

Innovation and Productivity in Developing Economies

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Abstract

We examine the determinants of innovation and its effect on productivity across 52 emerging and developing economies, comparing African firms to their counterparts elsewhere. We use a generalized structural equation model (GSEM) to estimate the causal links while accounting for endogeneity. Our estimates show that access to finance has the strongest effect on firms' decisions to invest in research and development (R&D) in all countries. And while the drivers of innovation are remarkably similar in developed economies, the keys for African firms are access to external knowledge – largely via information and communications technology (ICT)–

and skills development via on-the-job training. Only in Africa is the stand-alone effect of ICT adoption on innovation almost as strong as that of R&D; and the combined effect of firms' access to external knowledge through ICT and foreign-technology adoption and training is more than double that of R&D. Regardless of its content, the effect of employee training on innovation in Africa is double that in emerging markets. Finally, innovation is the key determinant of productivity in all countries, but the evidence is much stronger for product innovation by African firms.

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1. Introduction

Firms in developing countries, especially in African ones, tend to operate far below their productivity frontier. The value added per worker in the services sector of Sub-Saharan Africa is the lowest worldwide, at \$7,261 in 2018, far below the world average of \$23,736. In industry, Sub-Saharan Africa has the second-lowest value added per worker after South Asia's \$10,120, compared with the world average of \$25,075. More worryingly, the region exhibited a 17 percent decline in its labor productivity in industry over the past decade (World Bank, 2020).³

Innovation is essential for scaling up and enhancing productivity. The strong relationship between firm innovation and productivity in developed economies is well established in the literature, where positive effects on productivity of introducing innovations are consistently observed (e.g., Mohnen & Hall, 2013). These effects hold for both technological innovations, such as process and product innovations, and non-technological ones, such as marketing and organizational innovations. However, evidence on the effect of innovation on the productivity of firms in developing countries is inconclusive, making it hard to infer and generalize policy implications (e.g., Raffo et al., 2008). While some studies show that productivity is positively associated with innovation (e.g., Crespi & Zuniga, 2012; Jefferson et al., 2006), other studies indicate no effects at all (e.g., Benavente, 2006).

The determinants of firm innovation output are generally consistent in developed countries, and research and development (R&D) investment is the focus of most studies (e.g., Griffith et al., 2006). In developing countries, though, the key drivers of innovation output are not so clear cut. In addition to R&D, innovation determinants may include the firm's internal capabilities as reflected by, for instance, its size or workforce skillfulness, and the firm's access to external knowledge as enabled by, for instance, adoption of foreign technology or information and communications technology (ICT) or even being located in a capital city or being affiliated to a large firm. Some studies find a positive effect of firm innovation investment on technological innovation but variable effects of export orientation and foreign ownership (e.g., Crespi & Zuniga, 2012). Unlike most developed country literature, innovation investment as reported by Crespi & Zuniga (2012) encompasses expenditures on all innovation or knowledge generation activities rather than just R&D. Such activities include all efforts by the firm to acquire and assimilate new knowledge through the acquisition of embodied or

³ All figures are in constant 2010 US\$.

disembodied technology and know-how; tooling-up, industrial engineering, and so forth; employee training linked to process/product innovations; and marketing for technologically new or improved products. Other studies, which typically identify R&D as the sole innovation or knowledge generation activity, find no significant impact of R&D expenditure on innovation if firm size and sector are controlled for (e.g., Benavente, 2006). Álvarez et al. (2010) show that R&D has a positive impact on process but not on product innovation. Interestingly, ICT use has been recognized by a relatively recent study as a main enabler of product, process, and organization innovation (Cirera et al., 2016). As innovation inputs and output as well as productivity links remain ambiguous in developing, and especially African, economies, these economies will hardly be able to escape the technology and low-productivity traps.

This study seeks to fill this gap in the literature by identifying the significant determinants of innovation and its impact on firm productivity across 52 emerging market and developing economies between 2006 and 2019, with special focus on African firms. Exploiting a perfectly harmonized dataset of more than 80,000 firms, we build on the Crépon, Duguet, and Mairesse (henceforth CDM) framework and apply a generalized structural equation model (GSEM) to estimate the knowledge generation, innovation, and productivity relationships.

The novelty of the study is twofold. Methodologically, diverging from previous developing country studies, our estimation strategy of the CDM model attenuates endogeneity concerns, especially those arising from omitted-variable bias. This is achieved by including a “latent” variable to reflect the effect of the unobserved factors presumed to underlie correlations in the system. Such factors can be particularly relevant in the context of developing economies. Adding a latent variable to the right-hand side of the CDM system of equations is new to the CDM literature and, to our knowledge, was only implemented once by Baum et al. (2017) on a panel of Swedish firms. However, unlike that study, where no latent variable is included in the productivity equation, we successfully add a latent variable to all the CDM model equations while overcoming convergence issues. Moreover, improving on previous studies that follow a three-step estimation routine, we *jointly* estimate the model, accounting for contemporaneous correlations. Thus, while the quality of evidence from developing countries is undermined by limited robustness of estimates due to endogeneity issues arising from the complex interactions of knowledge generation, innovation, and productivity, our estimation strategy offers reliable evidence of these interactions.

Conceptually, we allow for innovation determinants other than R&D to affect the likelihood of a firm to introduce innovations, accounting for the fact that knowledge developed through R&D may not be as significant in developing economies as that developed through, for example, the adoption of new technologies developed elsewhere. Unlike innovation surveys used by most studies, a distinctive feature of the Enterprise Survey (ES) used in this study is that innovative firms are not by definition conductors of R&D. Our results confirm that firm-level determinants of innovation are highly heterogeneous, and the effect of some factors, such as ICT use, is almost as significant for African firms as investing in R&D. Another interesting feature of this study is that, rather than focusing on a single country or group, our dataset covers a total of 52 countries in different regions, allowing for cross-group comparisons and results generalization.

Our study has intriguing results. We provide fresh evidence that access to finance has the largest impact on firms' decision to invest in R&D in all emerging market and developing economies, especially in Africa. And while the systems driving innovation are remarkably similar across developed economies, our results indicate that the essential ingredient for African firms is access to external knowledge. We also find that while employee training has a significant positive effect on innovation in all countries, its effect on African firms is double that on firms in emerging markets.

The organization of this paper is as follows. Section 2 reviews the relevant literature; Section 3 lays out the model specification and estimation methodology; Section 4 presents the empirical data; Section 5 discusses the estimated results; and Section 6 concludes.

2. Literature review

Knowledge generation, innovation, and firm performance. Crépon et al. (1998) were the first to empirically estimate the simultaneous link between knowledge generation, innovation, and firm performance. They introduced a robust framework incorporating research investment, innovation output, and productivity in a recursive structural model, known as the CDM model. Within this framework, firm performance, specifically productivity, is a function of innovation output, which is, in turn, a function of research investment. Drawing from data on French manufacturing firms, they show that R&D capital intensity correlates positively with firm innovation output and that this output correlates positively with firm productivity.

