The Effects of Digital-Technology Adoption on Productivity and Factor Demand: Firm-level Evidence from Developing Countries*

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Abstract

This paper presents firm-level estimates of revenue-based total factor productivity (TFPR) premiums associated with the adoption of digital technologies in 82 developing economies with data from 2003-18. The paper estimates TFPR using the control function approach. It endogenizes the productivity process, making it a function of digital technology adoption (e.g., email and website), learning-by-exporting, and managerial experience. The results reject the null hypothesis of an exogenous TFPR process. Digital technology adoption, along with the other firm-choice variables (exporting status and managerial experience), affects productivity and factor demand. The estimated premiums are positive for 63.38 (email adoption), 54.73 (website adoption), 59.08 (learning by exporting), and 60.05 (managerial experience) percent of the sample. The probability-adjusted median (log) TFPR premium associated with email

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adoption is 1 percent, and that of website adoption is 2.3 percent. The latter is higher than the expected premiums associated with exporting and managerial experience. On average, changes in digital technology adoption (e.g., email and website) are labor and capital augmenting. The estimated jobs gains from digitization fall within the range of estimates previously reported in the literature. The paper also explores the role of complementarities among firm investments and provides insights for the targeting of firm-level interventions aimed at boosting TFPR.
JEL Codes: D22, D24, L25, O47. Keywords: productivity, jobs, digital technology, exporting, management.

1 Introduction

The global digital economy accounted for 15.5 percent of the world's GDP in 2016 ($11.5 trillion). Yet, not everybody has benefited equally from the arrival of digital technologies. There are still huge disparities across and within countries when it comes to the adoption and usage of digital technologies (Comin and Mestieri 2018). While more than half of the world's population now has access to the internet, the penetration rate in the least developed countries is only 15 percent or 1 in 7 individuals (World Development Report 2019).[1]

The benefits of adopting digital business solutions like email, launching a business website, or connecting to two-sided digital platforms can be substantial, especially, for firms (Goldfarb and Tucker 2019). The transfer of information and data over the internet helps reduce production costs and therefore expands the demand for a firm's goods and services. This, in turn, increases factor demand as well. Reductions in search costs enable buyers and sellers of products or services to get better access to the other side of the market by increasing the speed or efficacy with which firms find workers or input suppliers (De Loecker 2019). Digital business solutions also help expand market opportunities. Reductions in search, transaction, or tracking costs allow firms to overcome geographical barriers, penetrate new markets, and enlarge the volume of trade (World Development Report 2020).

The existing evidence on the impact of digital-technology adoption on productivity and factor demand is, however, surprisingly thin, especially for developing countries. It is even thinner when it comes to quantifying these effects using firm-level data. This paper aims to fill these gaps in the literature. Specifically, we estimate the effects of adopting digital business solutions, namely email to communicate with clients and suppliers and launching a business website, on firm-level revenue-based total factor productivity (TFPR) and the demand for labor and capital.

We rely on publicly available information from the World Bank's Enterprise Survey database (WBES) to conduct the analysis. The WBES collects information on sales, factor and input usage, exporting status, managerial experience, and digital-technology adoption (e.g., email and web-

1. https://www.worldbank.org/en/topic/digitaldevelopment/overview.

site) at the firm level for the manufacturing industry corresponding to a sample of 82 developing economies during the period 2003-2018.[2]

To estimate TFPR, we first estimate a log-linearized Cobb-Douglas production function (PF) following Ackerberg, Caves, and Frazer (2015). Although, the Ackerberg, Caves, and Frazer (2015) method, which builds on Olley and Pakes (1996) and Levinsohn and Petrin (2003), assumes an exogenous productivity process, we follow De Loecker (2013) and endogenize TFPR. Thus, TFPR is a function of the adoption of digital business solutions (e.g., email and website) in addition to other firm-choice variables that can also affect firm performance, such as exporting and managerial experience, which have been studied separately in the literature. We validate our data and methodology by replicating the results presented in De Loecker (2013) for the specification that only includes learning-by-exporting effects. The evidence indicates that our estimates of the production function elasticities and the coefficients of the endogenous productivity process, covering 82 developing countries, are highly correlated across industries with those reported by De Loecker (2013) for Slovenia.

Assuming an exogenous TFPR would have implied that digital technologies would have no impact on efficiency, prices, and sales. This is not only unrealistic but also, from a methodological point of view, would have invalidated the moment conditions needed to identify the coefficients of the production function. In other words, if TFPR is a function of business digitization that does, in fact, affect factor demand, the estimated production-function elasticities would be biased as well as the factor demand effects. The sign of the TFPR bias would be ambiguous, depending on whether digitization is factor-augmenting or factor-saving. If business digitization is factor-augmenting, then TFPR would be underestimated. If improvements in TFPR are factor-saving, then TFPR would be overestimated.

There are good reasons to expect that firm TFPR is a function of business digitization, as well as of exporting as in De Loecker (2013), and managerial experience as in Bloom and Van Reenen

2. 2003-2018 period corresponds to the public release of the data, which was collected during the period 2002-2017. Since 2017, the WBES eliminated the question on email adoption. However, the survey for Chad, conducted in 2018, have both questions. This is the reason why the estimation sample goes up to 2018.

(2007) and Bloom and Van Reenen (2010). Using email to connect with clients or suppliers or having a business website to gain online presence can affect TFPR through different channels. On the demand-side, reductions in search and transaction costs affect firm profitability at the extensive and intensive margins by facilitating access to new clients or expanding the volume of transactions online. Dynamically, the scale-up of the demand for a firm's products or services increases profits, allowing it to pay the fixed cost of investing in TFPR-enhancing activities like innovation, managerial upgrading, or technology adoption. On the supply-side, using email to connect with suppliers helps improve production efficiency, enlarging the potential set of input providers in non-relationship specific investments. Alternatively, it reduces the number of suppliers in relationship-specific investments but enlarges the fraction of repeated interactions, thus addressing contract incompleteness and guaranteeing access to specific assets needed to produce more sophisticated goods (Aral, Bakos, and Brynjolfsson 2018).

The estimated TFPR premiums are positive for 63.38 (email adoption) and 54.73 (website adoption) percent of the estimation sample, respectively. TFPR premiums for learning-by-exporting and managerial experience are positive for 59.08 and 60.05 percent of the estimation sample, respectively.

The probability-adjusted median TFPR premium associated with email adoption is 1 percent and that of website adoption is 2.3 percent, while the premium corresponding to getting access to external markets and increasing managerial experience are 1.1 and near zero, respectively. Thus, our results show that digital technology adoption can deliver larger TFPR gains than exporting or upgrading managerial skills. Moreover, our estimates represent lower bounds of the marginal effects of technology adoption, as digitization can also increase TFPR by reducing distances and facilitating access to international markets. Counterfactual analysis about the aggregate TFPR gains from universal adoption of digital solutions indicate that website adoption, which we show is a proxy of a demand shock, delivers larger TFPR gains than email adoption, which we show is a proxy of a supply shock. Web-related TFPR gains can go up to 16.44 percent, on average at the country-level, for regions like the Middle-East and North Africa.

Our findings also highlight the role of complementarities across different determinants of firm performance (e.g., technology adoption, learning-by-exporting, and managerial experience) and shed light on program targeting at the firm-level to boost revenue productivity. They show that targeting low-productivity firms can deliver larger aggregate TFPR gains than targeting high-productivity firms if programs focus exclusively on digitization. However, the opposite applies when digitization is coupled with a treatment aimed at building firm capabilities to access foreign markets.

Given these results, it is noteworthy that TFPR is an indicator of profits (revenues) conditional on input use. Hence when markets become more competitive firms' TFPR can fall as prices fall. Although the lack of price data in the WBES does not allow us to disentangle the price effects from changes in technical efficiency (TFP based on quantities), it is worth noting that price reductions associated with declines in TFPR could bring welfare gains for consumers, at the expense of lower profits for firms.

Last, on average, changes in digital-technology adoption are labor- and capital-augmenting. TFPR improvements are also labor-augmenting, while they do not have an impact on the demand for capital. Globally, the direct effects of digitization on jobs are larger than the indirect effect through TFPR. Counterfactual analysis about the aggregate job gains from universal adoption of digital solutions indicate that website adoption changes positively the labor demand more than email adoption. Web-related job gains can go up to 9.77 percent of an economy's formal employment in the manufacturing sector. On average, for regions like South Saharan Africa. Our estimates are in line with previous findings in the literature.

This paper relates to two strands of research on to the economics of technology adoption. The first one analyzes the impact of digitization on total factor productivity. It is associated with the productivity paradox debate, which refers to the global contraction in productivity growth rates, which occurred despite the spectacular technological progress observed in recent decades (Brynjolfsson, Rock, and Syverson 2017; Cusolito and Maloney 2018). The second strand of research focuses on the creation (or destruction) of jobs brought about by technological change. It is related to the debate about the effects of digitization or robotization on job destruction and the skill-biased labor demand (Autor 2015; Autor et al. 2020; Autor and Salomons 2018; Acemoglu and Restrepo 2018, 2019a, 2019b, 2020a, 2020b; World Development Report 2019)). These debates are intertwined because job losses from technology adoption could result from firms' investments to become more productive (Autor et al. 2020). The evidence presented in this paper suggests that digital technology adoption among formal manufacturing firms in developing countries tends to raise labor demand, as mentioned above.

The rest of this paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes the enterprise data used in the econometric estimations. Section 4 explains the estimation strategy. Section 5 validates the data and methodology by comparing our estimates with those in the existing literature. Section 6 presents the effects on productivity. Section 7 discusses the effects on factor demand. Section 8 compares our estimates with those from the literature and shows that they belong to the range of estimated effects found in analogous papers. Section 9 explores the issue of ICT program targeting by showing how the marginal impact of the adoption of digital tools depends on other firm capabilities such as exporting status and managerial experience. The final section concludes.

2 Related Literature

As mentioned in the introduction, this paper relates to two strands of the literature on technology adoption. One concerns the effect of technology adoption on productivity. The other is involves the impact of adoption on the demand for factors of production, particularly labor.

2.1 Productivity and Technology Adoption

The productivity paradox debate has recently shifted its focus towards the contribution of digital-technology adoption to productivity. Estimates for developing countries are rare due to data limitations. Recent calculations for the United States show that the sector has been a bright spot in the economy, accounting for 6.5 percent of GDP and 3.9 percent of total employment in 2016 (Barefoot et al. 2018). The new estimates, which ranked the U.S. digital sector just below professional, scientific, and technical services, have encouraged some Economists to argue, before the covid-19 pandemic shock, that if the digital economy plays a limited role in advanced economies, we should not expect much for less developed economies, where digital technologies are less affordable and penetration rates (i.e., adoption and usage) lower.[3]

In a recent influential paper on the United States, Brynjolfsson et al. (2020) argue that in the "discordance between high hopes and disappointing statistical realities, one of the two elements is presumed to be somehow wrong."[4] However, there are good reasons to be optimistic about the contribution of new technologies, including digital business solutions, to productivity and jobs. These technologies are general purpose technologies (GPTs) that have broad cross-sectoral and cross-task applications (Jovanovic and Rousseau 2005; Helpman and Trajtenberg 1996). Brynjolfsson, Rock, and Syverson (2017), Syverson (2017), and Brynjolfsson et al. (2020) argue that GPTs have an impact in the economy after firms make the necessary complementary investments or organizational changes needed to take advantage of them. Yet the productivity gains from these investments or restructuring processes do not materialize immediately. It takes time to discover, develop, and implement them (Bresnahan, Brynjolfsson, and Hitt 2002).

Nonetheless, emerging evidence from advanced economies provides room for optimism. Recently, Gal et al. (2019) document that digital adoption in an industry is associated with productivity gains at the firm-level in 20 countries in the European Union and Turkey. Two earlier literature reviews by Syverson (2011) and Draca, Sadun, and Van Reenen (2006) concluded that there is a

3. Early attempts to explain the productivity paradox have emphasized two hypotheses. The first one relates to the presence of diminishing returns from the digital revolution. Gordon (2015) argues that once firms adjust to the digital electronic wave, by installing new equipment or adopting new business practices, the impact of ICT technologies on productivity began to display diminishing returns. To complement this argument, Bloom et al. 2020 document that it takes progressively more researchers to generate a unit of TFP. The second hypothesis relates to measurement aspects associated with the supply of digital products or services for which the price paid by consumers is zero. Consequently, these transactions are not captured in the data (Mokyr 2014; Hatzius and Dawsey 2015; Byrne, Fernald, and Reinsdorf 2016). However, this hypothesis was challenged by evidence indicating that the size of the productivity slump was unrelated to the spread of digital technologies across countries (Syverson 2017).

4. Brynjolfsson, Rock, and Syverson (2017) refers to artificial intelligence, but the argument is equally applicable to other types of general purpose technologies such as digital technologies.

positive and significant association between ICT and productivity. These findings are, however, in contrast with recent evidence by DeStefano, Kneller, and Timmis (2018) for the United Kingdom, who show that ICT causes increases in firm size (captured by either sales or employment) but not on productivity.

While evidence for developing countries is scarce, Hjort and Poulsen (2019) find positive effects of the arrival of internet on firm-level productivity in Africa. World Bank research on Argentina, Brazil, Chile, Colombia, and Mexico concludes that digital technology adoption offers a pathway to higher productivity (Dutz, Almeida, and Packard 2018). According to the study, the total factor productivity of technology-adopting firms increased in all country studies where data were available, with the findings in Argentina based on labor productivity (Brambilla and Tortarolo 2018; Iacovone and Pereira-López 2018; Almeida et al. 2017; Dutz et al. 2017). However, systematic firm-level for a large sample of developing countries was not available at the time of writing this paper. Several papers that aimed at estimating the effect of digitization on productivity use a two-step estimation procedure that invalidates the moment conditions needed to identify the coefficients of the production function and, as a result, delivers biased TFPR estimates and marginal effects.

