$; (iii) free variables are chosen at time t, *after* the firm realizes the productivity shock. Levinsohn and Petrin add a new assumption: (iv) firms *observe* their productivity shock and are able to adjust their optimal level of intermediate inputs according to a demand function $m = (\omega_{it}, \mathbf{x}_{it})$.

Under this set of assumptions, intermediate input demand is orthogonal to the set of state variables in t such that $E(m_{it} \mid \mathbf{x}_{it}) = 0$. Moreover, because m_{it} can be inverted, the following technical efficiency proxy is obtained:

$$\omega_{it} = h(m_{it}, \mathbf{x}_{it}) \tag{16}$$

which is an unknown function of observable variables. Plugging (11) into (1) and distinguishing the intermediate input variable from the rest of free variables (e.g., labor) yields

$$\begin{aligned} y_{it} &= \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + m_{it}\delta + h(m_{it}, \mathbf{x}_{it}) + \epsilon_{it} \\ &= \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \Phi_{it}(m_{it}, \mathbf{x}_{it}) + \epsilon_{it} \end{aligned} \tag{17}$$

where

$$\epsilon_{it} = \xi_{it} + \varepsilon_{it}$$

Equation (12) is a partially linear model identified only in the free variable vector but not in the proxy variable, m_{it}. Similar to Olley and Pakes, this equation can be nonparametrically estimated approximating $\Phi_{it}(m_{it}, \mathbf{x}_{it})$ by an nth-degree polynomial or by local linear regression (first stage). The residual function ϵ_{it} can be estimated as the following:

$$\epsilon_{it} = y_{it} - \mathbf{w}_{it}\widehat{\boldsymbol{\beta}} - \mathbf{x}_{it}\boldsymbol{\gamma} - m_{it}\delta - g\left(\widehat{\Phi}_{it-1} - \mathbf{x}_{it-1}\boldsymbol{\gamma} - m_{it}\delta\right) \tag{18}$$

A GMM estimator can be constructed by exploiting these residuals and the set of moment conditions $E\left(e_{it}z_{it}^{k}\right) = 0, \forall k$, where k is the index of the instrument vector $\mathbf{z} = [\mathbf{x}_{it}, m_{it-1}]$. Similarly to OP, $[\gamma^*, \delta^*]$ is the vector of parameters that minimizes the criterion function:

$$\begin{bmatrix} \gamma^* \\ \delta^* \end{bmatrix} = \text{argmax}\left\{-\sum_k \left(\sum_i \sum_t e_{it}z_{it}^{k}\right)^2\right\} \tag{19}$$

B.3 Ackerberg, Caves, and Frazer correction

Ackerberg *et al.* (2015) observe a conditional dependency issue in the two previous methods due to the collinearity that might occur between the factors of production. This collinearity is generated because the decision variables (labor, inputs, and investment) depend on the same state variables (capital and productivity). It can be explained as follows:

Consider the Levinson and Petrin setting, where labor and intermediate inputs are assumed to be allocated simultaneously at time t. This implies that labor and materials are both chosen as a function of productivity ω_{it} and state variables $\mathbf{x}_{it}$:

$$m_{it} = m\left(\omega_{it}, \mathbf{x}_{it}\right) \tag{20}$$

$$l_{it} = l\left(\omega_{it}, \mathbf{x}_{it}\right) \tag{21}$$

By the monotonicity and invertibility conditions, equation (15) is also $\omega_{it} = h\left(m_{it}, \mathbf{x}_{it}\right)$. Plugging this into equation (16), we obtain

$$l_{it} = l\left\{h\left(m_{it}, \mathbf{x}_{it}\right), \mathbf{x}_{it}\right\} \tag{22}$$

That is, the labor input becomes a function of the same variables as the productivity function. This way, a collinearity issue arises in estimating the first stage, where labor appears both as a free variable and in the nonparametric polynomial approximation $\widehat{\Phi}_{it}$. These authors propose an alternative approach based on the following assumptions:

(i) $p_{it} = f\left(\mathbf{x}_{it}, l_{it}, \omega_{it}\right)$ is the proxy variable policy function, invertible in ω_{it} and also monotonically increasing in ω_{it}.

(ii) State variables are decided at time $t - b$.

(iii) The labor input, l_{it}, is chosen at time $t - \zeta$, where $0 < \zeta < b$. The free variables, $\mathbf{w}_{it}$, are chosen at time t, when the firm productivity shock is realized.

(iv) The production function is value added in the sense that the intermediate input m_{it} does not enter the production function to be estimated.