Some studies, mostly in developed countries, have attempted to apply the same framework. Overall, these studies provide evidence that the greater a firm's R&D effort, the more likely it is to introduce process or product innovations (e.g., Baumann & Kritikos, 2016; Duguet, 2006; Griffith et al., 2006; Lööf & Heshmati, 2006). Findings on the innovation-productivity link are less consistent but, with some exceptions, indicate positive effects of technological and non-technological innovations on firm performance, typically captured by productivity (Mohnen & Hall, 2013). These positive effects hold whether firm productivity is measured by value added per employee (Masso & Vahter, 2008; Musolesi & Huiban, 2010), sales per employee (Griffith et al., 2006; Raymond et al., 2015; Van Leeuwen & Klomp, 2006), or total factor productivity (TFP) growth (Duguet, 2006; Parisi et al., 2006). The effects also hold regardless of firm size (Baumann & Kritikos, 2016; Hall et al., 2009), sector (Lööf & Heshmati, 2006), or firm knowledge intensity (Janz et al., 2004; Musolesi & Huiban, 2010).

A relatively recent study by Baum et al. (2017) presents a new approach to estimating the relationship between R&D, innovation, and productivity based on a generalization of structural equation models that accounts for cross-equation correlation of the errors and the effect of unobserved factors by adding a latent variable. Drawing from a panel survey of Swedish manufacturing and service firms, the study finds highly significant positive effects of R&D intensity on innovation sales and of innovation sales on labor productivity.

Other studies of developed countries, however, provide contradictory results. Griffith et al. (2006), for instance, show that while process innovation is correlated with higher productivity in French manufacturing firms, no such evidence is observed in Germany, Spain, or the United Kingdom. Another exception is Roper et al. (2008), who find no effect of process innovation and even a negative effect of product innovation on labor productivity of manufacturing firms in Ireland and Northern Ireland. The negative effect is interpreted as a short-term 'disruption' effect of product innovation on labor productivity.

Results from emerging market economies generally indicate a positive association between R&D, innovation, and productivity (e.g., Jefferson et al., 2006). Evidence from other developing economies is limited, and concentrated on Latin America. The findings are also inconclusive. Crespi & Zuniga (2012) demonstrate that firms that invest in knowledge in six Latin American countries have higher innovation outputs as captured by the introduction of new technological advances, and that firms that innovate have higher labor productivity than those that do not. On the contrary, evidence from Chile suggests that research expenditure does

not have a significant impact on innovation sales, and that innovation does not have a significant impact on firm productivity (Benavente, 2006).

Heterogeneous effects of engaging in innovation activities and of introducing product and/or process innovations are reported for Argentinian manufacturing firms (Chudnovsky et al., 2006). The study shows that whereas technology acquisition expenditures by a firm do not increase its odds of introducing new products and/or processes, in-house R&D enhances the likelihood of both product and process innovations. In addition, the study finds no correlation between product innovation and labor productivity but finds a positive correlation between process innovation and a combination of process and product innovation and productivity.

Comparing innovation inputs, innovation output, and productivity linkages across European and Latin American countries, Raffo et al. (2008) verify that R&D intensity affects product innovation of firms in all countries and that product innovation affects the productivity of firms in all three European countries and in two out of three Latin American countries. A weaker interaction of innovation activities with national systems is also observed in Latin America.

Co-innovation and firm performance. In addition to innovation, there is evidence from developed economies that technology adoption by a firm, even if this technology is an ICT, improves firm performance. Akerman et al. (2015) find that the adoption of broadband internet by Norwegian firms enhanced labor market outcomes and productivity of skilled workers but exacerbated those of the unskilled. The study shows that while broadband adoption complements skilled workers in performing non-routine abstract tasks, unskilled workers are substituted for in performing routine tasks. A study of Italian manufacturing firms indicates that R&D appears to be more important for innovation while ICT appears to be more important for productivity (Hall et al., 2013).

These findings are consistent with earlier evidence that information technology (IT), such as computer systems, and skilled labor are relative complements (Bresnahan et al., 2002; Black & Lynch, 2001). As depicted by Bartel et al. (2007), adopting new IT-enhanced machinery can promote productivity growth through several mechanisms, including by shifting the firm's business strategy, improving the efficiency of all stages of the production process, raising the skill requirements of machine operators, and adopting new human resource practices to support these skills.

Other studies, nonetheless, argue that increases in ICT use and R&D expenditure are not translated into equivalent increases in firm product, process, and organizational innovations (e.g., Martin & Nguyen-Thi, 2015). Contrary to the evidence provided for larger firms, Díaz-Chao et al. (2015) find that co-innovation, in the form of ICT use, human capital and training, and new organization forms, does not directly affect the productivity of small Spanish firms.

The impact of ICT investments on the innovation and productivity of firms in developing economies has barely been investigated. Álvarez (2016) provides evidence that ICT investment has a positive effect on the innovation and productivity of Chilean manufacturing and services firms both directly or through its effect on innovation. Similarly, Grazzi & Jung (2016) show that broadband adoption by firms in Latin America and the Caribbean increases their propensity to innovate, with intensive broadband use being associated with additional positive effects. They further show that broadband adoption and use raise firm productivity. ICT use has also been identified as a key enabler of product, process, and organization innovation in six countries in Sub-Saharan Africa, with less clear links to firm productivity (Cirera et al., 2016).

3. Model

3.1 Generalized structural equation model (GSEM)

We use the CDM model – developed by Crépon et al. (1998) – to integrate the links between innovation inputs, innovation output, and productivity in a recursive framework at the firm level. The model consists of three stages (equations): (a) firms decide to invest in knowledge generation captured by R&D spending (innovation inputs equation); (b) innovations are produced as a result of this investment along with other innovation inputs (knowledge production function); and (c) output is produced with innovations as inputs along with other inputs (firm performance equation). This framework both accommodates the selectivity of reporting R&D expenditure and innovation output for only a subsample of firms and handles the endogeneity of the R&D-innovation-productivity relationship. We realize that some factors can jointly affect firm productivity, the firm’s decision to innovate, and its decision to invest in knowledge generation activities such as R&D. Some of these factors are unobserved.

We specify the following model to estimate the relationship between knowledge generation, innovation, and productivity.

$$KG_i = \gamma_o + \gamma_x X_{i,KG} + \mathbf{L}_i + \epsilon_{i,KG} \quad (1)$$

$$IO_i = \delta_o + \delta_{KG} KG_i + \delta_x X_{i,IO} + \delta_L \mathbf{L}_i + \epsilon_{i,IO} \quad (2)$$

$$FP_i = \zeta_o + \zeta_{IO} IO_i + \zeta_x X_{i,FP} + \zeta_L \mathbf{L}_i + \epsilon_{i,FP} \quad (3)$$

KG_i is a dichotomous variable for firm i 's decision to acquire knowledge, or more precisely, to spend on R&D. $X_{i,KG}$ is a vector of potential determinants of the firm's decision to invest in R&D, including internal capabilities (firm size, human capital, ownership structure, firm age, and product concentration), access to external knowledge (location in a capital city and affiliation to a large firm), demand-pull factors (export orientation and international competition), and outstanding barriers (credit constraints and inadequate education). L_i is a latent variable accounting for unobserved factors. The main rationale for introducing latent variables is to mitigate omitted-variables bias, because we suspect that there are other factors that we do not observe but are relevant in the equations. The significance of the latent variable coefficients obtained in section 5 confirms this. One example of these factors is management practices.

In equation (2), IO_i is a dichotomous variable for process and/or product innovation by firm i . $X_{i,IO}$ is a vector of other innovation inputs and potential determinants of the firm's decision to innovate: relative to $X_{i,KG}$, $X_{i,IO}$ adds training provision and capital intensity to the firm's internal capabilities and, more importantly, it adds foreign-technology adoption and ICT adoption to the firm's sources of access to external knowledge. Export orientation is the demand-pull factor identified in $X_{i,IO}$.