2.2 Jobs and Technology Adoption

Recent technological innovations have also revamped an old concern associated with to the trade-off between efficiency and jobs. This debate is related to the potential labor-saving and skill-biased effects of technology adoption (Brynjolfsson and McAfee 2014; Frey and Osborne 2017). Evidence about the effect of automation on jobs is, primarily, available for the United States as in Acemoglu and Autor 2011; Acemoglu and Restrepo 2018, 2019a, and the European Union as in Autor and Salomons 2018. For example, Acemoglu and Autor (2011) explore the role of task routinization due to the arrival of ICT technologies in job polarization. The article concludes that job polarization in the United States and the European Union is partly the result of the secular price decline in the real cost of information technologies. This is because routine tasks are characteristic of middle-skilled cognitive and manual jobs, which made them more vulnerable to the effects of technology adoption.

Recent evidence for the United States suggests that automation through the adoption of robotics can displace certain types of jobs (Acemoglu and Restrepo 2018). The estimates imply that one more robot per thousand workers reduces the employment-to-population ratio by about 0.2 percentage point and wages by 0.42 percent. In a follow-up paper, the authors explore the types of workers that have a higher probability of being replaced, concluding that robots replace, primarily, middle-aged workers between the ages of 21 and 55 (Acemoglu and Restrepo 2019b).

While evidence for developing countries is thin, the recent World Development Report (World Development Report 2019) shows that the variance of the labor-saving effect is so large that it is hard to conclude that robots will indeed decrease the net demand for labor. Furthermore, as highlighted by Acemoglu and Restrepo (2018, 2019a, 2019b), at the aggregate level, the job displacement effects will push wages down and encourage the introduction of new labor-intensive tasks, as labor regains a price advantage relative to robots.

Evidence on firm- and country-level job effects from technology adoption are only available for a handful of middle-income countries. A World Bank study (Dutz, Almeida, and Packard 2018), which summarizes findings for Argentina, Brazil, Colombia, Chile, and Mexico, shows that for all the economies except Brazil, ICT adoption by firms is associated with increases in total employment and in employment of low-skilled labor (Brambilla and Tortarolo 2018; Dutz, Almeida, and Packard 2018; Iacovone and Pereira-López 2018; Almeida et al. 2017; Dutz et al. 2017). This paper advances the literature by providing evidence about the effect of digital-technology adoption on factor demand across a large sample of formal manufacturing enterprises in developing countries and by identifying the channels through which factor demand is affected. The two channels are factor-saving productivity improvements and scale effects. The latter channel reflects the impact of digital-technology adoption on a firm's customer base.

3 Data

The empirics rely on panel data of manufacturing firms from the World Bank Enterprise Survey Database (WBES). The estimation sample covers 82 countries from a maximum sample of 90 countries in the six regions where the World Bank operates: Europe and Central Asia - ECA (30), Sub-Saharan Africa - SSA (27), Latin America and the Caribbean - LAC (18), East Asia and Pacific - EAP (6), South Asia - SA (6), and Middle East and North Africa - MENA (3).

The survey is nationally representative of the formal private sector. It is built based on a stratified random sampling frame designed by the WBES team. Three variables are used to construct the strata: firm size, sector, and geographic area within a country. Under the WBES sampling framework, firms are divided into three categories according to their size: small, medium-sized, and large. Small firms are those with 5-19 full-time employees; medium-sized firms have 20-99 full-time employees; and the large ones have more than 99 full-time employees. The industries are classified according to the ISIC Revision 3.1 classification at 2-digits. The regions within a country are defined by the WBES team. The database also includes sampling weights that can be used to mimic nationally representative samples in the empirics.

The WBES collects data on a broad range of variables related to firm production, performance, and the business environment in which firms operate. Variables associated with production include sales, capital, labor, materials, investment, exports, and manager's education, among others. Due to the lack of information on prices at the firm-level, we use the consumer price index from the World Bank's World Development Indicators to deflate sales, capital, materials, and investment, thus transforming nominal values into 2010-dollar values. Firms' labor is equal to the number of permanent employees that work for the firm. The survey collects data on the percentage of firms' sales that are exported. Last, a firm's managerial capability is measured by the number of years of experience of the manager. The novelty of the WBES is that it also collects information on technology adoption at the firm-level. Thus, at every wave, firms are asked whether they use a business email to communicate with clients and suppliers and whether they have a business website in order to carry out their operations.

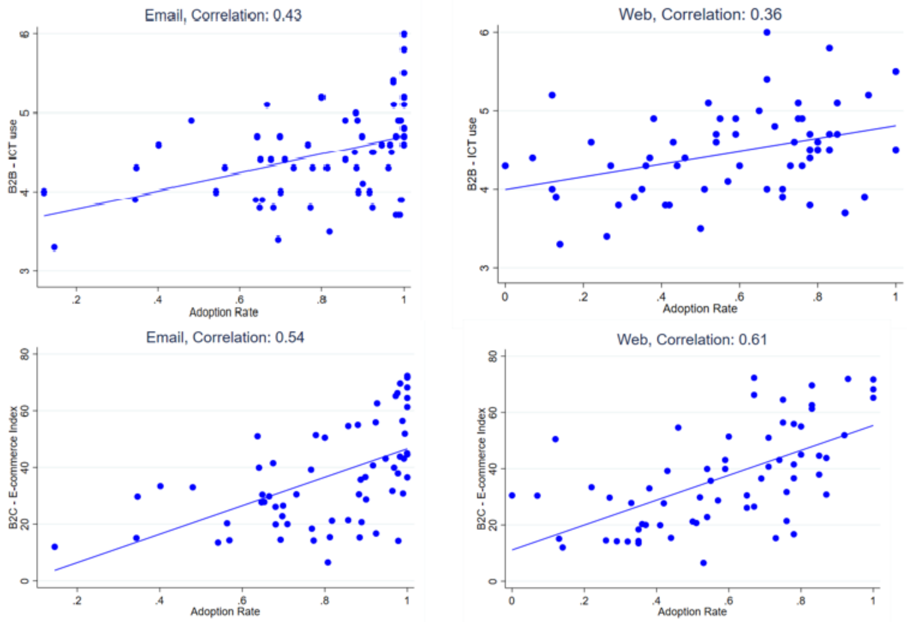
Given that transaction costs of interacting with clients by email are high and given that customers are more frequent users of businesses' websites than suppliers, our prior is that email adoption is associated with supply changes, while website adoption is related to demand changes. To test our prior, we pairwise correlate measure of email and website adoption at the country level with B2B and B2C indicators from the World Economic Forum and UNCTAD, respectively. The B2B indicator captures the extent to which firms in a country use ICTs to make transactions with other firms. It is measured by the World Economic Forum and corresponds to year 2015. The B2C indicator measures the extent to which firms in a country use e-commerce for transactions with their clients. It is calculated by UNCTAD and corresponds to year 2015. Country adoption rates are a weighted average of the adoption rates at the sectoral level, where the weights are the shares of sectoral sales on total sales.[5] We find that email adoption is more correlated than website adoption with B2B transactions (e.g., 0.43 versus 0.36 correlation coefficient), while website adoption is more correlated than email adoption with B2C transactions (0.61 versus 0.54 correlation coefficient). Thus, providing some evidence in line with our prior (See Figure 3.1).

To construct the estimation sample, we first compiled all the WBES waves available from 2002-2017. This creates a sample of 145,626 observations, which corresponds to 118,868 firms, operating in the manufacturing or service industries. Table 8 in section A of the Appendix provides detailed information about this sample across countries and years. After this, we drop firms for which we cannot identify the sector in which they operate. This give us a sample of 131,347 observations.

If we further restrict this sample to manufacturing industries, which is the focus of our analysis, we end up with a sample of 74,723 observations corresponding to 59,820 firms. Of these firms, 79.4 percent appear only once in the database; 17.0 percent appear twice; 3.0 percent appear three times; 0.5 percent appear four times; and 0.1 percent appear five times. Table 9 in section A of the Appendix displays detailed information about this sample across countries and years.

5. It is important to note that the timing corresponding to the last wave varies across regions, because the World Bank Enterprise Group does not collect the information for all countries simultaneously. Hence, we only use countries for which the last wave is between 2013 and 2017 to make it comparable with the 2015 B2B indicator.

Figure 3.1: B2C and B2B transactions



A common feature of many firm-level databases from developing countries is the presence of missing values for variables needed to measure firm performance (e.g., labor, sales, capital, and materials, and investment). For example, in our sample, labor is the variable with the least proportion of missing values (2.3 percent), followed by sales (14.2 percent), materials (31.8 percent), capital (32.8 percent), and investment (58.2 percent).

To maximize sample size, correct selection in misreporting, and gain efficiency, we impute data for sales, labor, capital, materials, and investment using the largest WBES database available, which contains 131,347 observations, and a pseudo-Gibbs sampler (Lee and Carlin 2010; Van Buuren, Boshuizen, and Knook 1999).[6] The explanatory variables used for imputation include email adoption, website adoption, export status, managerial experience proxied by a dummy variable that identifies firms with managers with above-median years of experience or otherwise. It also controls for country, industry, and survey year. We do not impute data for email adoption, website adoption, export status, and managerial experience as we are interested in understanding their effect on TFPR. Table 10 in section A of the Appendix presents summary statistics of the main variables

6. The only observations that were not included in the imputation method were those that did not report any sector activity.

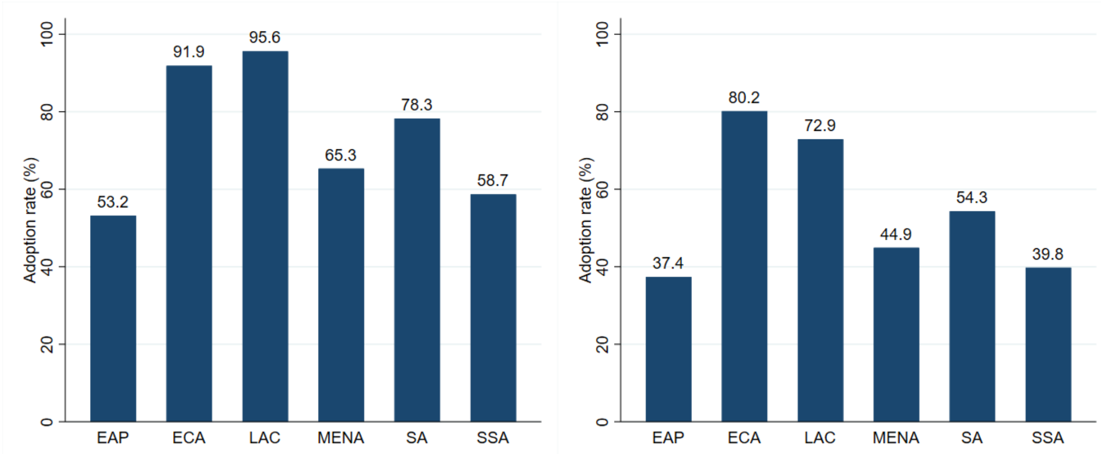
with and without imputation. As can be observed, the imputation method performs well, as there are not statistically significant differences in the descriptive statistics across sample groups.

To construct the estimation panel database, we drop all firms that have a missing value in at least one of the variables used in the analysis (e.g., email, website, exports, management, sales, capital, materials, labor, and investment). In turn, we eliminate all the firms with information only for one wave and we keep industries that have at least 250 observations as this is the minimum sample size we used to estimate TFPR at the sectoral level. Table **??** in section A of the Appendix presents descriptive statistics corresponding to the variables used to estimate TFPR using the estimation sample.

Figure 3.2 displays GDP-weighted regional average email (panel a) and website (panel b) adoption rates using the last wave of the WBES data for each country included in the sample. This involves 26 countries from ECA, 26 from SSA, 16 from LAC, 6 from SA, 5 from EAP, and 3 from MENA. These adoption rates are not fully comparable across regions, as the WBES team collects information for different countries at several points in time. As Table 8 shows, the timing corresponding to the last wave of the WBES varies across regions. It is 2015-2016 for the EAP region, 2012-2013 for the ECA region, 2009-2017 for LAC, 2007-2016 for MENA, 2013-2015 for SA, and 2007-2018 for SSA.

Figure 3.2: **Regional Adoption Rates**

(a) Email **(b) Website**



Note: Panel a and Panel b of Figure 3.2 display GDP-weighted regional average email and website adoption rates corresponding to the last wave of the WBES database for each of the countries included in the panel database, respectively. The rates consider sampling weights and therefore, they are representative at the national level. However, adoption rates are not fully comparable across regions, as the World Bank collects data for different countries at different points in time. As Table 6-9 shows, the timing corresponding to the last wave of the WBES varies across regions. The timing corresponding to the last wave of the WBES varies across regions. It is 2015-2016 for the EAP region, 2012-2013 for the ECA region, 2009-2017 for LAC, 2007-2016 for MENA, 2013-2015 for SA, and 2007-2018 for SSA. The region and country composition of the sample is as follows: Europe and Central Asia - ECA (26 countries), Sub-Saharan Africa - SSA (26 countries), Latin America and the Caribbean - LAC (16 countries), South Asia - SA (6 countries), East Asia and Pacific - EAP (5 countries), and Middle East and North Africa - MENA (3 countries).

4 Methodology

The estimation strategy proceeds in two stages. The first one focuses on estimating TFPR. The second step estimating factor demand.

4.1 Estimating productivity premiums from digitization

The productivity variable to be estimated is revenue-based total factor productivity (TFPR). We estimate this measure, instead of physical TFP, because the WBES does not collect information on prices at the firm-level. Thus, in order to construct proxy variables for output and inputs in comparable units across countries and over time, we use country deflators like the consumer price index. Our measure of TFPR thus confounds variations in prices and efficiency. It is therefore a measure of firm profitability.