Under these assumptions, as in Olley and Pakes and in Levinson and Petrin, the policy function p_{it} can be inverted into $h(\cdot)$ and plugged into (1), substituting for ω_{it}. This process yields

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\gamma} + \mathbf{w}_{it}\boldsymbol{\beta} + l_{it}\mu + h\left(p_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}, l_{it}\right) + \varepsilon_{it} \tag{23}$$

where, because $\omega_{it} = h\left(p_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}, l_{it}\right)$,

$$\mathbf{x}_{it}\boldsymbol{\gamma} + \mathbf{w}_{it}\boldsymbol{\beta} + l_{it}\mu + \omega_{it} = \Phi_{it}\left(p_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}, l_{it}\right). \tag{24}$$

and equation (18) becomes

$$y_{it} = \Phi_{it}\left(p_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}, l_{it}\right) + \varepsilon_{it}$$

Once $\widehat{\Phi}_{it}$ is recovered, it is possible to estimate ω_{it} in equation (19) above:

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \mathbf{x}_{it}\gamma - \mathbf{w}_{it}\boldsymbol{\beta} - l_{it}\mu \tag{25}$$

Then, exploiting the Markov chain assumption $\omega_{it} = E\left(\omega_{it} \mid \omega_{it-1}\right) + \xi_{it} = g\left(\omega_{it-1}\right) + \xi_{it}$, we can obtain the residuals $\epsilon_{it} = \xi_{it} + \varepsilon_{it}$.

These residuals, combined with the set of moment conditions $E\left(\epsilon_{it} z_{it}^{k}\right) = 0, \forall k$, where k is the index of the instrument vector $\mathbf{z} = [\mathbf{x}_{it}, \mathbf{w}_{it-1}, l_{it-1}]$, lead to the GMM criterion function (second stage):

$$\begin{bmatrix} \boldsymbol{\gamma}^* \\ \boldsymbol{\beta}^* \\ \mu^* \end{bmatrix} = \operatorname{argmax}\left\{ -\sum_k \left(\sum_i \sum_t \epsilon_{it} z_{it}^{k} \right)^2 \right\} \tag{26}$$

B.4 Wooldridge method

Wooldridge (2009) proposes to address the problems of both the Olley and Pakes and Levinson and Petrin methods by replacing the two-step estimation procedure with a GMM setup. More concretely, this author shows how to write the relevant moment restrictions in terms of two simultaneously estimated equations that have the same dependent variable (y_{it}), but are characterized by a different set of instruments.

The intuition behind the equivalence of these equations comes from the Olley and Pakes and Levinson and Petrin first stage assumption:

$$E\left(\varepsilon_{it} \mid \omega_{it-1}, \mathbf{w}_{it}, \mathbf{x}_{it}, m_{it}, \mathbf{w}_{it-1}, \mathbf{x}_{it-1}, m_{it-1}, \ldots, \mathbf{w}_{i1}, \mathbf{x}_{i1}, m_{i1}\right) = 0 \tag{27}$$

without imposing any functional form on the control function $\omega_{it} = h(.)$.

In the second stage, the assumptions on (i) the Markovian nature of productivity and (ii) the orthogonality between productivity shocks and *current* values of the state variables, as well as *past* realizations of the free variables and the intermediate inputs, imply that

$$\begin{aligned} E\left(\omega_{it} \mid \mathbf{x}_{it}, \mathbf{w}_{it-1}, \mathbf{x}_{it-1}, m_{it-1}, \ldots, \mathbf{w}_{i1}, \mathbf{x}_{i1}, m_{i1}\right) &= E\left(\omega_{it} \mid \omega_{it-1}\right) \\ &= f\left\{h\left(\mathbf{x}_{it-1}, m_{it-1}\right)\right\} \end{aligned} \tag{28}$$

where, as for $h(.)$, no functional form is imposed on $f(\cdot)$.

Assumptions (22) and (23) directly lead to the formulation of the following two equations:

$$y_{it} = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + h\left(\mathbf{x}_{it}, m_{it}\right) + \varepsilon_{it} \tag{29}$$

$$y_{it} = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + f\left\{h\left(\mathbf{x}_{it-1}, m_{it-1}\right)\right\} + \eta_{it} \tag{30}$$

where $\eta_{it} = \xi_{it} + \varepsilon_{it}$.

Wooldridge (2009) deals with the unknown functional forms $h(.)$ and $f(.)$ by using nth-degree polynomials in $\mathbf{x}_{it}$ and m_{it}, where the limiting case with $n = 1$ (that is, entering linearly) should always be allowed.