In equation (3), FP_i denotes performance of firm i as measured by TFP and, in some specifications, labor productivity. $X_{i,FP}$ is a vector of determinants of the firm's productivity other than its innovation output. These determinants are firm size, human capital, physical capital, ownership structure, location in a capital city, and fuel intensity.

$\epsilon_{i,KG}$, $\epsilon_{i,IO}$, and $\epsilon_{i,FP}$ are the error terms of equations (1), (2), and (3), respectively. The error processes of the equations are allowed to be correlated. As proposed by Baum et al. (2017), we add the latent variable L_i to further attenuate omitted-variable bias. The use of latent variables as independent variables in the system of equations is new to the CDM literature and, to our knowledge, has been only applied once before – by Baum et al. (2017) on a panel of

Swedish firms. This is an innovative approach that corrects for omitted-variable bias by capturing the effects of the unobservables. Nevertheless, unlike Baum et al. (2017), who do not include a latent variable in the productivity equation of the CDM model, we successfully add a latent variable to all equations while overcoming convergence issues. Industry and year effects are controlled for.

Estimation methodology. Within the GSEM framework, we estimate the CDM model as a recursive system of equations (1–3) by the full-information maximum likelihood (FIML) method. This is inspired by the new approach proposed by Baum et al. (2017) to estimating the R&D-innovation-productivity relationship. We rely on Stata’s *gsem* command because it has unique modeling capabilities that are crucial in our analysis, allowing us to incorporate generalized (non-continuous) responses and latent variables in our model. Cross-equation residual correlation or contemporaneous correlations is also accounted for as the model is *jointly* estimated, unlike previous studies, which follow a three-step estimation routine.

Thus, while the quality of evidence from developing countries is undermined by the limited robustness of estimates due to unresolved endogeneity issues, our proposed model specification and estimation methodology seek to attenuate all endogeneity concerns and offer reliable evidence on R&D, innovation, and productivity links in a developing country context.

The data feeding the innovation input equation [equation (1)] comprise the full sample of firms. This equation can be regarded as a selectivity equation that reflects the likelihood of a firm engaging in R&D. In equations (2) and (3), however, the data are limited to firms for which innovation inputs and output are observed. *gsem* allows the estimation of each equation in the system drawing from the available observations for each.

Since the metric of the latent variable L_i is arbitrary, its coefficient must be normalized to one in equation (1) to allow its magnitude to be estimated in equations (2) and (3), and its variance is constrained to one.

3.2 Presumptuous innovation effort

We test the sensitivity of our CDM estimates obtained by Stata’s *gsem* to the fact that only a subsample of firms is used to run the model. It may be that some of the excluded firms exert some kind of innovative effort but choose not to report it because the effort is below a certain

threshold. This has been hypothesized by some studies such as Crespi & Zuniga (2012) and Griffith et al. (2006). The latter study, for instance, argues that production workers may invest some time in considering (or even experimenting) how to improve the efficiency of the production process they are involved in; however, this effort is not reported by the firm as R&D until a certain threshold is surpassed.

Assuming that some innovative effort is exerted by all firms, we specify a structural CDM model in which innovation effort and output are considered as latent variables. This diverges from our previous specification in which none of the dependent variables is latent, a latent variable is included as an explanatory variable on the right-hand side of the system, and only a subsample of firms is used at the second and third stages.

We reformulate equations (1–3) as follows. The knowledge generation “innovation inputs” equation estimates the impact of various determinants on the *probability* that firm i invests (or reports investing) in knowledge acquisition:

$$KG_i = \begin{cases} 1 & \text{if } KG_i^* = \gamma_o + \gamma_x X_{i,KG} + \epsilon_{i,KG} > c \\ 0 & \text{if } KG_i^* = \gamma_o + \gamma_x X_{i,KG} + \epsilon_{i,KG} \leq c \end{cases} \quad (4)$$

KG_i^* is an unobserved “latent” variable, where firm i decides to invest to acquire knowledge (and report that it does so) if KG_i^* exceeds a specific threshold level c , and KG_i is a binary endogenous variable for this decision, which equals one for firms spending on R&D and zero otherwise. $X_{i,KG}$ is as defined before.

The second equation of the model estimates the impact of knowledge generation effort, KG_i^* , derived from equation (4), on innovation output:

$$IO_i^* = \delta_o + \delta_{KG} KG_i^* + \delta_x X_{i,IO} + \epsilon_{i,IO}. \quad (5)$$

IO_i^* denotes “latent” innovation output by firm i , which is a binary variable that equals one if the firm decides to conduct process and/or product innovation. Other variables are as defined before. δ_{KG} is our coefficient of interest that estimates the impact of investing in knowledge generation on the probability of a firm being innovative.

The third “firm performance” equation below is specified within the general framework of the Cobb-Douglas production function to estimate the impact of innovation, IO_i , derived

from the second stage, together with other key inputs, on firm productivity or, more generally, firm performance.

$$FP_i = \zeta_o + \zeta_{IO}IO_i^* + \zeta_x X_{i,FP} + \epsilon_{i,FP} \quad (6)$$

All variables are as defined before. ζ_{IO} is our coefficient of interest that estimates the impact of innovation on productivity.

Estimation methodology. Improving on previous studies that follow a three-step estimation procedure, we *jointly* estimate our CDM model [equations (4–6)] within the conditional mixed-process (CMP) framework by the limited-information maximum likelihood (LIML) method. We use Stata’s *cmp* command, an earlier implementation of GSEM developed by Roodman (2011). *cmp* allows us to jointly estimate equations (4–6) while taking account of correlations among their error processes. Note that the CDM model is estimated for all firms, not only innovative ones.

4. Data

Exploiting a harmonized dataset from the World Bank’s ES, we conduct the analysis for 52 developing countries in which 81,119 firms were interviewed between 2006 and 2019. Of these countries, 15 are African and 15 others are emerging market economies. A full list of countries is provided in [Appendix A](#). The ES covers firms in the manufacturing and services sectors.⁴ One advantage of the ES data is that they are comparable across countries and regions.

Knowledge generation. In general, innovation activities cover all firms’ efforts to acquire and assimilate new knowledge through the acquisition of embodied or disembodied technology and know-how; tooling-up, industrial engineering, and so forth; employee training linked to process/product innovations; and marketing for technologically new or improved products. The knowledge generation activity typically reported by former studies is investing in R&D. In our first model specification [equations (1–3)], innovation input is measured as reported R&D expenditure. In the second specification [equations (4–6)], we assume that all firms exert some innovation effort but some choose not to report this activity if it is below a certain threshold.

⁴ A comprehensive description of the data and survey methodology is provided online at: www.enterprisesurveys.org.

Unlike innovation surveys used by most studies, one distinctive feature of the ES is that innovative firms do not by definition conduct R&D. Put simply, in our sample, some firms report introducing innovations while reporting *not* spending on R&D. This is pertinent in the context of developing economies. To explain the endogenous decision of a firm to innovate, we rely not only on the limited information available for firms that conduct R&D but also on the information available for all firms. Hence, innovation determinants other than R&D, such as firm's internal capabilities and access to external knowledge, are allowed to influence the likelihood of a firm to introduce innovations. This aligns with the significant heterogeneity in the characteristics of innovation systems across developing and advanced economies: developing economies differ greatly in terms of, for example, the structures and concentration of their innovative activities. In this sense, our analysis appropriately accommodates the fact that the role of knowledge developed through R&D may not be as significant in developing economies as that developed through, for instance, adopting technologies developed elsewhere.