To estimate TFPR, we first estimate a log-linearized Cobb-Douglas production function (PF), assuming that the PF elasticities vary at the 2-digit sector level. The estimation method follows Ackerberg, Caves, and Frazer (2015), who rely on the control function approach (CFA) to deal with endogeneity of input choices. We use materials to make productivity observable. Since the WBES follows a sub-sample of firms interviewed in previous waves to construct the panel, the data do not capture firm entry and exit dynamics. As a result, we can not control for selection in factor choice and materials usage.

While the Ackerberg, Caves, and Frazer (2015) method assumes an exogenous productivity process, we follow De Loecker (2013) and endogenize it. Thus, in our specification, TFPR is a function of the adoption of digital business solutions (e.g., email and website) as well as exporting status and managerial experience. Assuming an exogenous TFPR process, by contrast, would have implied that digital business solutions would have no impact on efficiency or sales. This is not only unrealistic, but also would have invalidated the moment conditions needed to identify the coefficients of the production function, as the productivity shock would not have been orthogonal to factor choices. In other words, if TFPR is a function of digitization, the PF elasticities will be biased. The sign of the bias is ambiguous, depending on whether digitization is factor-augmenting or factor-saving. If business digitization is factor-augmenting, then TFPR would be underestimated. By contrast, if TFPR is factor-saving, TFPR will be overestimated.

There are important reasons to make TFPR a function of business digitization. Using email to connect with clients and suppliers or having a business website to gain online presence can affect TFPR through various channels. On the demand-side of the market for an enterprise's goods and services, reductions in search and transaction costs affect firm profitability at the extensive and intensive margins by facilitating access to new clients or expanding the volume of transactions online. Dynamically, the scale-up of the demand for a firm's products or services increases profits, allowing it to pay the fixed cost of investing in TFPR-enhancing activities like innovation, managerial upgrading, or technology adoption (Bustos 2011). On the supply-side, using email to connect with suppliers helps improve production efficiency by enlarging the potential set of input providers in non-relationship specific investments. Alternatively, it reduces the number of suppliers in relationship-specific investments but enlarges the fraction of repeated interactions, thus addressing contract incompleteness and guaranteeing access to specific assets needed to produce more sophisticated goods (Aral, Bakos, and Brynjolfsson 2018). Because adoption of digital business solutions is not exogenous, we lagged the corresponding variables used to estimate their effects on TFPR.

Since the WBES data are not census data, a key question is whether we need to perform a weighted estimation, using country-specific sampling weights, to estimate the coefficients of the production function and TFPR. Following Cameron and Trivedi (2005), sampling schemes such as stratification lead to the conditional density of any variable in the sample differing from that in the population. However, if stratification is purely exogenous, such that it does not take into consideration the dependent variable to stratify the sample, then the estimated parameters are consistent, regardless of differences between the estimation sample and the true underlying population. By contrast, under pure endogenous sampling, the marginal distribution of the dependent variable in the sample differs from that in the population, and as a result, the estimated coefficients are inconsistent. Since firms' sales have not been used to stratify the WBES, we do not use country-specific weights for the estimation of the coefficients of the PF. Last, following the literature on PF estimation using the CFA, we bootstrapped the standard errors using 100 replications, using country and year to construct the strata.

After estimating the PF elasticities, we use equation 4.1 to estimate TFPR. Then, with unbiased estimates of TFPR at the firm-level in hand, we pool all the observations and run an OLS regression of unbiased-TFPR on digital business solutions (e.g., email and website) to estimate the weighted average marginal effects of digitization on TFPR. The OLS coefficients are mathematically equivalent to the weighted average of the estimated coefficients obtained from the PF estimation, where the Markov coefficients vary at the sector-level (see Appendix B for the proof).

Using the weighted average coefficients implies assuming homogeneous effects of digital-technology adoption on TFPR instead of sector effects. We do this for two reasons. First, the type of digitization we are interested in falls under the category of general-purpose technologies instead of sector-specific technologies. Second, by pooling all the observations we gain efficiency and increase the degrees of freedom in the estimation, especially with sectors that have few observations after we lag the explanatory variables to deal with endogeneity concerns. Provided we focus the interpretation of the results (inference) on the entire sample, our approach eliminates imprecision coming from making estimations with small sub-samples.

Thus, our empirical strategy to estimate TFPR and the marginal effects from digitization is a three-step procedure. Step 1 and 2 are the standard Control Function Approach step, with the difference that we extend Ackerberg, Caves, and Frazer (2015) and endogenize TFPR as a function of four firm-choice variables, email adoption, website adoption, exporting status, and managerial experience as in De Loecker (2013). Step 3 recovers the weighted average email and website marginal effects on TFPR at the firm-level. The following sub-sections provide further details about the specifications estimated in each stage.

4.1.1 TFPR estimation: CFA Step 1

We first estimate a log-linearized Cobb-Douglas production function at the sectoral level:

$$y_{ijct} = a_j + b_j l_{ijct} + c_j k_{ijct} + d_j m_{ijct} + tfpr_{ijct} + D_c + D_t + e_{ijt},^{7} \tag{4.1}$$

where y_{ijct}, l_{ijct}, k_{ijct}, and m_{ijct} refer to output, labor, capital, and materials used by firm i, which operates in sector j of country c, at time t. e_{ijct} is an i.i.d error term that captures unanticipated shocks to production or measurement error. D_c and D_t are country fixed-effects and time fixed-effects, respectively. Since productivity, $TFPR_{ijct}$, is unobservable, we follow Ackerberg, Caves, and Frazer (2015) and use materials to make it observable:

$$m_{ijct} = h\left(l_{ijct}, k_{ijct}, tfpr_{ijct}, Email_{ijct}, Website_{ijct}, X_{ijct}, D_c, D_t\right), \tag{4.2}$$

7. Henceforth $x = \ln(X)$, for $X = \{Y, L, K, M, TFPR\}$.

where X_{ijct} is a set of control variables that can affect materials demand (e.g., exporting status, managerial experience). Since materials are a strictly monotonic function of TFPR, we can invert function $h(\cdot)$, and express TFPR as a function of labor, capital, materials, digital business solutions and other determinants of firm performance:

$$tfpr_{ijct} = h^{-1}\left(l_{ijct}, k_{ijct}, m_{ijct}, Email_{ijct}, Website_{ijct}, X_{ijct}, D_c, D_t\right). \tag{4.3}$$

Inserting equation (4.3) into (4.1) yields:

$$\begin{aligned} y_{ijct} \quad = \quad & a_j + h^{-1}\left(l_{ijct}, k_{ijct}, m_{ijct}, Email_{ijct}, Websiteijct, X_{ijct}, D_c, D_t\right) \\ & +b_j l_{ijct} + c_j k_{ijct} + d_j m_{ijct} + D_c + D_t + e_{ijt}. \end{aligned} \tag{4.4}$$

Equation (4.4) can be estimated by OLS. We approximate function $h(\cdot)$ using a third degree polynomial on labor, capital, and materials. Following Ackerberg, Caves, and Frazer (2015), in the first step we cannot identify the coefficients of the PF. However, we can remove the estimated error term, and use output minus its predicted value to estimate the TFPR process and use the productivity shock for the moment conditions needed to estimate the PF elasticities.

4.1.2 TFPR estimation: CFA Step 2

As mentioned, the Ackerberg, Caves, and Frazer (2015) CFA relies on an exogenous Markovian TFPR process to estimate the PF elasticities:

$$tfpr_{ijct} = g\left(tfpr_{ijct-1}\right) + \varepsilon_{ijct} \tag{4.5}$$

Following De Loecker (2013), the standard CFA can be extended by endogenizing TFPR as a function of digital business solutions or any firm choice variable. Moreover, we adopt a flexible functional approach, which allows the marginal effects of digital business solutions to vary with a firm's initial level of TFPR. To deal with endogeneity concerns, we lagged email and website adoption as well as the variables included in X_{ijct}. The resulting estimation equation is:

$$\begin{aligned} tfpr_{ijct} &= \alpha_j + \rho_{j1} tfpr_{ijct-1} + \rho_{j2} tfpr^2_{ijct-1} + \rho_{j3} tfpr^3_{ijct-1} + D_c + D_t + \varepsilon_{ijct} \\ &\quad + \Psi \left(Email_{ijct-1}, Website_{ijct-1}, Exp_{ijct-1}, Man_{ijct-1}, tfpr_{ijct-1} \right), \end{aligned} \tag{4.6}$$

where Ψ is a function that includes $Email_{ijct-1}$,$Website_{ijct-1}$, Exp_{ijct-1} (Export), and $Mana_{ijct-1}$ (Managerial) as free-standing variables, as well as all the possible interaction terms with all the arguments of function Ψ. The term ε_{ijct} is by assumption uncorrelated with any lagged choice variable because the latter are in the firm's information set. This forms the basis for the identification of the labor, capital, and material elasticities in the final stage of the Ackerberg, Caves, and Frazer (2015) procedure. Thus, the PF elasticities are estimated based on the following moment conditions:

$$E \left[\varepsilon_{ijct} \left(b_{jc},\ c_{jc},\ d_{jc} \right) \begin{pmatrix} l_{ijct-1} \\ k_{ijct} \\ m_{ijct-1} \end{pmatrix} \right] = 0. \tag{4.7}$$

The extended specification nests other, more traditional approaches used in the literature such as OLS with fixed effects. This explains why papers like De Loecker (2013), Braguinsky et al. (2015) and De Loecker et al. (2016) do not control for firm or plant fixed effects when endogenizing the Markov process. As De Loecker (2013) explains, the timing assumption on the arrival of the productivity shock is what gives identification of the learning-by-exporting effect. The firm's decision to export was made prior to the firm receiving the productivity shock. Therefore, unexpected shocks to the production process are orthogonal to its export decision. This identification assumption has been validated by the theoretical and empirical literature that shows that firms need time to prepare themselves to enter into new markets.

Analogously, the same identification strategy applies to digital-technology adoption. It is the timing assumption of the arrival of the productivity shock and delayed adoption what ensures identification. In the case of technology adoption, there is by now, extensive theoretical and empirical literature showing that it takes time for firms operating both in developed and developing countries to adopt new technologies. Thereby rejecting the possibility of firms changing their adoption status instantaneously to productivity shocks.

Slow technological adoption rates have been puzzling for Economists for decades as there is evidence highlighting the benefits firms can obtain from adopting new technologies, let alone the fact that adoption decisions appear empirically to be rational and well-explained by heterogeneous net benefits (Suri 2011). Experimental evidence have evolved extensively to show that low adoption rates can be explained by several factors. For technologies that do not display network effects, this includes preferences and behavioral bias (e.g., risk aversion, hyperbolic preferences, status-quo bias, and change-holding behavior),[8] informational constraints and limitations to individual and social learning (e.g., lack of knowledge on how to use the new technology, uncertainty about its effectiveness, sustainability and returns, heterogeneous conditions, and ineffective knowledge transmission channels),[9] weak demand (e.g., trade shocks, other demand shocks),[10] lack of incentives (e.g., principal-agent misalignment within the firm, and lack of product market competition),[11] and need of making complementary investments to take advantage of new technologies (e.g., skill upgrading, organizational changes, re-organization of production, and complementary equipment).[12] For technologies with network effects, main factors delaying adoption decisions include coordination and trust problems.[13]

The Ackerberg, Caves, and Frazer (2015) approach uses a value-added instead of output PF to estimate TFPR. It is intentionally done in this way to avoid estimating the elasticity corresponding

8. See Liu (2013), Duflo, Kremer, and Robinson (2011), Beaman, Magruder, and Robinson (2014), Giné and Yang (2009), Mullainathan (2004), and Knight, Weir, and Woldehanna (2003).

9. See Beaman et al. (2021), Cole and Fernando (2020), Gupta, Ponticelli, and Tesei (2020) , Casaburi et al. (2019), BenYishay and Mobarak (2019), Hanna, Mullainathan, and Schwartzstein (2014), Dupas (2014), Nicholas Bloom et al. (2013), Conley and Udry (2010), Bandiera and Rasul (2006), Munshi (2004), Foster and Rosenzweig (1995), and David (1990).

10. See Hardy and McCasland (2021), Verhoogen (2020), Atkin, Khandelwal, and Osman (2017b), and Bustos (2011).

11. See Atkin et al. (2017a) on principal-agent misalignment, Nicholas Bloom et al. (2013) and Bloom and Van Reenen (2007, 2010) on product market competition, and Mokyr (1990) Mokyr (1990), Lazonick (1979) on workersâ resistance to change.

12. See Juhász, Squicciarini, and Voigtländer (2020), Brynjolfsson, Rock, and Syverson (2017), Emerick et al. (2016) Emerick, Sadoulet, and Dar (2016), Brynjolfsson and Milgrom (2013), Beaman et al. (2013), Bresnahan and Trajtenberg (1995), David (1990) and Rosenberg (1982).

13. See Belleflamme and Peitz (2015) for a comprehensive theoretical review, and Jin and Sun (Working Paper), Couture et al. (2021), Luo and Niu (2019) for experimental evidence

to materials and therefore address the concern that lagged materials is not a valid instrument. Bond and Söderbom (2005) argue that materials are a flexible input, which implies that it does not follow an auto-regressive process. To explore this issue, we estimated an AR (1) model for materials and found that the coefficient of interest is equal to 0.86. We prefer this approach instead of the value-added approach, as the latter implicitly assumes an output elasticity with respect to materials equal to 1. The coefficients of the production functions are thus estimated by minimizing the sample analogue of equation (4.7) using GMM.

4.1.3 TFPR estimation: Step 3. Estimating global average digital premiums

With unbiased estimates of TFPR in hand, we pool all the observations and estimate equation (4.6) using OLS. Appendix B shows that the estimated coefficients in the whole sample are a weighted average of the coefficients obtained across sub-samples.