Specifically, the author proposes the following assumption:

$$h\left(\mathbf{x}_{it}, m_{it}\right) = \lambda_0 + \mathbf{k}\left(\mathbf{x}_{it}, m_{it}\right)\lambda$$

where $k(.)$ is a $1 \times Q$ collection of functions,

$$f(h) = \delta_0 + \delta_1 h + \delta_2 h^2 + \cdots + \delta_G h^G$$

which implies

$$\begin{aligned} f\left(\omega_{it}\right) = \delta_0 + \delta_1 \left\{\mathbf{k}\left(\mathbf{x}_{it-1}, m_{it-1}\right)\lambda_1\right\} + \delta_2 \left\{\mathbf{k}\left(\mathbf{x}_{it-1}, m_{it-1}\right)\lambda_1\right\}^2 + \cdots \\ + \delta_G \left\{\mathbf{k}\left(\mathbf{x}_{it-1}, m_{it-1}\right)\lambda_1\right\}^G \end{aligned}$$

For the sake of simplicity, consider the case with $G = 1$ and $\delta_1 = 1$. Substituting $f(\omega_{it})$ in (24) and (25) yields

$$y_{it} = \zeta + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + \mathbf{k}\left(\mathbf{x}_{it}, m_{it}\right)\lambda_1 + \varepsilon_{it} \tag{31}$$

$$y_{it} = \theta + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + \mathbf{k}\left(\mathbf{x}_{it-1}, m_{it-1}\right)\lambda_1 + \eta_{it} \tag{32}$$

where ζ and θ are the new constant parameters obtained through aggregation of all the constant terms.

Under the assumptions of $G = 1$ and $\delta_1 = 1$, the system GMM has linear moments. The choice of instruments $\mathbf{z}_{it}$ for (26) and (27) is straightforward and reflects the orthogonality conditions listed above:

$$\mathbf{z}_{it1} = [1, \mathbf{x}_{it}, \mathbf{w}_{it}, \mathbf{k}(\mathbf{x}_{it}, m_{it})], \tag{33}$$

$$\mathbf{z}_{it2} = [1, \mathbf{x}_{it}, \mathbf{w}_{it-1}, \mathbf{k}(\mathbf{x}_{it-1}, m_{it-1})], \tag{34}$$

and

$$\mathbf{Z}_{it} = \begin{pmatrix} \mathbf{z}_{it1} \\ \mathbf{z}_{it2} \end{pmatrix}.$$

For each $t > 1$, the usual GMM with IV setup applies, and the moment conditions are derived from the residual functions:

$$\mathbf{r}_{it}(\theta) = \begin{bmatrix} r_{it1}(\theta) \\ r_{it2}(\theta) \end{bmatrix} = \begin{bmatrix} y_{it} - \zeta - \mathbf{w}_{it}\boldsymbol{\beta} - \mathbf{x}_{it}\boldsymbol{\gamma} - \mathbf{k}(\mathbf{x}_{it}, m_{it})\lambda_1 \\ y_{it} - \theta - \mathbf{w}_{it}\boldsymbol{\beta} - \mathbf{x}_{it}\boldsymbol{\gamma} - \mathbf{k}(\mathbf{x}_{it-1}, m_{it-1})\lambda_1 \end{bmatrix} \tag{35}$$

and $E\{\mathbf{Z}'_{it}\mathbf{r}_{it}(\theta)\} = 0$.

B.5 Mollisi and Rovigatti method

Mollisi & Rovigatti (2018) propose a modification to the Wooldridge estimator based on a matrix of dynamic panel instruments to avoid losing degrees of freedom in the estimation of the parameters when using lagged values as instrumental variables.

Mollisi and Rovigatti follow the proposal of dynamic panel instruments of Blundell and Bond (1998). This way, by using as values of the instruments the lagged data available at each moment, information from the first years is not lost. This approach allows increasing moment restrictions without losing information, something that is useful when using "large N, small T" data sets, which are often common in practical applications of firm-level data. Mollisi and Rovigatti show that their estimator outperforms that of Wooldridge in simulated data and produces more-stable results, particularly in overidentified models (thanks to the increase in sample size).

The process of estimating the simultaneous equations of Wooldridge (2009) using the GMM with IV applies in the same way, but with the variant that moment conditions are derived from a residual function vector of dynamic instruments.