Investing in R&D is directly indicated by whether the firm reports spending on R&D during the past fiscal year. We use a large set of determinants to explain the firm's decision to undertake this effort. These determinants are categorized into four sets: internal capabilities, access to external knowledge, demand-pull factors, and outstanding barriers.

A firm's internal capabilities are largely reflected by its size, human capital, ownership structure, age, and product concentration. The size of the firm has been consistently identified in the literature as a main determinant of knowledge generation activities because larger firms are better positioned to benefit from economies of scale related to R&D production and to appropriate external knowledge spillovers. We measure firm size as the (log) employment, or specifically the (log) number of production employees. Human capital constraints can also restrict the ability of a firm to undertake R&D. We proxy human capital accumulation by the proportion of workers who completed high school, the proportion of skilled labor force, and top manager's years of experience working in the sector. We also expect foreign ownership to induce innovation effort. The productivity advantage of foreign multinationals has been identified and linked by some studies to their knowledge assets such as know-how, technology, etc., which can be transferred to their subsidiaries elsewhere (e.g., Girma & Gorg, 2007). We also control for the share of state ownership because recent studies indicate that state ownership can enable firms to channel additional resources to finance R&D activities (e.g., Zhou et al., 2017). We include a fourth determinant, firm age, to capture the impact of tacit knowledge

that, through interactions with explicit knowledge, is essential to innovation management (Seidler-de Alwis & Hartmann, 2008). Our final indicator of internal capabilities is product concentration as measured by the main product/service share of the firm's total annual sales. We hypothesize that a firm's decision to invest in R&D decreases with product concentration since high product concentration reflects the narrow scope of the firm's production capability, which is likely to restrict the firm from operating easily in other industries, thereby worsening the expected returns to its R&D investments (Crespi et al., 2016).

The second set of determinants reflects firms' access to external knowledge as captured by being located in a capital city and being affiliated with a large firm, both of which are anticipated to have positive spillovers on firms' decision to engage in R&D. Previous research shows that agglomeration economies can raise the returns to R&D and innovation-related activities (e.g., Moretti, 2004). In parallel, affiliation to a large firm can improve a firm's access to an extended pool of knowledge assets with potential spillovers on its knowledge generation activities.

The third set of determinants includes two demand-pull factors: export orientation and competition intensity. Export orientation is measured as exports' share of total sales and is expected to positively induce firm knowledge generation activities through "competition" and "learning" effects (Crespi & Zuniga, 2012). Competition intensity is measured by international competition, captured by whether the main market of the firm's main product is local/national or international.

Finally, we include two outstanding barriers to investing in knowledge generation: credit constraints and inadequately educated workforce reported by a firm as a major or very severe obstacle. Industry, country, and year effects are controlled for to capture the effect of other unobserved factors. The idiosyncratic characteristics of national innovation systems are accounted for by country dummies. Table 1 provides definitions of the variables used.

[Table 1 near here]

Innovation output. We use two measures of innovation: process innovation and product innovation. Process innovation is captured by whether the firm introduced new or significantly improved process in the past three years. Product innovation is captured by whether the firm introduced new products and/or services in the past three years. We recognize that in the context of developing countries, innovation is better reflected by these two measures

than by other measures typically used for advanced economies, such as the number of patents or the share of innovative sales.

A larger set of determinants is used to explain what determines a firm's decision to introduce innovations. In addition to the firm's internal capabilities previously discussed, a variable is included here to reflect whether formal training programs are provided for employees. If its content is appropriate, training can strengthen a firm's capacity to innovate or at least enable it to effectively adopt new technologies innovated elsewhere. Even in the absence of R&D, there is strong evidence that employee training has a significant positive effect on firm innovation. A recent study by Dostie (2018) of Canadian firms shows that higher employee training leads to more process and product innovation. Bauernschuster et al. (2009) also report a positive causal effect of training provision by German firms on innovation through guaranteeing access to leading-edge knowledge. Laursen & Foss (2003) confirm these findings and show that firm internal and external training are strongly significant in explaining innovation performance of Danish manufacturing and non-manufacturing firms. Physical capital or capital intensity, measured as the (log) deflated replacement value of machinery, vehicles, and equipment (per employee), is also included as a firm internal capability in the innovation output equation.

Access to external knowledge is also facilitated by foreign-technology adoption and ICT adoption. Foreign-technology adoption is measured by whether the firm uses technology licensed from a foreign-owned company. We argue that, through learning-by-doing, foreign-technology adoption can increase the odds of introducing innovations by firms in developing countries. ICT adoption is proxied by whether the firm uses e-mail to communicate with clients and suppliers and whether the firm has its own website. ICT use can act as a basic enabler of product, process, and even organization innovation (Cirera et al., 2016).

There is no theoretical reason to include international competition as a demand-pull factor in the innovation output equation. Similarly, there is no theoretical reason to assume that credit constraints affect the successful transformation of innovation inputs into process or product innovations.

Firm performance. Process innovation can have a direct positive impact on productivity as new or significantly improved processes are typically used by firms to reduce production costs. We hypothesize that product innovation can also have a direct positive impact

as the introduction of new products and/or services creates new demand that induces economies of scale in the production of these products and/or services (Mohnen & Hall, 2013).

The end goal is to estimate the causal effects on the main dependent variable, firm performance, for which two measures are used: TFP and labor productivity. Labor productivity is measured by (log) sales per worker for both the manufacturing and services sectors. In addition to innovation output, other production function inputs and determinants are included: firm size, human capital, physical capital, ownership structure, location in a capital city, and fuel intensity (as an outstanding barrier). Firm age and capacity utilization are included in some model specifications.

Summary statistics of the main variables in our analysis are reported in Table 2 for African countries, other developing countries, and emerging market economies. The productivity of firms in emerging market economies is the highest, followed by the productivity of firms in other developing countries, while African firms have the lowest productivity. This result holds regardless of the measure of productivity used. We also observe that the proportion of firms that reported introducing process and/or product innovations in emerging market economies (43 percent) is significantly higher than that reported by African firms (32 percent) or firms in other developing countries (33 percent).

[Table 2 near here]

To explain what could have driven such results, we explore where the variations between the three groups are the most substantial. Most importantly, Table 2 shows that the proportion of firms that reported spending on R&D in Africa is as low as 9 percent, which is less than half the proportion reported in other developing countries and almost one-third of that in emerging countries. Second, in terms of firm internal capabilities, we observe that while 42 percent of firms in emerging market economies reported providing formal training programs for their employees, only 22 percent of firms in African countries reported doing so. Another notable difference is observed with respect to firm access to external knowledge: 61 percent of African firms reported using ICT in its simplest forms (e-mail use and website ownership) compared to 82 percent and 77 percent of firms in other developing and emerging market economies, respectively. Finally, access to finance could be one barrier to knowledge generation and innovation activities in African countries, with only 20 percent of firms

reporting a line of credit or loan from a financial institution as opposed to 34 percent and 32 percent in other developing and emerging market economies, respectively.