4.2 Estimating the Effects on Labor and Capital Demand

Recent technological innovations have revamped an old concern about productivity-driven displacement effects on jobs and shifts of the labor demand towards skilled workers. New task theories developed to understand the potential effects of automation on jobs depart from the skill-biased technological change models and show that the effect of technology-adoption on jobs is ambiguous. Under the new settings, robots compete against workers. Initially, machines replace workers in tasks previously performed by humans (Acemoglu and Restrepo 2018, 2019b, 2020a; Autor and Salomons 2018). However, as the economy grows, new tasks are introduced. Dynamically, in general equilibrium, the initial labor displacement effect pushes wages down and allows labor to regain a price advantage relative to machines. As a result, the new tasks are labor intensive. This effect is known as the reinstatement effect.

Our estimation framework with enterprise balanced panel data is, by definition, partial equilibrium. In our framework, technology affects jobs through two different channels. A scale direct effect and a factor-augmenting or factor-saving effect that operates through TFPR changes. However, we cannot identify whether the final effect on jobs is driven by the displacement, reinstatement, or a combination of both effects. This is because the WBES does not collect information on tasks and the allocation of labor across tasks at the firm-level.

Moreover, since our TFPR measure confounds both prices and efficiency, our productivity-driven effect is not fully comparable to the displacement effect cited in the literature (Acemoglu and Restrepo 2018, 2019a). This is because the price-related component of this effect could be labor-augmenting if efficiency gains are passed-through onto product prices and product demand is elastic. However, if efficiency gains are large, they are not pass-through onto prices and demand is inelastic, the effect could be labor-saving, just like the displacement effect cited in the literature. The scale effect is unambiguously labor-augmenting. It is associated with an expansion in firms' profits due to a reduction in marginal costs or the scale-up of demand for a firm's output, as digitization allows firms to find better input suppliers and reach a larger potential customer base. Thus, to estimate the factor demand effects from digitization, as well as that from exporting and managerial experience, we estimate the following equation:

$$\Delta fp_{ijc} = \theta_1 + \theta_2 \Delta Email_{ijc} + \theta_3 \Delta Website_{ijc} + \theta_4 \Delta tfpr_{ijc} + \theta_5 \Delta X_{ijc} + D_c + D_j + D_t + \upsilon_{ijc},$$

where $\Delta fp_{ijc} = \Delta \ln \left(FP_{ijc} \right)$ stands for changes in the use of factors of production, labor and capital.

5 Data and Method Validation

To validate the estimations of the effect of digital- technology adoption on TFPR using the WBES database, we estimate the same specification as the baseline specification reported in De Loecker (2013) who employs data from Slovenia. This involves the estimation of a value-added Cobb-Douglas production function on labor, capital, and productivity, where the latter is assumed to be an endogenous process of learning-by-exporting. Table 1 presents the results from the production function elasticities, while Table 2 displays the median learning-by-exporting effect on TFPR.

Table 1: WEBS-De Loecker Comparison: Production Function Elasticities

Sector Description	WBES			De Loecker		
	L	K	K/L	L	K	K/L
Food & beverages	0.933	0.241	0.258	0.810	0.131	0.162
Textiles	0.925	0.206	0.223	0.562	0.165	0.294
Garments	0.911	0.251	0.276	0.833	0.152	0.182
Leather	0.735	0.364	0.495	0.542	0.356	0.657
Wood	0.868	0.160	0.184	0.885	0.063	0.071
Publishing, printing and reproduction	0.978	0.262	0.268	0.603	0.337	0.559
Chemicals	1.038	0.205	0.197	0.601	0.274	0.456
Rubber & plastics	1.071	0.204	0.190	0.669	0.142	0.212
Other non-metallic products	0.974	0.254	0.261	0.614	0.255	0.415
Basic metals	1.202	0.198	0.165	0.751	0.042	0.056
Fabricated metal prods.	1.097	0.184	0.168	0.666	0.194	0.291
Machinery and equipment	0.991	0.225	0.227	0.700	0.199	0.284
Electrical machinery	1.102	0.230	0.209	0.558	0.223	0.400
Furniture	0.877	0.307	0.350	0.709	0.146	0.206

Notes. Table 1 presents the production function elasticities from estimating a value-added log-linearized Cobb-Douglas production function following De Loecker (2013). In this paper, value-added is a function of labor and capital. The estimating method is based on the Control Function approach by Ackerberg, Caves, and Frazer (2015). However, it departures from the latter by assuming an endogenous Markovian productivity process, which is a function of learning by exporting. WBES data covers a sample of 7,916 manufacturing enterprises from 82 developing countries during the period 2003-2018; while De Loecker (2013) study focuses on 7,915 manufacturing firms in Slovenia during the period 1994-2000. Data for WBES come from the World Bank, while data fromDe Loecker (2013) come from the Slovenian Central Statistical Office. The correlation coefficient between the K-to-L estimated ratio using the WBES and De Loecker (2013) database is 0.55. It is also statistically significant at the 5 percent level.

Using the production function elasticities from Table 1, we calculate sector-specific factor intensities, defined as the capital-to-labor PF elasticity ratio, and examine the pairwise correlations between the results obtained using the WBES database and those from De Loecker (2013). We found a correlation coefficient of 0.55 between factor intensities, which is significant at the 5 percent level. The correlation coefficient between median productivity-premium from exporting is 0.36. This is high given that we only have 15 observations and there is a lot of cross-country variation in the WBES database.

Table 2: WBES-De Loecker Comparison: Non-Parametric Estimates of Exporting on TFPR (in percent)

Sector Description	Median Productivity Premium from Exporting	
	WBES	De Loecker
Food & beverages	5.953	2.280
Textiles	4.949	1.980
Garments	3.696	1.660
Leather	-1.577	1.830
Wood	7.186	1.920
Publishing, printing and reproduction	5.732	4.880
Chemicals	6.541	3.930
Rubber & plastics	6.122	4.500
Other non-metallic products	5.246	2.730
Basic metals	5.141	3.190
Fabricated metal products	6.071	3.320
Machinery and equipment	4.218	3.450
Electrical machinery	3.687	4.640
Furniture	1.862	1.990

Note: Table 2 presents the median TFPR-premium from exporting following De Loecker (2013) method. The latter is based on the estimation of a value-added log-linearized Cobb-Douglas production function based on the Control Function approach by Ackerberg, Caves, and Frazer (2015) and assuming an endogenous (cubic) Markovian (AR 1) productivity process, which is a function of learning by exporting. WBES data covers a sample of manufacturing enterprises from 82 developing countries during the period 2003-2018; while De Loecker (2013) study focuses on 7,915 manufacturing firms in Slovenia during the period 1994-2000. Data for WBES come from the World Bank, while data from De Loecker (2013) come from the Slovenian Central Statistical Office. The correlation coefficient is 0.36.

6 Nonparametric Estimates of the Digital-Technology Adoption Effect (DAE) on TFPR

This section presents the semi-parametric estimates of the productivity premiums from digitization. Table 3 reports the median effects, the percentage of the estimation sample with positive marginal effects, and the F-test associated with each variable of interest. Column (1) displays the results from estimating an endogenous TFPR process that is a function of learning-by-exporting, as in De Loecker (2013). Column (2) reports the results from estimating an endogenous TFPR process that is a function of the adoption of digital business solutions, namely email and website. Column (3) presents the results from estimating an endogenous TFPR process that is a function of managerial experience. Column (4) shows the most complete specification that includes digitization, exporting status, and managerial experience effects.

Table 3 also displays the probability-adjusted margnal effects. Column (1) reports a probability-adjusted expected median productivity premium from exporting of 1.7 percent for the entire sample. This is calculated as the sample probability of becoming an exporter times the estimated marginal productivity effect (0.3 times 0.056). As in De Loecker (2013), we reject the null hypothesis of an exogenous productivity process, in favor of a specification with learning by exporting effects.

Column (2) shows a positive productivity premium from email adoption for almost 50 percent of the estimation sample. The probability-adjusted premium is almost negligible. The probability-adjusted median TFPR-premium from website adoption is negative (2.8 percent), with 24.64 percent of the estimation sample showing a positive impact. The large proportion of firms displaying negative marginal effects could mirror the same measurement problem associated with estimating the effects of process innovation on productivity. If innovation (in this case digital- technology adoption) is cost saving and the demand for the good a firm sells is not sufficiently price responsive, then TFPR can decrease when digitization-triggered cost reductions are passed-through onto prices (see the literature review by Hall and Monhen 2013). As with the first specification, we reject an exogenous productivity process in favor of a specification, where digital technology adoption affects firm performance.

Column (3) shows a positive managerial-experience premium for all firms with more educated managers. The median premium effect is 0 percent and the F-test rejects an exogenous TFPR process. However, these three model specifications can yield biased estimates because they omit the other firm-choice variables. Therefore, our preferred specification reported under column 4 includes all four choice variables simultaneously.

Table 3: Estimated Median Productivity Premium: Digital-Technology Adoption, Learning by Exporting, and Managerial Experience

Productivity Determinants	(log)-Productivity Premium	Endogenous Markov Specification				Probability-adjusted Effects			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Exporting status	Median TFPR Effect (MPE)	0.056			0.036	0.017			0.011
	% of obs. with MPE >0	100.000			59.084	100.000			59.084
	F-test	4.362***			8.175***	4.362***			8.175***
Email Adoption	Median TFPR Effect (MPE)		-0.001		0.014		-0.001		0.010
	% of obs. with MPE >0		49.697		63.386		49.697		63.386
	F-test		9.689***		5.615***		9.689***		5.615***
Website Adoption	Median TFPR Effect (MPE)		-0.056		0.047		-0.028		0.023
	% of obs. with MPE >0		24.640		54.731		24.640		54.731
	F-test		4.887***		3.240**		4.887***		3.240**
Managerial Experience	Median TFPR Effect (MPE)			0.001	0.001			0.000	0.000
	% of obs. with MPE >0			82.993	60.056			82.993	60.056
	F-test			2.264*	7.470***			2.264*	7.470***
R^2		0.877	0.886	0.890	0.887	0.877	0.886	0.890	0.887
F-Total			11.762***		6.766***		11.762***		6.766***
N					7,926				

Note: Table 3 presents the results from estimating equation 4.6 using the Control Function approach by Ackerberg, Caves, and Frazer (2015) and endogenizing the (cubic) Markovian (AR 1) productivity process to make it a function of digital-technology adoption, learning by exporting, and managerial experience. The estimated marginal effects represent weighted average of the effects estimated at the sectorial level. Thus, the pool specification used to recover the coefficients from equation 4.6 controls for sector, country, and time fixed effects. Productivity determinants have been instrumented with a one-period lag to control for endogeneity. Standard errors have been bootstrapped using 100 replications and country-year strata. The F-statistics are used to evaluate the null hypothesis of an exogenous productivity process against an alternative hypothesis of an endogenous process. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" is measured by number of years of experience of the manger.The reported effect of experience is for firms with managers with above median years of experience (17 years). Outliers were removed after the productivity premium effects were calculated. We define outliers those observations whose corresponding productivity premiums is higher than "U" or lower than "L", where U is defined as the first quartile minus 2.5 times the interquartile range (IQR) and L is defined as the third quartile plus 2.5 times IQR.

The results of the preferred model indicate that the omission of any of these variables would have biased the results. Figure 6.1 displays the corresponding kernel densities for the TFPR premium associated with email adoption (panel a), website adoption (panel b), learning-by-exporting (panel c), and managerial experience (panel d) after removing outliers. There are two kernels in each panel. One represents the distribution of the TFPR premium for the partial model and the other one for the complete model. The (log)TFP premiums are positive for 63.38 (email adoption), 54.73 (website adoption), 59.08 (learning-by- exporting), and 60.05 (managerial experience) percent of the estimation sample. The probability-adjusted median TFPR premium associated with email adoption is 1 percent and that of website adoption is 2.3 percent. The probability-adjusted median TFPR-premium from getting access to external markets is 1.1 percent, while that of increasing managerial experience is near zero.