More concretely, for each $t > 1$, a $2(T-1)$ residual function vector is defined the following way:

$$\mathbf{r}_i(\theta) = \begin{bmatrix} y_{i2} - \zeta - \mathbf{w}_{i2}\boldsymbol{\beta} - \mathbf{x}_{i2}\boldsymbol{\gamma} - k\left(\mathbf{x}_{i2}, \mathbf{m}_{i2}\right)\lambda_1 \\ y_{i2} - \theta - \mathbf{w}_{i2}\boldsymbol{\beta} - \mathbf{x}_{i1}\boldsymbol{\gamma} - k\left(\mathbf{x}_{i1}, \mathbf{m}_{i1}\right)\lambda_1 \\ \cdots \\ \cdots \\ y_{iT} - \zeta - \mathbf{w}_{iT}\boldsymbol{\beta} - \mathbf{x}_{iT}\boldsymbol{\gamma} - k\left(\mathbf{x}_{iT}, \mathbf{m}_{iT}\right)\lambda_1 \\ y_{iT} - \theta - \mathbf{w}_{iT}\boldsymbol{\beta} - \mathbf{x}_{iT}\boldsymbol{\gamma} - k\left(\mathbf{x}_{iT-1}, \mathbf{m}_{iT-1}\right)\lambda_1 \end{bmatrix} \tag{36}$$

For each panel i, the last available lag is defined as $t-b$ (that is, when $b = 1$ at $t = 2; b = 2$ at $t = 3$, and $b = T - 1$ at $t = T$). Then, $\mathbf{Z}_i$ denotes the dynamic panel instrument matrix for each panel (the subscript i is suppressed to avoid an abuse of notation):

$$\mathbf{Z} = \begin{bmatrix} \mathbf{z}_2' & \mathbf{z}_3' & \cdots & \mathbf{z}_T' & 0 & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & \widetilde{\mathbf{z}}_3' & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \widetilde{\mathbf{z}}_4' & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \widetilde{\mathbf{z}}_T' \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{37}$$

where component $\widetilde{\mathbf{z}}_t$ is a vector of dimension $1 \times b$ consisting of $\mathbf{z}_{t-1}, \ldots, \mathbf{z}_{t-b}$. As usual, GMM conditions are defined as $E\left\{\mathbf{Z}_i\mathbf{r}_i(\theta)\right\} = 0$.

C Chequeo Digital Questionnaire Appendix

The selection of questions from Chequeo Digital are reorganized in the following four dimensions.

- Digital Skills

  Q1 Digital training: In your SME, have you been educated or trained in digital issues?

  (Answers are from 1 to 7: 1 means they have not been trained and 7 means they have formal instances of training.)

  Q2 Ease of use of digital technology: How easily do you manage the use of digital technologies in your SME?

  (Answers are from 1 to 7: 1 means they use it at a basic level and 7 means they use it very easily.)

  Q3 Teleworking: In your organization, is remote working or teleworking allowed?

  (Answers are from 1 to 3: 1 means they do not allow teleworking, 2 means they allow some instances of teleworking, and 3 means they have established regular use of teleworking.)

- Organizational Capacity

  Q4 Digital technology importance: How important are digital technologies for the operation of your SME?

  (Answers are from 1 to 7: 1 means digital technologies are not important for the operation of the SME and 7 means digital technologies are very important.)

  Q5 Work flexibility: To what degree have digital technologies made the way you work in your business more flexible? For example, through collaborative work platforms, remote communication, or data clouds.

  (Answers are from 1 to 7: 1 means the company has not altered its way of doing things and 7 means the company has altered its way of doing work by adapting to digital technologies.)

- Digital Communication

  Q6 Online presence: Does your SME have an online presence? This means that your customers can find out about your SME, its location and find out about your products or services through the internet.

  (Answers are from 1 to 7: 1 means the SME does not have online presence and 7 means the SME has an online presence, in the forms of a social media network and web page.)

  Q7 Digital communication in the workplace: Do your workers communicate with each other through digital media? For example: email, WhatsApp, Messenger, Slack, etc.

  (Answers from 1 to 7: 1 means workers do not communicate via digital channels and 7 means they always communicate with each other via digital channels.)

Q8 Digital communication with clients: Do you communicate digitally with your customers? For example, digital media (WhatsApp, Facebook, Instagram, etc.) are used to express doubts, opinions and/or claims.

(Answers from 1 to 4: 1 means the company does not digitally communicate with clients and 4 means it has multiple digital communication channels with its clients.)

Q9 Digital communication with providers: Are digital communication channels maintained with your suppliers?

(Answers from 1 to 7: 1 means the company does not have digital communication channels with it providers and 7 means it always has digital contact with providers.)

- Processes

  Q10 Digital technology on processes: In general terms, have digital technologies been integrated to support the processes of your SME? For example, services offered on the web, electronic commerce, digitized quality control, etc.

  (Answers from 1 to 7: 1 means the company's processes are manual, without digital technologies and 7 means the company has integrated digital technologies in the majority of its processes.)

  Q11 Processes automation: Has any degree of automation been implemented in your SME's processes? For example, automatic responses to your customers for the services or products offered.

  (Answers from 1 to 7: 1 means the company's processes are manual and do not need automation and 7 means the company has implemented general automation of SME processes.)