5. Results and discussion

5.1 GSEM estimates

Knowledge generation. Table 3 presents the results from the R&D equations (1) and (4). We report the FIML estimates of our first model, which includes a latent variable and feeds on the sample of firms for which innovation inputs and output are reported, in columns (1), (3), and (5). The obtained estimates of the pooled sample, comprising firms in all emerging market and developing economies, show that access to finance, export orientation, and access to external knowledge through affiliation to a large firm are the most significant factors affecting the likelihood that a firm invests in R&D. Access to finance is the most influential determinant for African firms and comes second for firms in emerging market economies. Export orientation is the most influential determinant for emerging market firms but has a much smaller effect in terms of magnitude on the likelihood of African firms to conduct R&D. For firms in Africa, a firm's internal capabilities as reflected by its size comes third but, overall, consistent with the literature, our estimates show that bigger firms in all economies are more likely to engage in R&D.

[Table 3 near here]

Human capital proxied by high-school completion also appears to have a significant positive but limited effect across all groups. However, only in emerging markets does the skillfulness of the labor force have a significant positive effect on the probability of engaging in R&D, providing evidence of skill mismatches in developing and African labor markets (Morsy & Mukasa, 2019). In parallel, Table 3 shows that foreign ownership has no effect on in-house R&D, refuting the hypothesis of unconditional knowledge and technology spillovers from foreign firms. We also find that firms whose main market is international have a significantly lower propensity to conduct R&D than firms whose main market is local or national. The effect is significant for the pooled sample and African countries. One interpretation is that as firms face fierce competition, investing in R&D become riskier and more costly. Interestingly, recent experimental evidence shows that increased competition has a negative causal effect on R&D investments by firms that are lagging behind, specifically in a short-term horizon (Aghion et al., 2018).

The LIML estimates of the second model, estimated not only for innovative firms but for all firms assuming some innovation effort, are reported in columns (2), (4), and (6) of Table 3. The obtained estimates confirm our earlier findings of the significance of export orientation to the firm's decision to spend on R&D for the pooled sample and especially for emerging markets. Despite its significance for all countries, access to finance appears to be the most influential for firms in Africa. Our LIML estimates provide further evidence of the instrumental role of access to external knowledge by being located in a capital city in addition to affiliation to larger firms.

Innovation output. Table 4 presents the GSEM estimates from the innovation output equations (2) and (5). The first model's FIML estimates are reported in columns (1), (3), and (5), drawing from the sample of firms for which innovation inputs and output are observed. Consistent with the original CDM estimates of Crépon et al. (1998), all our R&D coefficients are positive and highly significant, especially for the pooled sample; yet R&D expenditure has the least effect on process and/or product innovation in African countries. Access to external knowledge through both ICT and foreign-technology adoption is the second most significant innovation determinant in the context of emerging market and developing economies, followed by skills development through on-the-job training. The two determinants appear to be essential ingredients for African firms, as their combined effect equals that of R&D.

[Table 4 near here]

ICT adoption is particularly relevant, as reflected by the magnitude and significance of its coefficient. It has the largest effect on firms in Africa compared to those in other emerging market and developing economies. The highly significant impact of employee training on innovation output in all countries is also remarkable. Regardless of its content, the impact of training provision on the innovation output of African firms (0.744) is almost double its impact in emerging markets (0.446). This is especially interesting in light of the insignificant effects of other human capital variables, such as high-school completion. The theoretical foundation underlying this finding is that innovation effort is associated with successful introduction of innovations, with positive end effects on firm productivity, subject only to the adaptability and skills of the involved workforce. Therefore, innovative firms must acquire new appropriately skilled workers and/or upgrade the skills of the existing workers. Employee training is a typical option in this context. One reason is that it is less costly under many circumstances such as stringent labor market regulations. Training can also alter employees' attitudes toward adopting

new technologies, which is key for the effective use of these technologies (Ouadahi, 2008). This reinforces the positive impact on innovation by facilitating the adoption of ICT and foreign technologies, both of which already been found to have a highly significant effect on firm's propensity to introduce process and/or product innovations.

Table 4 also shows that while foreign ownership is associated with a higher likelihood of introducing innovations only in African countries, firms in these countries are benefiting less from adopting foreign-licensed technologies than do firms in emerging market economies.

Importantly, the coefficient of the latent variable (L) is highly significant for the pooled sample, suggesting that the effect of unobserved factors is vital in the context of developing countries and should be accounted for.

Furthermore, we report the LIML estimates of our second model's specification, assuming innovation effort by all firms, in columns (2), (4), and (6) of Table 4. This specification's results provide novel evidence on innovation inputs-output relationship in Africa, suggesting that the stand-alone effect of ICT adoption (0.444) on innovation output is almost as great as the effect of R&D (0.527). Additionally, we find that the combined effect of a firm's access to external knowledge through ICT and foreign-technology adoption (0.742) and training provision (0.379) is more than double that of R&D (0.527).

Firm performance. The FIML and LIML estimates of the firm performance equations (3) and (6) are reported in Table 5. The estimates indicate that innovation is key to firms' in all regions improving their performance as reflected by TFP or labor productivity. However, the impact of innovation appears to be much greater for African firms. A plausible explanation is that these firms operate far below their technological and productivity frontiers, implying that substantial productivity gains can be realized by introducing incremental innovations, especially product ones.

[Table 5 near here]

Interestingly, we find that although larger firms generally have higher productivity, smaller firms are more innovative (see the firm size coefficients in Tables 5 and 4, respectively). Table 5 also shows that labor force education has a positive but limited effect on firm productivity in all regions. Foreign ownership appears to be particularly influential for firms in Africa. Fuel intensity is found to have a significant negative impact on productivity.

The highly significant coefficients of the latent variable (L) in Table 5 confirm that unobserved factors have a substantial impact on firm productivity in all emerging market and developing economies, especially in Africa. This impact is even higher than that of innovation output in some specifications, emphasizing the importance of including a latent variable in our system of equations to resolve endogeneity issues.

5.2 Heterogeneity of effects

We examine effect heterogeneity by firm size of determinants in our CDM model. The GSEM estimates by firm size are reported for the pooled sample in [Tables B.1–B.3 \(Appendix B\)](#)⁵. We find that the determinants of innovation effort and output and productivity are generally similar across size groups in emerging market and developing economies.

However, interestingly, regarding knowledge generation, workforce skillfulness appears to have a significant positive effect on small firms' probability of engaging in R&D but a significant negative effect on large firms, indicating that skillfulness and internal R&D are regarded as complements by small firms and substitutes by large firms. We also observe that while access to finance is the most significant factor affecting the likelihood that a large or medium firm invests in R&D, credit constraints appear to be less influential for small firms than demand-pull factors, specifically export orientation and access to external knowledge through affiliation to larger firms ([Table B.1](#)).

With respect to innovation output, in contrast to the evidence from developed countries, [Table B.2](#) shows that smaller firms in emerging market and developing economies are more likely to benefit from R&D expenditure for introducing process and/or product innovations. In parallel, our FIML estimates show that employee training and access to external knowledge through foreign-technology and ICT adoption have more significant effects on the likelihood of small firms to introduce innovations. Unobserved factors captured by the latent variable (L) appear to have a significantly stronger effect on smaller firms.