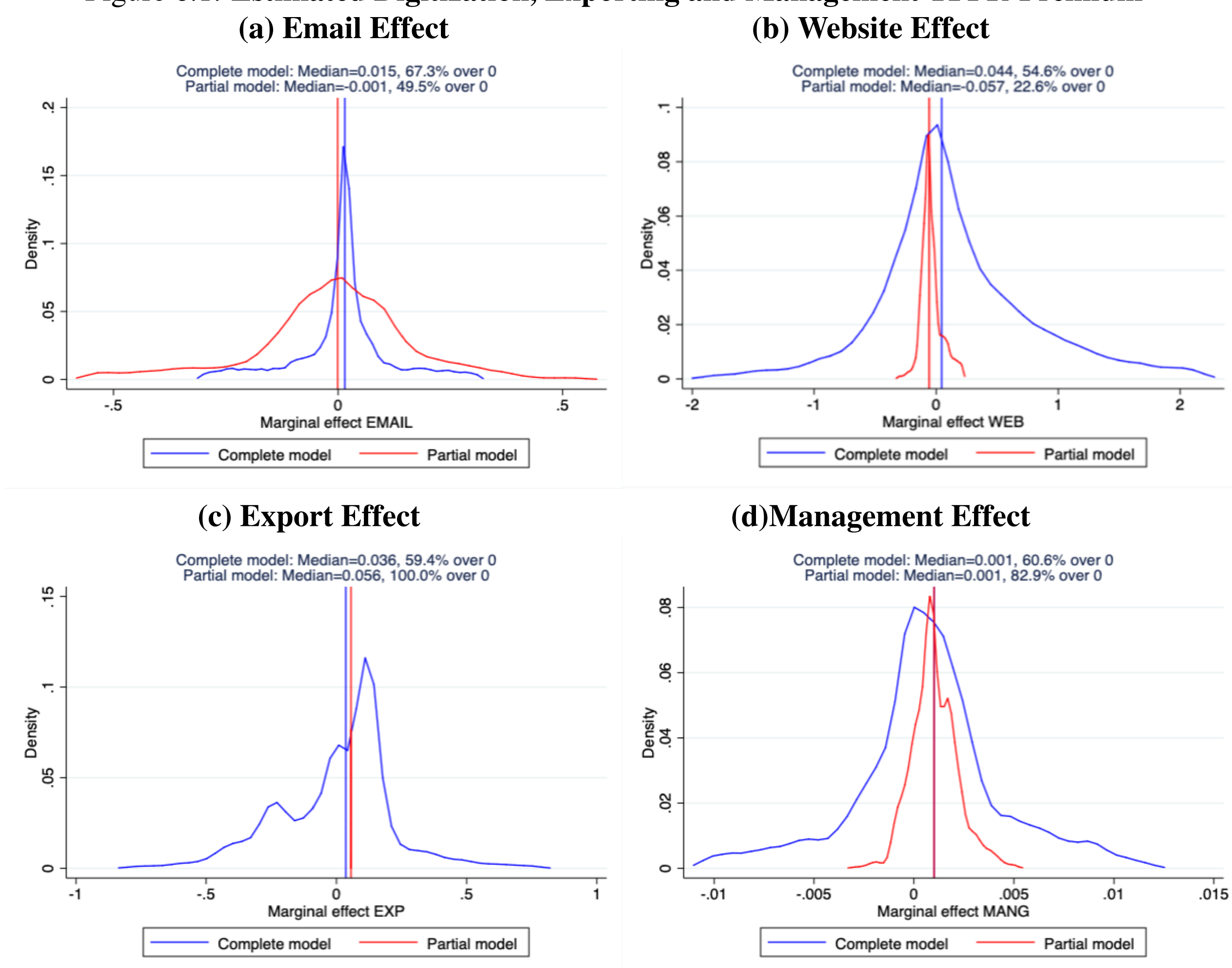
As Figure 6.1 shows, several firms display negative marginal TFPR gains from adopting digital solutions. Firms may experience a reduction in revenue-based productivity when the pro-competitive effects from digitization on prices overcome the efficiency and scale gains, as the TFPR measure confounds both pries and efficiency. Digitization lower search costs and facilitates price comparisons. Thus, it is expected to lower prices and price dispersion. The broad literature examining various U.S retail contexts has been summarized in Goldfarb (2020) and Goldfarb and Tucker (2019). It concludes that prices fall and price dispersion often exhibits a decline, although it remains high, as a result of digitization.[14]

Evidence on digitization-driven price and price dispersion reductions is even more compelling for developing countries. This could be explained by several reasons, including the fact that new communication technologies are far more useful in these economies than in advanced ones; and

14. Persistent of dispersion is, primarily, explained by the intentional manipulation of search costs by firms (Goldfarb 2020). Retailers design their interfaces to make price search relatively difficult, lowering customer price sensitivity to make price comparison more difficult. This will allow them to keep markups high (e.g. Ellison and Ellison 2009, Hossain and Morgan 2006). Brynjolfsson and Smith (2000) compare the prices of books and CDs at online and offline retailers. They showed that online prices were lower than offline prices, though substantial price dispersion remains. Lower online prices have also been found in automotive products (Morton, Zettelmeyer, and Silva-Risso 2001) and airlines (Orlov 2011).

that managers in developing countries lack the skills or the funding to hire experts, who can manipulate search algorithms, and help them obtain high rents (See Nicholas Bloom et al. (2013) and Bloom and Van Reenen (2007, 2010)). For example, Jensen (2007) examines the impact of mobile phone service on the fishing industry in the Indian state of Kerala and finds that mobile phones led to a sharp decline in price dispersion. Underlying the result is rapid adoption in mobile phones coupled with the use of phones in fish markets. Aker (2010) also finds a similar result in the context of grain markets in Niger. Mobile phone service reduced price dispersion substantially. Parker, Ramdas, and Savva (2016) examine a text message service in India, finding that the service reduced price dispersion for crops.

Figure 6.1: **Estimated Digitization, Exporting and Management TFPR-Premium**



Note: Figure 6.1 displays the marginal effects from digitization, learning by exporting, and accumulation of managerial experience that result from estimating the econometric model displayed in equations 4.1-4.7. The corresponding specification assumes an endogenous productivity process that it is a function of digital-technology adoption (email and website), learning by exporting, and accumulation of managerial experience above the country-median. The panels in figure 6.1 display the marginal effects for the estimation sample removing outliers. Outliers were removed after the productivity premium effects were calculated. We define outliers those observations whose corresponding productivity premiums is higher than "U" or lower than "L", where U is defined as the first quartile minus 2.5 times the interquartile range (IQR) and L is defined as the third quartile plus 2.5 times IQR. Variable "EXP" takes value 1 if the firm sells a product in international markets; "EMAIL" takes value 1 if the firm uses email to connect with clients and suppliers; "WEB" takes value 1 if the firm has a business website; "MANG" is the log of the number of years of experience of the manager.

7 Estimates of the Effects of Digitization on Factor Demand

The objectives of this section are twofold. First, we quantify the effects of digitization on factor demand. Second, we identify the direct and indirect channels through it operates.

7.1 Effects on Jobs

Table 4 presents the results from estimating equation (4.8) for each of the endogenous TFPR specifications estimated in previous section (see Table 3 columns 1-4 for reference). Column (1) displays estimated labor-demand effects when assuming an endogenous TFPR process that is a function of learning-by-exporting. Column (2) excludes exporting effects and assumes an endogenous TFPR process that is a function of digitization (e.g., email and website adoption). Column (3) assumes TFPR evolves over time as a function of managerial experience. The most complete specification is the one displayed in Column (4), which assumes that job changes are a function of changes in digitization, learning-by-exporting, and managerial experience. All specifications control for endogeneous changes in TFPR to capture indirect digitization effects.

Table 4: Estimates of the Digital-Technology Adoption Effects on Jobs

Variable of Interest		WBES			
		(1)	(2)	(3)	(4)
Change in Export Status	Coeff.	0.341			0.304
	St.Dev	(0.082)			(0.066)
	T-test	[4.167]			[4.596]
Change in Email Adoption	Coeff.		0.240		0.220
	St.Dev		(0.077)		(0.069)
	T-test		[3.109]		[3.193]
Change in Website Adoption	Coeff.		0.227		0.217
	St.Dev		(0.046)		(0.040)
	T-test		[4.919]		[5.375]
Change in Manager's experience	Coeff.			0.087	0.072
	St.Dev			(0.031)	(0.027)
	T-test			[2.821]	[2.611]
Change in TFPR	Coeff.	0.083	0.062	0.097	0.034
	St.Dev	(0.022)	(0.021)	(0.022)	(0.015)
	T-test	[3.841]	[2.953]	[4.454]	[2.286]
R^2		0.073	0.081	0.373	0.103
N		7,926			

Note: Table 4 presents the results from estimating equation 4.8 for the pool sample. For each of the estimated specifications, we use changes in estimated TFPR assuming the same corresponding specification as in Table 3. The estimation controls for sector, country, and time fixed effects. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" takes value 1 if the firm has a manager with years of experience above the country-median. "Employment" measures full-time employees; "Exporting status" takes value 1 if the firm sells a product in international markets; "Email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "Website adoption" takes value 1 if the firm has a business website; "Manager's experience" takes value 1 if the firm has a manager with years of experience above the country-median.

Table 4 shows that changes in digital-technology adoption, exporting, and accumulation of managerial experience have positive and statistically significant effects on jobs. For our preferred specification, which is the one displayed in Column 4, the largest effect comes from exporting (30 percent, approximately), followed by digitization (22 and 21 percent for email and website, respectively), and managerial experience (7 percent percent). Interestingly, in all the specifications, the TFPR-related effect is positive and statistically significant, meaning that, contrary to conventional wisdom, TFPR improvements are labor-augmenting. However, this does not necessarily means that the effect is positive for all the sectors, as Table 4 displays pooled regressions, which are a weighted-average of the sector-specific ones. Sector-specific regressions, which are available upon request, show that the positive TFPR effect is mainly explained by sectors like garments and fabricated metals. This contrasts with other sectors such as chemicals, where the estimated effects are negative.

7.2 Effects on Capital

Table 5 reports the results for the demand for capital. For the variable of interest, the results are similar to those reported in Table 4. That is, changes in digital-technology adoption, exporting status, and managerial experience have a positive and statistically significant effect on changes in the demand for capital. The largest effect is observed for email adoption (57 percent), followed by exporting (35 percent), and website adoption (17 percent, approximately) (Table 5, column 4). In contrast to the job findings, changes in TFPR have no statistically significant effect in any specification.

Table 5: Estimates of the Digital-Technology Adoption Effects on Capital

Variable of Interest		WBES			
		(1)	(2)	(3)	(4)
Change in Export Status	Coeff.	0.418			0.348
	St.Dev	(0.115)			(0.104)
	T-test	[3.623]			[3.341]
Change in Email Adoption	Coeff.		0.594		0.565
	St.Dev		(0.137)		(0.132)
	T-test		[4.340]		[4.285]
Change in Website Adoption	Coeff.		0.207		0.173
	St.Dev		(0.065)		(0.063)
	T-test		[3.201]		[2.747]
Change in Manager's experience	Coeff.			0.192	0.176
	St.Dev			(0.060)	(0.058)
	T-test			[3.173]	[3.034]
Change in TFPR	Coeff.	-0.003	-0.026	0.010	0.075
	St.Dev	(0.076)	(0.075)	(0.076)	(0.050)
	T-test	[-0.045]	[-0.353]	[0.129]	[1.494]
R^2		0.254	0.260	0.252	0.265
N		7,926			

Note: Table 5 presents the results from estimating equation 4.8 for the pool sample. For each of the estimated specifications, we use changes in estimated TFPR assuming the same corresponding specification as in Table 3. The estimation controls for sector, country, and time fixed effects. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" takes value 1 if the firm has a manager with years of experience above the country-median. "Capital" measures the replacement value of the firm's assets; "Exporting status" takes value 1 if the firm sells a product in international markets; "Email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "Website adoption" takes value 1 if the firm has a business website; "Manager's experience" takes value 1 if the firm has a manager with years of experience above the country-median.

8 Benchmarking Results with the Literature

With the new estimates of the impact of website and email adoption on revenue productivity in hand, it is worthwhile assessing the credibility of the estimates by comparing them to those presented in existing literature.

8.1 Estimated TFPR Gains compared to Previous Estimates

We first compare our estimated coefficient for the specification that only includes learning-by-exporting effects with that from De Loecker (2013). In our paper, the estimated coefficient corresponding to the first specification implies a (log)TFPR-premium of 5.6 percent for the median firm, while that from De Loecker (2013) is 2.96 percent. While our estimate is larger than that from De Loecker (2013), it is within the range reported in his paper (e.g., -5 to 20 percent). Further, it would not be surprising to find that firms far from the frontier can benefit more from learning-by-exporting than firms closer to it. Given that our sample involves several developing countries that exhibit lower levels of development than Slovenia, the country explored in De Loecker (2013), this can explain our larger estimated effect.

Regarding the impact of digitization on productivity, in order to analyze the aggregate TFPR gains a country can obtain from digitization, we take our estimates, and work with the last wave of WBES data in our estimation sample. In turn, we conduct the counterfactual exercise of measuring the TFPR aggregate gains from universal adoption of digital solutions. Table 6 shows the regional average corresponding to the aggregate TFPR gains a country can obtain from universal adoption of digital solutions. Panel A displays the results when we conduct the counterfactual exercise by truncating the firm distribution of non-adopters to those that display positive marginal effects. Panel B presents the results when conducting the counterfactual analysis for without truncating the sample of non-adopters. As we explain in previous sections, if the pro-competitive effects on prices from digitization are larger than the efficiency and scale gains, TFPR can decrease as a result of digitization.

Panel A shows productivity gains from universal adoption of email and website. Web-related TFPR gains are larger than email-related gains. They vary between 10.019 percent for ECA to 20.171 percent for SA. The large value observed for LAC is, primarily, explained, by the presence of regional outliers like Paraguay, Panama, El Salvador, and Peru. Panel B, which shows TFPR gains for the complete set of non-adopters, displays smaller TFPR gains from digitization than those presented in Panel A. Email-related gains are negligible for LAC, MENA, and ECA.

Table 6: Aggregate TFPR Gains from Universal Digitization

Region	Panel A: With Truncation		Panel B: Without Truncation	
	(1) EMAIL	(2) WEB	(3) EMAIL	(4) WEB
EAP	2.146	15.309	1.457	2.260
ECA	0.363	10.019	-0.127	7.544
LAC	0.157	16.318	-0.003	12.732
MENA	0.971	20.160	0.011	16.447
SA	1.153	20.171	-0.183	1.955
SSA	1.567	16.223	1.053	1.145

Note: Table **??** presents the regional average country-level TFPR gains from universal adoption of digital solutions. To calculate them, we take our estimates and work with the last wave of WBES data in our estimation sample. In turn, we conduct the counterfactual exercise of analyzing what would happen if on an annual basis, 10 percent of the low-productivity and non-adopter firms adopt digital solutions, for a period of 30 years to achieve universal digitization. *: Although the LAC region includes several countries with relatively large initial adoption rates, the high value calculated for TFPR gains from WEB adoption are, primarily, explained by countries like Paraguay, Panama, El Salvador, and Peru, with gains of 30.5,29.9,28.7 and 19.7 percent, respectively.

There are few papers in the literature that estimate the effect of digitization on TFPR using firm-level data from developing countries. While most of them show a positive effect, its magnitude varies substantially. Two recent papers are Hjort and Poulsen (2019) and DeStefano, Kneller, and Timmis (2018). These papers use firm-level data and the control function approach to examine the effects of digital-technology adoption on firm-level productivity (TFPR). Hjort and Poulsen (2019) explores the impact of the arrival of fast internet on firm-level productivity (value-added TFP) in Ethiopia. Using the Ethiopian manufacturing census for the period 2006-2013 and implementing the De Loecker (2011) methodology, the authors estimate an increase in firm-level productivity of 12.7 percent when fast internet becomes available.[15] This value is a few percentage points lower than our estimates corresponding to the sample of SSA non-adopters with positive marginal effects. However, the effects reported in Hjort and Poulsen (2019) are by far larger than ours if we consider the complete set of non-adopters, which includes firms with negative marginal effects due to the pro-competitive negative effects of digitization on firm-level prices.

Moreover, DeStefano, Kneller, and Timmis (2018) examines the effect of ICT capital on firm-level productivity (TFPR) in the UK. The authors use firm-level data from the Office for National Statistics (ONS) and apply the method by Ackerberg, Caves, and Frazer (2015) to estimate TFP.

15. The authors endogenize the productivity process to make it a function of the arrival of internet.

When correcting for the endogeneity bias between ICT capital and TFP, the paper shows that there is no causal effect between these variables.[16] As DeStefano, Kneller, and Timmis (2018) find, TFPR gains from universal email adoption are almost negligible for several regions in our paper when considering the entire distribution of non-adopters. This includes regions like ECA, LAC, MENA, and SA. Further, although EAP and SSA exhibit positive TFPR gains from universal email adoption, the gains do not exceed 1.5 percent.

Another related paper is Gal et al. (2019). The authors estimate the effect of digitization on productivity, following Wooldridge (2009), by combining firm-level data from Orbis with industry-level data on digital-technology adoption. Their results imply that a 1 percentage point increase in adoption of high-speed broadband (or cloud computing) is associated with an increase in TFPR growth of 0.14 percentage points for the average firm. This estimate is not directly comparable to ours because our estimate is on the level whereas Gal et al. (2019) estimate a permanent increase in TFPR growth rate. However, it is noteworthy that after ten years, the level effects in Gal et al. (2019) would surpass ours.[17] Overall, our results are in line with those in the literature.

8.2 Estimated Jobs Gains Compared to Previous Estimates

Firm-level evidence on the effect of digital-technology adoption on input demand is scarce. In fact, at the time of writing, we could not find a comparable paper to ours that measures the effect

16. This result holds irrespective of the sample of firms the authors use to conduct their analysis and the control function approach method implemented (e.g., ACF, LP, or OP).

17. Bartelsman, Hagsten, and Polder (2018) find that an increase in the share of broadband internet connected employees by 1 percentage point is associated with an increase in productivity by approximately 0.36 percent both for manufacturing and service firms in ten European countries. The authors work with firm-level data for the period 2002-2010 and estimate an augmented Cobb-Douglas value-added production function. Using a different approach, Brynjolfsson, Mitchell, and Rock (2018) explore the effect of intangible investments (e.g., generic RD investments, computer hardware, software, and more speculatively, AI) on TFP. By combining Tobin's q-theory of investment with neoclassical growth accounting, the authors derive an expression for productivity mismeasurement as a function of the growth rates, size, and shadow values of intangible capital. Assuming an intangible multiplier of 10, which is, as the authors explain, somewhat lower than the levels estimated in Brynjolfsson, Hitt, and Yang (2002) and Rock (2019), the authors calculate that the net software-correlated (hardware-correlated) adjusted TFP level is over 12.4 percent (3.2 percent) higher than measured TFP at the beginning of 2017 (at the end of 2016). Last, Brynjolfsson and Hitt (2003) estimate the effect of computerization on productivity, using a nearly balanced panel of 527 firms in the Fortune 1000 over an 8-year period. Their instrumental variables regression shows productivity premiums that range from 0.093 to 3.57 percent for various duration that vary from 1 to 7 years. Our estimates seem well within this range as well.

of digitization on the demand for capital. Therefore, the discussion in this section focuses on labor demand. Our results in Table 4 column (4) suggest that digital technology adoption is associated with an increase in firm-level employment of 22 percent and 21.7 percent for email and website, respectively. However, these estimates are not comparable to studies that estimate the impact of fast speed internet on the probability of employment in a labor market. The reason is that the universe of manufacturing firms does not equal the population of workers in a local labor markets. Therefore, to compare our estimates to those in the literature, we need to convert them into an object that approximates the population of workers.

Thus, to analyze the aggregate employment gains a developing country could obtain from firm digitization, we took our estimates to the last wave of WBES data. We conducted a counterfactual exercise analyzing what would happen in terms of aggregate jobs gains in the manufacturing labor market if there were universal adoption of digital solutions. We conduct the counterfactual analysis using two samples of non-adopters. The first one considers only firms that exhibit positive marginal effects from digitization. The second sample includes all non-adopters. The aggregate jobs gains from digitization will therefore depend on three factors: the estimated direct effect at the firm-level, the estimated indirect effect (through TFPR changes) at the firm-level, and the characteristics of each country-specific sample of non-adopters.

Table 7 displays total, direct, and indirect regional averages of the country-level job gains from digitization. Three conclusions can be drawn from the analysis. First, web-related job gains are larger than email-related gains for all the regions. Second, the ranking of regions in terms of the magnitude of simulated gains is the same for email and website. Third, most of the job gains are explained by the direct effects, as indirect effects for email and website adoption do not surpass more than 1 percent. Since the indirect effects are small, there are not significant differences in total gains between the sample of non-adopters and the sample of non-adopters, who exhibit positive TFPR gains from digitization.

Table 7: Aggregate Employment Gains from Universal Digitization

	Panel A: With Truncation					
	(1)	(2)	(3)	(4)	(5)	(6)
Region	EMAIL			WEB		
	Total	Direct	Indirect	Total	Direct	Indirect
EAP	4.975	4.931	0.044	9.614	9.240	0.375
ECA	1.024	1.015	0.009	3.576	3.372	0.204
LAC	0.294	0.292	0.002	2.394	2.193	0.201
MENA	2.537	2.525	0.011	6.968	6.687	0.281
SA	2.662	2.642	0.021	6.842	6.480	0.362
SSA	4.133	4.102	0.031	10.194	9.871	0.323
	Panel B: Without Truncation					
	(1)	(2)	(3)	(4)	(5)	(6)
Region	EMAIL			WEB		
	Total	Direct	Indirect	Total	Direct	Indirect
EAP	4.747	4.748	-0.001	9.170	9.001	0.170
ECA	1.022	1.015	0.006	3.563	3.372	0.190
LAC	0.301	0.292	0.009	2.237	2.183	0.054
MENA	2.380	2.387	-0.007	6.617	6.430	0.187
SA	2.635	2.642	-0.007	6.499	6.350	0.149
SSA	3.548	3.517	0.031	9.400	9.702	-0.302

Note: Table 7 presents the regional average country-level aggregate gains (e.g., total, direct, and indirect) from universal adoption of digital solutions. To calculate these gains, we take our estimates and work with the last wave of WBES data in our estimation sample. In turn, we conduct the counterfactual exercise of analyzing what would happen in terms of aggregate jobs gains in the manufacturing labor market if 10 percent of the low productivity firms adopt digital solutions each year, for a period of 30 years to achieve universal adoption of digital solutions.

Since our estimates at the firm-level may a priori look large, one may wonder if we are properly identifying the impact of digitization on employment. Perhaps the estimates suffer from omitted variable bias, such as tangible and intangible capital. We rule out this possibility for two reasons. First, we explore the correlation between investment and digital-technology adoption for the sample of firms where data on investment is available. We found statistically insignificant correlations of 0.01 (web) and 0.006 (email) at the 5 percent level. Second, our regression controls for firm fixed effects, changes in managerial experience and changes in endogenous TFPR to account for the effect of changes in intangible capital.

Moreover, our firm-level and aggregate estimated effects fall within the range of estimates in the literature. The two closest papers to ours, which explore the effect of digital-technology adoption on employment, are Hjort and Poulsen (2019) and DeStefano, Kneller, and Timmis (2018). Hjort and Poulsen (2019) examine the impact of the arrival of fast internet in Africa on employment. The authors worked with firm-level data from the Ethiopian manufacturing firm census for the period 2006 to 2013. They found that the estimated increase in total employment per firm when fast internet arrives is about 16 percent, controlling for firm and year fixed effects. The effect increases to about 22 percent in specifications with additional interactions.[18] Our results display lower job gains than those reported by Hjort and Poulsen.

Hjort and Poulsen also worked with data from various surveys with employment information for individuals, including Demographic Health Surveys, household surveys from Afrobarometer, and the South African Quarterly Labor Force Surveys. Their results show a 4.6 percentage point, or 6.0 percent, increase in the probability that an individual is employed when fast internet arrives, using DHS data. The effects were even bigger when using Afrobarometer data, 7.7 percentage point, or 13.2 percent increase in the employment rate. In South Africa, they found a 2.2 percentage point or 3.1 percent increase in employment. Our estimates of the impact of digital-technology adoption (email and website) for South Africa are 1.828 percent, which is lower than the magnitudes estimated by the authors. Most of the effect (97.9 percent) is explained by website adoption.[19]

Last, DeStefano, Kneller, and Timmis (2018) explore the effect of ICT capital per employee on employment in the UK, using firm-level data on the physical units of ICT used within a firm from the Ci Technology Database (CiTDB) and ICT data from the UK Census Bureau, the Office for National Statistics (ONS) for year 2000. Their results show a strong significant effect of ICT capital on firm employment of 87.8 percent (all wave 1) and 72.2 percent (enabled by 2000). These magnitudes are by far larger than our estimates. Thus, implying that our estimates are unlikely to be upwardly biased.[20]

18. When controlling for grid-cell x connected and industry x year fixed effects.

19. DHS data was available for eight countries: Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania. Afrobarometer data was available for nine countries: Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, Tanzania, and South Africa.

20. All wave 1 exchangesâ refers restricts the sample of to those firms that are connected to telephone exchanges that were ADSL enabled by the end of 2001 (wave 1). Enabled by 2000 exchanges restricts the sample of firms to those that were connected to telephone exchanges that were ADSL enabled in 2000.

9 Program Targeting and Complementarities among TFPR-Enhancing Investments

A fundamental question that emerges from the analysis is how governments can use the previous findings to guide the design of public programs aimed at fostering digital-technology adoption. Governments are often concerned with "targeting". That is, identifying the types of firms that can benefit the most from a specific policy. Targeting is important when public resources are limited. Targeting is not trivial as there is heterogeneity in firms' attributes and performance, even within narrowly defined industries (Syverson 2014).

Another relevant policy question is related to the existence of potential complementarities between productivity-enhancing investments (e.g., upgrading for exporting, improving managerial capabilities, adopting complementary business solutions). This is because complementarities can make multiple-treatment business support programs more effective than those that provide only one arm of support. For example, recent firm-level evidence on digital-technology adoption shows the importance of making complementary investments and organizational changes to help adopting firms take advantage of their newly adopted digital business solutions (Brynjolfsson et al. 2020; Brynjolfsson, Rock, and Syverson 2017; Bresnahan, Brynjolfsson, and Hitt 2002).

Panels (a) and (b) of Figure 9.1 show the (log)TFPR-premium from email and website adoption depending on a firm's initial level of TFPR (i.e., profitability). Based on the estimation sample, the typical firm does not export, does not have a business website, and has a manager with 17 years of experience. Thus, the typical enterprise, a non-exporter, has low initial profits, it is small, it is a price taker and therefore has no impact on the markets in which it operates.

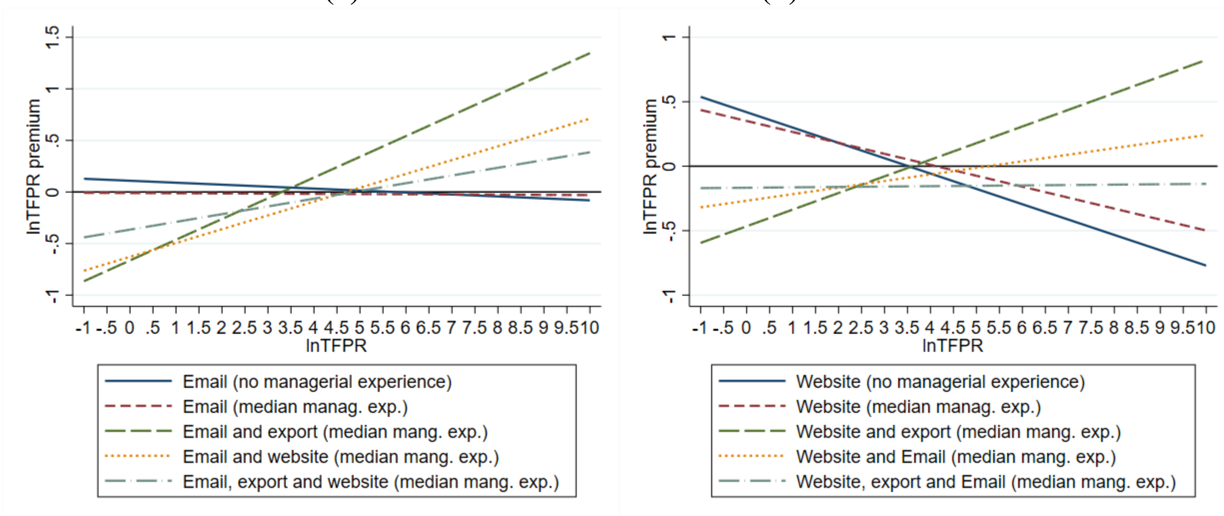
When their scale of production increases due to email (proxy for a supply shock) or website adoption (proxy for a demand shock), domestic prices do not fall much because of the atomistic nature of the firm, while production costs fall, thereby yielding a net increase in the firmsâfirmâs profits. However, the domestically oriented firm, with high initial profits often is large, and when it adopts, for example, a website, its resulting expanded production scale drives down domestic prices. Thereby lowering the firmâs profits, despite the cost savings gained.