Our FIML and LIML estimates provide mixed evidence on how the impact of innovation on productivity varies by firm size. Drawing from the sample of firms for which innovation inputs and output are observed, we find that the larger the firm, the stronger the impact of innovation output on productivity. Nonetheless, presuming some innovation effort

⁵ The three firm size groups are small (< 20 employees), medium (20–99 employees), and large (100+ employees) firms.

by all firms, the LIML estimates show that innovation has a more significant impact on the productivity of small firms. Finally, we observe that, when measured by labor productivity, the impact of innovation output on the productivity of large firms appears to be relatively too limited (0.337) compared with medium firms (1.480) and small firms (1.313) (Table B.3).

5.3 ICT use

The highly significant effect of ICT use on firms' propensity to introduce process and/product innovations, especially in Africa, warrants further investigation into the behavior of firms toward ICT. If a firm does not use e-mail to communicate with clients or suppliers and/or does not have its own website, is it because of underdeveloped ICT infrastructure on the supply side or adoption issues on the demand side?

On the supply side, we examine regional variation in firms' access to ICT infrastructure, as proxied by the proportion of firms that have a high-speed, broadband internet connection on their premises. We compare African firms to those in other developed and emerging market economies as well as (newly) developed countries. The latter are mostly "graduated" developed economies that are included for benchmarking (see Appendix A). Figure 1 shows that while only 34 percent of firms in Africa have a high-speed, broadband internet connection on their premises, 67 percent and 85 percent of firms in other developing and in emerging market economies, respectively, do. As anticipated, the proportion is the highest in (newly) developed countries (90 percent).

[Figure 1 near here]

Importantly, on the demand side, we examine ICT adoption by firms that already have access to broadband internet connection. Figure 2 provides evidence that the relationship between *access* to and *adoption* of ICT varies across country groups and significantly by ICT level. In general, African firms are the weakest ICT adopters, with 92 percent of firms with access to broadband internet connection reporting using e-mail to communicate with clients or suppliers compared to 93 percent, 95 percent, and 98 percent of firms in other developing, emerging market, and (newly) developed economies, respectively (Figure 2, left panel). The gap widens if a relatively more advanced ICT application – website ownership – is considered. Only 51 percent of African firms with access to broadband internet connection report having their own website, compared to 63 percent, 72 percent, and 78 percent in other developed countries, emerging markets, and developed economies, respectively (Figure 2, right panel).

We also find that, generally, the more advanced the ICT level, the weaker the association between *access* and *adoption* across all regions.

[Figure 2 near here]

Hence, in Africa, both underdeveloped ICT infrastructure and weak adoption behavior appear to be driving the observed lower level of ICT use, with the former being a stronger deterministic factor at lower levels of ICT.

6. Conclusion

Boosting productivity growth is key for developing economies to close the income gap vis-à-vis the developed world. It is well established in the macroeconomic literature that innovation performance can provide the basis for improved productivity. At the micro level, there is consistent evidence on the links between knowledge generation, innovation, and productivity for developed countries. But limited evidence can be identified for developing countries, mostly drawn from studies on Latin American countries, and findings are controversial. In addition, numerous methodological concerns undermine the reliability of the obtained estimates.

Drawing from a harmonized dataset of more than 80,000 firms in 52 emerging market and developing economies, we estimate the CDM model of the R&D-innovation-productivity links within the GSEM framework. We put special emphasis on African firms, and compare their behavior to that of their counterparts. Unlike most previous studies, our estimation strategy attenuates endogeneity concerns, especially those due to omitted-variable bias, by including a latent variable to capture the effect of unobserved factors. This is a relatively new approach and, to our knowledge, was only implemented once, by Baum et al. (2017) on a panel of Swedish firms. Moreover, improving on previous studies that follow a three-step estimation routine, we *jointly* estimate the CDM model, accounting for contemporaneous correlations. We argue that our model specification and estimation strategy offer exclusively reliable evidence of knowledge generation–innovation-productivity interactions in emerging market and developing economies.

We provide fresh evidence that access to finance has the strongest effect on the decision of the firm to invest in R&D in emerging market and developing economies, especially in Africa. And while R&D spending significantly affects innovation output in all countries, the

effect is the weakest for African firms. Regarding innovation output determinants, the essential ingredient for firms in Africa is access to external knowledge, with the combined effect of firms' access to external knowledge through ICT and foreign-technology adoption and skills development via on-the-job training being more than double that of R&D spending. The role of ICT use appears to be vital for African firms, where, in one specification, the effect on innovation is almost as that of R&D. Employee training is also instrumental to process/product innovation in all countries; interestingly, its effect on African firms is double that on firms in emerging markets regardless of the training content. Consistent with the theoretical and empirical literature, our estimates show that innovation is the main determinant of productivity in all emerging market and developing economies; however, we find that the effect of innovation is more significant for firms in Africa, especially product innovation.

Our findings suggest that substantial productivity gains can be achieved in African and other developing economies through process and/or product innovations realized by access to finance, ICT adoption, and on-the-job training, in addition to R&D. As these economies operate far below their technological frontier, it is possible to claim a considerable fraction of these gains by adopting new technologies developed elsewhere rather than introducing radical innovations.

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Table 1: Definition of variables

Variable	Definition
Firm performance	
Labor productivity	
Sales per worker	(log) deflated sales per worker
TFP	Revenue-based estimates computed as the residual term of the transformed production function
Innovation output	
Product innovation	=1 if the firm introduced new products and/or services in past three years
Process innovation	=1 if the firm introduced new/significantly improved process in past three years
Innovation	=1 if the firm introduced new products and/or services and/or introduced new/significantly improved process in past three years
Knowledge generation	
R&D spending	=1 if the firm spent on R&D in past fiscal year
Internal capabilities	
Firm size	
Number of workers	(log) number of permanent full-time production employees at the end of past fiscal year
Physical capital	(log) capital intensity = (log) deflated replacement value of machinery, vehicles, and equipment, divided by the number of permanent full-time employees in past fiscal year
Human capital	
Education	High school completion = percentage of full-time workers who completed high school
Skillfulness	Percentage of full-time production workers who were skilled at the end of past fiscal year
Manager experience	Number of years of experience working in this sector top manager has
Employee training	=1 if the firm provided formal training programs for its permanent full-time employees in past fiscal year
Foreign ownership	Percentage of the firm owned by private foreign individuals, companies, or organizations
State ownership	Percentage of the firm owned by government/state
Firm age	(log) number of years of firm operation
Product concentration	Main product/service share (percentage) of total annual sales
Access to external knowledge	
Foreign technology adoption	=1 if the firm uses technology licensed from a foreign-owned company
ICT adoption	
E-mail use	=1 if the firm uses e-mail to communicate with clients and suppliers
Website ownership	=1 if the firm has its own website
Location	=1 if the firm is located in the official capital city
Affiliation to a large firm	=1 if the firm is part of a larger firm
Demand pull factors	
Export orientation	Direct exports share (percentage) of sales
International competition	Whether the main market for the firm's main product is local/national or international
Outstanding barriers	
Inadequate education	Whether the firm reports "inadequately educated workforce" as very severe, major, moderate, minor, or no obstacle to its operations
Credit constraints	=1 if the firm has a line of credit or loan from a financial institution
Energy intensity	Proxied by fuel intensity = fuel cost as a fraction of sales
Other attributes	
Capacity utilization	Percentage capacity utilization of firm in past fiscal year
Industry	Industry of operation
Country	Country of operation

Table 2: Means/proportions of variables across regions

	Means/proportions			Number of observations		
	Africa	Other developing	Emerging	Africa	Other developing	Emerging
Firm performance						
Labor productivity						
Sales per worker	9.126	9.960	10.114	28,619	31,898	45,440
TFP	2.507	2.514	2.626	10,413	9,855	19,244
Knowledge generation / innovation						
R&D	8.6%	18.6%	24.1%	23,210	25,574	37,792
Process innovation	24.3%	21.1%	35.3%	23,110	32,920	40,097
Product innovation	23.1%	25.2%	30.6%	23,332	33,172	41,320
Process/product innovation	32.2%	33.3%	42.5%	23,355	33,209	41,393
Internal capabilities						
Firm size: Employment	2.901	3.193	3.506	38,785	50,278	62,015
Physical capital	11.589	12.374	11.406	11,154	10,686	24,521
Human capital						
High-school completion	61.309	66.240	64.415	17,532	19,048	28,576
Skillfulness	68.451	68.778	70.566	13,330	14,534	33,394
Manager experience	15.217	18.091	18.266	38,377	49,177	57,093
Employee training	21.8%	25.9%	41.9%	32,292	42,923	51,633
Foreign ownership	11.639	8.014	5.092	38,592	50,260	57,577
State ownership	0.734	1.035	0.438	38,630	50,278	57,576
Firm age	2.418	2.594	2.691	38,360	50,087	58,205
Product concentration	81.439	81.414	84.656	32,356	46,778	54,968
Access to external knowledge						
Foreign-technology adoption	9.3%	9.6%	11.4%	20,437	32,739	44,119
ICT adoption	60.7%	81.7%	76.7%	38,142	46,087	57,960
Location in a capital city	37.9%	24.1%	29.9%	23,487	25,379	33,946
Affiliation to a large firm	27.5%	11.9%	12.1%	38,084	49,776	57,503
Demand-pull factors						
Export orientation	4.874	7.815	7.868	38,248	50,028	58,568
International competition	0.071	0.115	0.099	18,803	30,896	44,482
Outstanding barriers						
Access to finance	19.6%	33.6%	32.1%	38,152	49,633	55,779
Energy intensity	68.644	63.266	57.801	39,301	50,595	62,288
Other attributes						
Capacity utilization	70.445	72.574	77.443	16,521	20,097	37,183

Note: Other developing countries excludes African and emerging market economies. Figures in bold are weighted proportions.

Source: Authors' calculations.

Table 3: GSEM estimates of knowledge generation (R&D) equation

R&D	Pooled sample		Africa		Emerging	
	FIML (1)	LIML (2)	FIML (3)	LIML (4)	FIML (5)	LIML (6)
Internal capabilities						
Firm size: employment	0.218*** (0.025)	0.168*** (0.009)	0.220*** (0.081)	0.156*** (0.021)	0.172*** (0.033)	0.166*** (0.011)
Human capital: high-school completion	0.008*** (0.001)	0.004*** (0.000)	0.008** (0.003)	0.002*** (0.001)	0.008*** (0.001)	0.004*** (0.000)
Human capital: skillfulness	-0.002 (0.001)	0.002*** (0.000)	-0.003 (0.003)	-0.000 (0.001)	0.011*** (0.002)	0.004*** (0.001)
Human capital: manager experience	-0.007** (0.004)	-0.002 (0.001)	-0.002 (0.009)	-0.001 (0.003)	-0.004 (0.005)	-0.002 (0.001)
Foreign ownership	-0.002 (0.002)	-0.000 (0.001)	-0.004 (0.003)	-0.000 (0.001)	0.004 (0.003)	0.000 (0.001)
State ownership	-0.011*** (0.004)	-0.007*** (0.002)	0.016 (0.013)	0.003 (0.004)	-0.029*** (0.006)	-0.014*** (0.002)
Firm age	-0.019 (0.050)	0.002 (0.017)	0.006 (0.127)	0.000 (0.037)	0.026 (0.066)	-0.008 (0.020)
Product concentration	0.002 (0.002)	-0.003*** (0.001)	-0.001 (0.004)	-0.003** (0.001)	-0.002 (0.002)	-0.001 (0.001)
Access to external knowledge						
Location in a capital city	0.127* (0.074)	0.256*** (0.029)	-0.214 (0.185)	0.184*** (0.051)	0.308*** (0.113)	0.300*** (0.038)
Affiliation to a large firm	0.471*** (0.086)	0.292*** (0.028)	0.413* (0.247)	0.307*** (0.062)	0.339*** (0.105)	0.274*** (0.034)
Demand-pull factors						
Export orientation	0.733*** (0.108)	0.348*** (0.036)	0.014** (0.007)	0.006*** (0.002)	0.810*** (0.138)	0.364*** (0.043)
International competition	-0.568*** (0.124)	-0.085** (0.038)	-1.044* (0.536)	-0.051 (0.125)	-0.131 (0.159)	-0.049 (0.043)
Outstanding barriers						
Firm has access to finance	0.744*** (0.063)	0.235*** (0.024)	0.554*** (0.196)	0.419*** (0.058)	0.746*** (0.079)	0.185*** (0.028)
Inadequate education (Ref: No obstacle)						
Minor	0.592*** (0.081)	0.110*** (0.027)		-0.091 (0.061)	0.470*** (0.096)	0.158*** (0.031)
Moderate	1.101*** (0.086)	0.342*** (0.030)		0.036 (0.070)	1.170*** (0.103)	0.420*** (0.036)
Major	0.628*** (0.111)	0.220*** (0.040)		0.155* (0.081)	0.668*** (0.145)	0.191*** (0.049)
Very severe	0.445** (0.188)	0.089 (0.064)		0.139 (0.131)	0.068 (0.243)	0.037 (0.079)
Latent variable (L)	1.000 Constr(d)		1.000 Constr(d)		1.000 Constr(d)	
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	Yes	No	Yes	No	Yes
Year effects	No	Yes	No	Yes	Yes	Yes
No. of obs.	12,409	18,538	917	3,790	9,276	12,667

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The pooled sample comprises firms in emerging market and developing economies, including African countries.

Source: Authors' calculations.