For exporting firms, growth in their scale of production has no impact on the output prices they face, as they are all small relative to their export markets. However, they may have an effect on prices of some of their inputs sourced in their home markets. Exporting firms with initially low TFPR levels will face falling profits, as the increased scaling of production, without increase in output price, amplifies the losses they initially have. Though this effect could be offset when input prices declines. Similarly, profits of exporting firms with initially high levels of TFPR will increase due to higher output at constant prices. And possible decreases in some domestically sourced input prices.

Those differential effects between domestic and exporting firms suggest that when a digital solution like website adoption is coupled with the goal of increasing access to foreign markets, then it may be better to target high-productivity exporting firms. This is because there are high complementarities between digital-technology business solutions and exporting. And these complementarities yield higher revenue productivity gains than if only one firm attribute is used to target firms when eligible for receiving business support services. Indeed, recent firm-level evidence on digital-technology adoption highlight the relevance of making complementary investments and organizational changes to help adopting firms take advantage of their newly adopted digital business solutions (Brynjolfsson et al. 2020; Brynjolfsson, Rock, and Syverson 2017; Bresnahan, Brynjolfsson, and Hitt 2002).

Figure 9.1: $\ln(\mathrm{TFPR})$ **Premium for Typical Firm**

(a) Email **(b) Website**



10 Conclusions

Technological change is altering the way firms produce their goods and services. Yet, estimates about their effects on firm-level productivity and factor demand are scarce, especially for developing economies. Concerns have focused, primarily, around two topics. The first one is the global contraction in productivity growth rates, which occurred despite the spectacular technological progress observed in recent years. The second one is the potential labor-displacement and skill-biased effects of technology adoption by profit-maximizing firms.

This paper presented firm-level estimates of the revenue productivity (TFPR) premium of adopting digital business solutions in manufacturing enterprises in 82 developing countries with data from 2002-2019. It examines the impact of adopting email to connect with clients or suppliers and launching a business website on TFPR and factor demand. The data and methodology appear to be consistent with the existing literature that focuses only on learning by exporting effects. The empirical strategy builds on the Control Function approach and thus controls for the endogeneity of input choices. In addition, we assume an endogenous productivity process that is a function of firm digitization, learning-by-exporting, and managerial experience. At the time of writing, this paper is the only study that utilizes a large sample of enterprises from across the developing world and simultaneously studies the impact of more than one choice variable on both TFPR and factor demand.

The resulting evidence suggests that digital-technology adoption affects manufacturing firm performance in developing countries. However, the productivity-premium from email and website adoption varies across firms, as do the effects of exporting and managerial experience. Nonetheless, estimates of the median effect of digital technology adoption on TFPR indicate that the expected economic magnitudes (probability-adjusted) of these effects are potentially larger for digital-technology adoption than for exporting or enhancing managerial capabilities. Moreover, there is evidence of complementarities among these choice variables when it comes to their impact on TFPR. Finally, we do not find a digitization-driven displacement effect on jobs or capital. By contrast, digital technology adoption seems to increase firms' demand for labor and capital. Last but not least, the evidence from the rich set of interactions suggests that program targeting in developing economies can yield substantial aggregate TFPR gains relative to random treatment selection. However, there might be welfare gains in the cases in which digital technology adoption is associated with declines in revenue productivity, which can be driven by declines in sales prices to the benefit of consumers. Disentangling the effects of digitization on technical efficiency and TFPQ from price effects remains an important area for future research with better data from developing countries.

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Online Appendix

A Tables

Table 8: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Afghanistan	-	-	-	338	-	-	647	-	526	-	-	-	410	-	-	-	-	1,921
Albania	170	-	-	204	-	304	-	175	-	-	-	360	-	-	-	-	-	1,213
Angola	-	-	-	-	425	-	-	-	360	-	-	-	-	-	-	-	-	785
Argentina	-	-	-	-	1,063	-	-	-	1,054	-	-	-	-	-	-	991	-	3,108
Armenia	171	-	-	351	-	-	-	374	-	-	-	360	-	-	-	-	-	1,256
Azerbaijan	170	-	-	350	-	-	-	380	-	-	-	390	-	-	-	-	-	1,290
Bangladesh	-	-	-	-	-	1,504	-	-	-	250	-	1,442	-	-	-	-	-	3,196
Belarus	250	-	-	325	-	-	273	-	-	-	-	360	-	-	-	-	-	1,808
Benin	-	-	197	-	-	-	-	150	-	-	-	-	-	-	150	-	-	497
Bhutan	-	-	-	-	-	-	-	250	-	-	-	-	-	253	-	-	-	503
Bolivia	-	-	-	-	613	-	-	-	362	-	-	-	-	-	-	364	-	1,339
Bosnia and Herzegovina	182	-	-	200	-	-	-	361	-	-	-	360	-	-	-	-	-	1,103
Botswana	-	-	-	-	342	-	-	-	268	-	-	-	-	-	-	-	-	610
Brazil	-	1,642	-	-	-	-	-	1,802	-	-	-	-	-	-	-	-	-	3,444
Bulgaria	250	-	-	300	-	1,015	-	288	-	-	-	293	-	-	-	-	-	2,146
Burkina Faso	-	-	-	-	139	-	-	394	-	-	-	-	-	-	-	-	-	533
Cambodia	-	-	-	-	-	-	-	-	-	-	-	472	-	-	373	-	-	845
Cameroon	-	-	-	-	207	-	-	363	-	-	-	-	-	-	361	-	-	931
Cabo Verde	-	-	-	-	98	-	-	156	-	-	-	-	-	-	-	-	-	254
Chad	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	-	153	303
Chile	-	-	-	-	1,017	-	-	-	1,033	-	-	-	-	-	-	-	-	2,050
Colombia	-	-	-	-	1,000	-	-	-	942	-	-	-	-	-	-	993	-	2,935
Croatia	187	-	-	236	-	633	-	159	-	-	-	360	-	-	-	-	-	1,575
CÃŽte d'Ivoire	268	-	-	343	-	-	-	250	-	-	-	254	-	-	-	-	-	1,115
Czech Republic	-	-	-	-	-	-	-	526	-	-	-	-	-	-	361	-	-	887
Congo, Dem. Rep.	-	-	-	-	340	-	-	-	359	-	-	529	-	-	-	-	-	1,228
Dominican Republic	-	-	-	-	-	-	-	-	360	-	-	-	-	-	359	-	-	719
Ecuador	-	453	-	-	658	-	-	-	366	-	-	-	-	-	-	361	-	1,838
Egypt, Arab Rep.	-	-	977	-	-	1,339	1,700	-	-	-	-	2,897	-	-	1,827	-	-	8,740
El Salvador	-	-	-	-	693	-	-	-	360	-	-	-	-	-	719	-	-	1,772
Estonia	170	-	-	219	-	-	-	273	-	-	-	273	-	-	-	-	-	935
Ethiopia	-	-	-	-	-	-	-	-	-	644	-	-	-	848	-	-	-	1,492
Georgia	174	-	-	200	-	-	-	373	-	-	-	360	-	-	-	-	-	1,107
Ghana	-	-	-	-	-	494	-	-	-	-	-	720	-	-	-	-	-	1,214
Guatemala	-	455	-	-	522	-	-	-	590	-	-	-	-	-	-	345	-	1,912
Honduras	-	450	-	-	436	-	-	-	360	-	-	-	-	-	332	-	-	1,578
Hungary	250	-	-	610	-	-	-	291	-	-	-	310	-	-	-	-	-	1,461
Indonesia	-	-	-	-	-	-	-	1,444	-	-	-	-	-	1,320	-	-	-	2,764
Kazakhstan	250	-	-	585	-	-	-	544	-	-	-	600	-	-	-	-	-	1,979
Kenya	-	-	-	-	-	657	-	-	-	-	-	781	-	-	-	-	-	2,439
Kosovo	-	-	-	-	-	-	-	270	-	-	-	202	-	-	-	-	-	472
Kyrgyzstan	173	-	-	202	-	-	-	235	-	-	-	270	-	-	-	-	-	1,240
Lao PDR	-	-	-	-	-	-	-	360	-	-	379	-	-	-	368	-	-	1,439
Latvia	176	-	-	205	-	-	-	271	-	-	-	336	-	-	-	-	-	988
Lesotho	-	-	-	-	-	-	-	151	-	-	-	-	-	-	150	-	-	301
Total	6,586	4,472	2,024	12,007	13,675	13,104	4,132	22,556	12,398	1,734	4,599	22,180	4,842	4,878	6,875	5,222	153	145,626

Table 1 Continued: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Liberia	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	151	-	301
Lithuania	200	-	-	205	-	-	-	276	-	-	-	270	-	-	-	-	-	951
North Macedonia	170	-	-	200	-	-	-	366	-	-	-	-	-	-	-	-	-	736
Malawi	-	-	-	160	-	-	-	150	-	-	-	-	523	-	-	-	-	833
Mali	-	155	-	-	-	490	-	-	360	-	-	-	-	-	185	-	-	1,190
Mexico	-	-	-	-	1,480	-	-	-	1,480	-	-	-	-	-	-	-	-	2,960
Moldova	174	-	-	350	-	-	-	363	-	-	-	360	-	-	-	-	-	1,247
Mongolia	-	-	-	-	-	-	-	362	-	-	-	360	-	-	-	-	-	722
Montenegro	20	-	-	18	-	-	-	116	-	-	-	150	-	-	-	-	-	304
Morocco	-	-	850	-	-	659	-	-	-	-	-	-	-	-	-	-	-	1,509
Myanmar	-	-	-	-	-	-	-	-	-	-	-	-	632	-	607	-	-	1,239
Nepal	-	-	-	-	-	-	-	486	-	-	-	482	-	-	-	-	-	968
Nicaragua	-	452	-	-	478	-	-	-	336	-	-	-	-	-	333	-	-	1,599
Niger	-	-	-	138	-	-	-	150	-	-	-	-	-	-	-	151	-	439
Nigeria	-	-	-	-	-	2,387	-	3,157	-	-	-	-	2,676	-	-	-	-	8,220
Pakistan	402	-	-	-	-	1,337	-	-	-	-	-	906	-	-	-	-	-	2,645
Panama	-	-	-	-	604	-	-	-	365	-	-	-	-	-	-	-	-	969
Paraguay	-	-	-	-	613	-	-	-	361	-	-	-	-	-	-	364	-	1,338
Peru	-	-	-	-	632	-	-	-	1,000	-	-	-	-	-	-	1,003	-	2,635
Philippines	-	-	-	-	-	-	-	1,326	-	-	-	-	-	1,335	-	-	-	2,661
Poland	500	-	-	975	-	-	-	455	-	-	-	542	-	-	-	-	-	2,472
Romania	255	-	-	600	-	-	-	541	-	-	-	540	-	-	-	-	-	1,936
Russian Fed.	506	-	-	601	-	-	-	1,004	-	-	4,220	-	-	-	-	-	-	6,331
Rwanda	-	-	-	-	212	-	-	-	-	241	-	-	-	-	-	-	-	453
Senegal	-	262	-	-	-	625	-	-	-	-	-	-	601	-	-	-	-	1,488
Serbia	230	-	-	282	-	-	-	388	-	-	-	360	-	-	-	-	-	1,260
Sierra Leone	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	152	-	302
Slovak Republic	170	-	-	220	-	-	-	275	-	-	-	268	-	-	-	-	-	933
Slovenia	188	-	-	223	-	-	-	276	-	-	-	270	-	-	-	-	-	957
South Africa	-	603	-	-	-	1,057	-	-	-	-	-	-	-	-	-	-	-	1,660
Suriname	-	-	-	-	-	-	-	-	152	-	-	-	-	-	-	-	-	385
Tajikistan	-	-	-	-	-	-	360	-	-	-	-	359	-	-	-	-	-	719
Tanzania	-	-	-	-	419	-	-	-	-	-	-	813	-	-	-	-	-	1,232
Timor Leste	-	-	-	-	-	-	-	150	-	-	-	-	-	126	-	-	-	276
Togo	-	-	-	-	-	-	-	155	-	-	-	-	-	-	150	-	-	305
Turkey	-	-	-	1,323	-	-	1,152	-	-	-	-	1,344	-	-	-	-	-	5,482
Uganda	-	-	-	-	563	-	-	-	-	-	-	762	-	-	-	-	-	1,325
Ukraine	463	-	-	594	-	-	-	851	-	-	-	1,002	-	-	-	-	-	2,910
Uruguay	-	-	-	-	621	-	-	-	607	-	-	-	-	-	-	347	-	1,575
Uzbekistan	260	-	-	300	-	-	-	366	-	-	-	390	-	-	-	-	-	1,316
Venezuela, RB	-	-	-	-	500	-	-	-	320	-	-	-	-	-	-	-	-	820
Vietnam	-	-	-	1,150	-	-	-	1,053	-	-	-	-	-	996	-	-	-	3,199
Yemen, Rep.	-	-	-	-	-	-	-	-	477	-	-	353	-	-	-	-	-	830
Zambia	207	-	-	-	-	603	-	-	-	-	-	720	-	-	-	-	-	1,530
Zimbabwe	-	-	-	-	-	-	-	-	-	599	-	-	-	-	600	-	-	1,199
Total	6,586	4,472	2,024	12,007	13,675	13,104	4,132	22,556	12,398	1,734	4,599	22,180	4,842	4,878	6,875	5,222	153	145,626

Table 9: Number of observations in WBES by Country and Year (manufacturing industries)

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Afghanistan	-	-	-	18	-	-	115	-	87	-	-	-	132	-	-	-	-	352
Albania	65	-	-	76	-	111	-	66	-	-	-	110	-	-	-	-	-	428
Angola	-	-	-	-	214	-	-	-	106	-	-	-	-	-	-	-	-	320
Argentina	-	-	-	-	695	-	-	-	767	-	-	-	-	-	-	646	-	2,108
Armenia	64	-	-	220	-	-	-	106	-	-	-	109	-	-	-	-	-	499
Azerbaijan	51	-	-	191	-	-	-	109	-	-	-	120	-	-	-	-	-	471
Bangladesh	-	-	-	-	-	926	-	-	-	242	-	1,171	-	-	-	-	-	2,339
Belarus	43	-	-	50	-	-	96	-	-	-	-	116	-	-	-	-	-	635
Benin	-	-	167	-	-	-	-	74	-	-	-	-	-	-	70	-	-	311
Bhutan	-	-	-	-	-	-	-	94	-	-	-	-	-	82	-	-	-	176
Bolivia	-	-	-	-	388	-	-	-	154	-	-	-	-	-	-	113	-	655
Bosnia and Herzegovina	68	-	-	75	-	-	-	125	-	-	-	117	-	-	-	-	-	385
Botswana	-	-	-	-	110	-	-	-	84	-	-	-	-	-	-	-	-	194
Brazil	-	1,606	-	-	-	-	-	1,481	-	-	-	-	-	-	-	-	-	3,087
Bulgaria	50	-	-	57	-	634	-	87	-	-	-	109	-	-	-	-	-	937
Burkina Faso	-	-	-	-	52	-	-	94	-	-	-	-	-	-	-	-	-	146
Cambodia	-	-	-	-	-	-	-	-	-	-	-	46	-	-	134	-	-	180
Cameroon	-	-	-	-	106	-	-	103	-	-	-	-	-	-	97	-	-	306
Cabo Verde	-	-	-	-	44	-	-	63	-	-	-	-	-	-	-	-	-	107
Chad	-	-	-	-	-	-	-	59	-	-	-	-	-	-	-	-	74	133
Chile	-	-	-	-	656	-	-	-	779	-	-	-	-	-	-	-	-	1,435
Colombia	-	-	-	-	647	-	-	-	700	-	-	-	-	-	-	563	-	1,910
Croatia	40	-	-	74	-	408	-	59	-	-	-	121	-	-	-	-	-	702
CÃŽte d'Ivoire	70	-	-	82	-	-	-	97	-	-	-	112	-	-	-	-	-	361
Czech Republic	-	-	-	-	-	-	-	195	-	-	-	-	-	-	102	-	-	297
Congo, Dem. Rep.	-	-	-	-	144	-	-	-	125	-	-	236	-	-	-	-	-	505
Dominican Republic	-	-	-	-	-	-	-	-	115	-	-	-	-	-	108	-	-	223
Ecuador	-	156	-	-	360	-	-	-	126	-	-	-	-	-	-	103	-	745
Egypt, Arab Rep.	-	-	578	-	-	767	1,112	-	-	-	-	1,935	-	-	1,156	-	-	5,548
El Salvador	-	-	-	-	445	-	-	-	131	-	-	-	-	-	405	-	-	981
Estonia	29	-	-	39	-	-	-	86	-	-	-	82	-	-	-	-	-	236
Ethiopia	-	-	-	-	-	-	-	-	-	299	-	-	-	380	-	-	-	679
Georgia	32	-	-	48	-	-	-	117	-	-	-	110	-	-	-	-	-	307
Ghana	-	-	-	-	-	290	-	-	-	-	-	374	-	-	-	-	-	664
Guatemala	-	410	-	-	315	-	-	-	349	-	-	-	-	-	-	141	-	1,215
Honduras	-	450	-	-	285	-	-	-	183	-	-	-	-	-	90	-	-	1,008
Hungary	51	-	-	355	-	-	-	110	-	-	-	97	-	-	-	-	-	613
Indonesia	-	-	-	-	-	-	-	1,131	-	-	-	-	-	1,067	-	-	-	2,198
Kazakhstan	55	-	-	345	-	-	-	186	-	-	-	200	-	-	-	-	-	786
Kenya	-	-	-	-	-	388	-	-	-	-	-	383	-	-	-	-	-	1,196
Kosovo	-	-	-	-	-	-	-	90	-	-	-	71	-	-	-	-	-	161
Kyrgyzstan	49	-	-	58	-	-	-	93	-	-	-	105	-	-	-	-	-	450
Lao PDR	-	-	-	-	-	-	-	143	-	-	86	-	-	-	115	-	-	478
Latvia	28	-	-	35	-	-	-	90	-	-	-	114	-	-	-	-	-	267
Lesotho	-	-	-	-	-	-	-	31	-	-	-	-	-	-	74	-	-	105
Total	1,602	3,766	1,566	5,886	7,880	6,727	2,319	11,106	6,909	973	1,443	11,046	2,169	3,306	3,246	2,533	74	74,723

Table 2 Continued: Number of observations in WBES by Country and Year (manufacturing industries)

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Liberia	-	-	-	-	-	-	-	48	-	-	-	-	-	-	-	75	-	123
Lithuania	42	-	-	45	-	-	-	101	-	-	-	107	-	-	-	-	-	295
North Macedonia	47	-	-	58	-	-	-	100	-	-	-	-	-	-	-	-	-	205
Malawi	-	-	-	59	-	-	-	70	-	-	-	-	196	-	-	-	-	325
Mali	-	63	-	-	-	301	-	-	165	-	-	-	-	-	98	-	-	627
Mexico	-	-	-	-	1,059	-	-	-	1,154	-	-	-	-	-	-	-	-	2,213
Moldova	49	-	-	193	-	-	-	105	-	-	-	110	-	-	-	-	-	457
Mongolia	-	-	-	-	-	-	-	127	-	-	-	115	-	-	-	-	-	242
Montenegro	7	-	-	4	-	-	-	38	-	-	-	49	-	-	-	-	-	98
Morocco	-	-	821	-	-	451	-	-	-	-	-	-	-	-	-	-	-	1,272
Myanmar	-	-	-	-	-	-	-	-	-	-	-	-	334	-	360	-	-	694
Nepal	-	-	-	-	-	-	-	165	-	-	-	239	-	-	-	-	-	404
Nicaragua	-	430	-	-	343	-	-	-	127	-	-	-	-	-	104	-	-	1,004
Niger	-	-	-	37	-	-	-	46	-	-	-	-	-	-	-	41	-	124
Nigeria	-	-	-	-	-	1,035	-	1,594	-	-	-	-	1,261	-	-	-	-	3,890
Pakistan	36	-	-	-	-	102	-	-	-	-	-	661	-	-	-	-	-	799
Panama	-	-	-	-	239	-	-	-	115	-	-	-	-	-	-	-	-	354
Paraguay	-	-	-	-	387	-	-	-	143	-	-	-	-	-	-	117	-	647
Peru	-	-	-	-	362	-	-	-	751	-	-	-	-	-	-	547	-	1,660
Philippines	-	-	-	-	-	-	-	937	-	-	-	-	-	1,027	-	-	-	1,964
Poland	120	-	-	520	-	-	-	140	-	-	-	183	-	-	-	-	-	963
Romania	83	-	-	381	-	-	-	178	-	-	-	169	-	-	-	-	-	811
Russian Fed.	125	-	-	143	-	-	-	687	-	-	1,357	-	-	-	-	-	-	2,312
Rwanda	-	-	-	-	30	-	-	-	-	78	-	-	-	-	-	-	-	108
Senegal	-	63	-	-	-	273	-	-	-	-	-	-	246	-	-	-	-	582
Serbia	61	-	-	84	-	-	-	139	-	-	-	117	-	-	-	-	-	401
Sierra Leone	-	-	-	-	-	-	-	35	-	-	-	-	-	-	-	77	-	112
Slovak Republic	32	-	-	39	-	-	-	85	-	-	-	100	-	-	-	-	-	256
Slovenia	45	-	-	58	-	-	-	101	-	-	-	84	-	-	-	-	-	288
South Africa	-	588	-	-	-	708	-	-	-	-	-	-	-	-	-	-	-	1,296
Suriname	-	-	-	-	-	-	-	-	76	-	-	-	-	-	-	-	-	155
Tajikistan	-	-	-	-	-	-	111	-	-	-	-	121	-	-	-	-	-	232
Tanzania	-	-	-	-	273	-	-	-	-	-	-	427	-	-	-	-	-	700
Timor Leste	-	-	-	-	-	-	-	56	-	-	-	-	-	60	-	-	-	116
Togo	-	-	-	-	-	-	-	36	-	-	-	-	-	-	45	-	-	81
Turkey	-	-	-	1,235	-	-	885	-	-	-	-	1,050	-	-	-	-	-	4,229
Uganda	-	-	-	-	304	-	-	-	-	-	-	358	-	-	-	-	-	662
Ukraine	140	-	-	182	-	-	-	557	-	-	-	717	-	-	-	-	-	1,596
Uruguay	-	-	-	-	375	-	-	-	371	-	-	-	-	-	-	110	-	856
Uzbekistan	52	-	-	72	-	-	-	124	-	-	-	132	-	-	-	-	-	380
Venezuela, RB	-	-	-	-	47	-	-	-	81	-	-	-	-	-	-	-	-	128
Vietnam	-	-	-	1,053	-	-	-	748	-	-	-	-	-	690	-	-	-	2,491
Yemen, Rep.	-	-	-	-	-	-	-	-	220	-	-	108	-	-	-	-	-	328
Zambia	68	-	-	-	-	333	-	-	-	-	-	361	-	-	-	-	-	762
Zimbabwe	-	-	-	-	-	-	-	-	-	354	-	-	-	-	288	-	-	642
Total	1,602	3,766	1,566	5,886	7,880	6,727	2,319	11,106	6,909	973	1,443	11,046	2,169	3,306	3,246	2,533	74	74,723

Table 10: Descriptive Statistics of observations in Manufacturing Industries

Sector Description	Imputation					No Imputation				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Sales	64,149	16.8	3.4	0.6	33.8	64,137	16.8	3.4	0.6	33.8
Capital	63,162	14.8	3.7	0.5	36.5	50,199	14.9	3.8	0.5	36.5
Materials	62,699	15.4	3.7	0.5	32.1	50,959	15.6	3.7	0.5	32.1
Labor	73,124	3.6	1.4	0.1	11.1	73,011	3.6	1.4	0.7	11.1
Investment	60,581	13.4	3.5	0.5	35.6	31,248	13.7	3.7	0.5	35.6
Export Status	63,569	0.3	0.4	0.0	1.0	63,569	0.3	0.4	0.0	1.0
Managerial Experience	65,664	17.8	11.8	0.0	75.0	65,664	17.8	11.8	0.0	75.0
E-mail Adoption	68,390	0.7	0.5	0.0	1.0	68,390	0.7	0.5	0.0	1.0
Website Adoption	71,769	0.4	0.5	0.0	1.0	71,769	0.4	0.5	0.0	1.0

Note: The descriptive statistics for sales, capital, materials, labor and investment are in natural logarithms. The following questions from the World Bank Enterprise Survey questionnaire have been used to create the variables for our empirical analysis: Sales: In fiscal year [insert last complete fiscal year], what were this establishment's total annual sales for ALL products and services?; Capital: From this establishment's Balance Sheet for fiscal year [insert last complete fiscal year], what was the net book value, that is the value of assets after depreciation, of the Machinery, vehicles, and equipment?; Materials: From this establishment's Income Statement for fiscal year [insert last complete fiscal year], please provide the total annual cost of raw materials and intermediate goods used in production?; Labor: At the end of fiscal year [insert last complete fiscal year], how many permanent, full-time individuals worked in this establishment?; Investment: In fiscal year [insert last complete fiscal year], how much did this establishment spend on purchases of new or used machinery, vehicles, and equipment?; Export Status: Coming back to fiscal year [insert last complete fiscal year], what percentage of this establishment's sales were direct exports?; Managerial Experience: How many years of experience working in this sector does the Top Manager have?; Email: At the present time, does this establishment use e-mail to communicate with clients or suppliers?; Website: At the present time, does this establishment have its own website?

B Proof: Estimates of Homogeneous Coefficients Reflect Sectoral-Weighted Averages of Estimates of Heterogeneous Coefficients

Suppose we have the following GMM estimator:

$$\hat{\theta} = \underbrace{\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1}}_{\Psi} \underbrace{\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} X_i' y_i\right)\right]}_{\Phi}, \tag{B.1}$$

where X is a $K \times N$ matrix of regressors, Z is a $Q \times N$ matrix of instruments, A is a $K \times K$ weighting matrix, and y is a $1 \times N$ vector.

The first bracket is a matrix of dimension $K \times K$, which is constructed based on a sample of size N:

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1} = \kappa_1 \underbrace{\left[\left(\sum_{i=1}^{N_1} X_i' Z_i\right) A_1 \left(\sum_{i=1}^{N_1} Z_i' X_i\right)\right]^{-1}}_{\Psi_1} \tag{B.2}$$

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1} = \kappa_2 \underbrace{\left[\left(\sum_{N_1+1=1}^{N} X_i' Z_i\right) A_2 \left(\sum_{N_1+1=1}^{N} Z_i' X_i\right)\right]^{-1}}_{\Psi_2} \tag{B.3}$$

N-size sample can be divided into two samples of size $N_1$and N_2, where $N = N_1 + N_2$. κ_1 and κ_2 are matrices mapping each component in Ψ to each component in $\Psi_1$and in Ψ_2.

The second component, Φ, is additive. Therefore, it can be written as the sum of the two components corresponding to the two sub-samples:

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} X_i' y_i\right)\right] = \underbrace{\left[\left(\sum_{i=1}^{N_1} X_i' Z_i\right) A_1 \left(\sum_{i=1}^{N_1} X_i' y_i\right)\right]}_{\Phi_1} + \underbrace{\left[\left(\sum_{N_1+1=1}^{N} X_i' Z_i\right) A_2 \left(\sum_{N_1+1=1}^{N} X_i' y_i\right)\right]}_{\Phi_2}. \tag{B.4}$$

Replacing B.2 - B.4 into B.1, we can write $\hat{\theta}$ in the following way:

$$\hat{\theta} = \kappa_1 \Psi_1 \Phi_1 + \kappa_2 \Psi_2 \Phi_2.$$

That is, the GMM estimator corresponding to the full sample can be written as a weighted sum of the two estimators corresponding to subsamples 1 and 2.