Table 4: GSEM estimates of innovation output equation

Innovation output	Pooled sample		Africa		Emerging	
	FIML (1)	LIML (2)	FIML (3)	LIML (4)	FIML (5)	LIML (6)
R&D	4.321*** (0.506)	1.075*** (0.079)	2.676** (1.310)	0.527** (0.239)	3.203*** (0.898)	1.155*** (0.095)
Internal capabilities						
Firm size: Employment	-0.068** (0.034)	-0.104*** (0.024)	-0.294* (0.158)	-0.089 (0.060)	0.063* (0.034)	-0.088*** (0.033)
Human capital: High-school completion	-0.005*** (0.001)	-0.003*** (0.001)	0.001 (0.003)	0.002 (0.002)	-0.000 (0.002)	-0.004*** (0.001)
Human capital: Skillfulness	0.000 (0.001)	-0.002*** (0.001)	-0.003 (0.004)	-0.003** (0.001)	0.001 (0.002)	-0.003*** (0.001)
Human capital: Manager experience	0.009** (0.004)	0.007*** (0.002)	0.006 (0.012)	0.005 (0.004)	0.014*** (0.005)	0.009*** (0.002)
Human capital: Employee training	0.590*** (0.098)	0.185*** (0.033)	0.744** (0.341)	0.379*** (0.099)	0.446*** (0.111)	0.114*** (0.037)
Physical capital	-0.048*** (0.015)	0.024*** (0.008)	-0.001 (0.037)	-0.005 (0.020)	-0.044** (0.020)	0.041*** (0.010)
Foreign ownership	-0.000 (0.002)	-0.002* (0.001)	0.012** (0.005)	0.004** (0.002)	-0.002 (0.003)	-0.002 (0.001)
State ownership	-0.023*** (0.004)	-0.004 (0.003)	0.037 (0.023)	-0.002 (0.006)	-0.023*** (0.005)	0.000 (0.004)
Firm age	0.071 (0.060)	0.008 (0.025)	0.288* (0.152)	-0.049 (0.063)	0.021 (0.064)	0.020 (0.030)
Product concentration	-0.023*** (0.003)	-0.005*** (0.001)	-0.003 (0.005)	-0.004* (0.002)	-0.014*** (0.003)	-0.007*** (0.002)
Access to external knowledge						
Foreign-technology adoption	0.951*** (0.139)	0.463*** (0.053)	0.667* (0.394)	0.298** (0.129)	0.958*** (0.199)	0.511*** -0.074
ICT adoption	0.958*** (0.129)	0.299*** (0.043)	1.221*** (0.433)	0.444*** (0.105)	0.853*** (0.175)	0.299*** (0.056)
Location in a capital city	0.195** (0.090)	-0.107** (0.053)	-0.118 (0.232)	0.197** (0.098)	0.022 (0.105)	-0.193*** (0.070)
Affiliation to a large firm	0.176 (0.112)	-0.105* (0.057)	0.264 (0.365)	-0.048 (0.138)	0.029 (0.111)	-0.096 (0.073)
Demand-pull factors						
Export orientation	-0.085 (0.113)	-0.167*** (0.059)	0.015 (0.011)	-0.001 (0.003)	-0.034 (0.131)	-0.199*** (0.077)
Outstanding barriers						
Inadequate education (Ref: No obstacle)						
Minor	0.793*** (0.105)	0.172*** (0.047)		0.115 (0.111)	0.600*** (0.112)	0.138** (0.066)
Moderate	0.941*** (0.116)	0.010 (0.068)		0.147 (0.124)	0.686*** (0.107)	-0.090 (0.098)
Major	0.891*** (0.146)	0.057 (0.069)		0.085 (0.160)	0.590*** (0.144)	0.074 (0.088)
Very severe / Major or very severe	1.670*** (0.264)	0.418*** (0.106)	0.170 (0.296)	0.100 (0.257)	1.814*** (0.378)	0.667*** (0.147)
Latent variable (L)	-1.654*** (0.310)		-1.012 (1.119)		-0.944 (0.653)	
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	Yes	No	Yes	No	Yes
Year effects	No	Yes	No	Yes	Yes	Yes
No. of obs.	12,409	18,538	917	3,790	9,276	12,667

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The pooled sample comprises firms in emerging market and developing economies, including African countries.

Source: Authors' calculations.

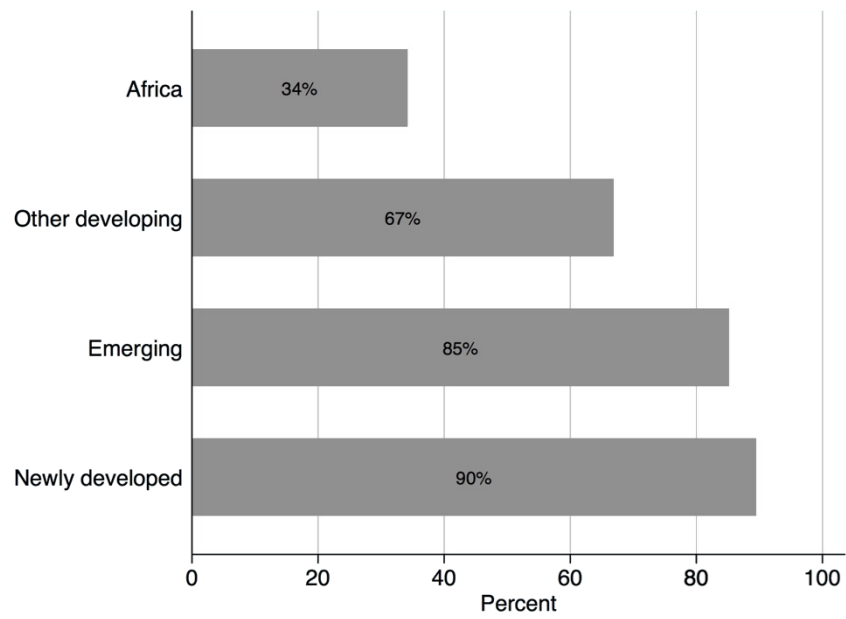
Table 5: GSEM estimates of firm performance equation

	Pooled sample			Africa				Emerging		
	TFP	TFP	Labor productivity	TFP	TFP	TFP	Labor productivity	TFP	TFP	Labor productivity
	FIML (1)	LIML (2)	LIML (3)	FIML (4)	FIML (5)	LIML (6)	LIML (7)	FIML (8)	LIML (9)	LIML (10)
Innovation (process/product)	0.098*** (0.024)	0.114*** (0.036)	0.295*** (0.046)	0.205 (0.196)		0.214* (0.128)	0.370*** (0.136)	0.048* (0.028)	0.086** (0.039)	0.306*** (0.061)
Innovation (product only)					0.289** (0.136)					
Employment	0.023*** (0.008)	0.021* (0.012)	0.044*** (0.012)	-0.050 (0.035)	-0.051 (0.035)	-0.054 (0.044)	0.123*** (0.043)	0.033*** (0.009)	0.024* (0.014)	0.048*** (0.014)
High-school completion	0.003*** (0.000)	0.001 (0.000)	0.000 (0.000)	0.003*** (0.001)	0.003** (0.001)	0.000 (0.002)	0.000 (0.002)	0.002*** (0.000)	0.000 (0.000)	0.001 (0.000)
Skillfulness	-0.001*** (0.000)	-0.000 (0.000)	-0.001* (0.000)	0.002 (0.002)	0.002 (0.002)	0.003* (0.002)	0.002 (0.002)	-0.000 (0.000)	-0.000 (0.001)	-0.002*** (0.000)
Physical capital	-0.020*** (0.004)	0.002 (0.008)	0.286*** (0.007)	0.006 (0.014)	0.004 (0.014)	0.013 (0.023)	0.248*** (0.020)	-0.010* (0.005)	0.003 (0.009)	0.293*** (0.008)
Foreign ownership	0.001* (0.001)	0.001 (0.001)	0.003*** (0.001)	0.003* (0.001)	0.003* (0.001)	0.002 (0.002)	0.008*** (0.002)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
State ownership	0.008*** (0.001)	0.007*** (0.002)	0.003** (0.002)	0.010 (0.006)	0.010 (0.006)	0.005 (0.007)	-0.001 (0.006)	0.007*** (0.001)	0.007*** (0.002)	0.006*** (0.002)
Firm age	-0.001 (0.015)	0.037* (0.020)	0.031* (0.018)	0.072 (0.065)	0.067 (0.065)	0.116* (0.066)	0.027 (0.063)	0.004 (0.017)	0.035 (0.023)	0.022 (0.021)
Fuel intensity	-0.003*** (0.000)	-0.001** (0.001)	-0.002*** (0.000)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	-0.005*** (0.002)	-0.001** (0.000)	-0.002*** (0.001)	-0.001*** (0.000)
Latent variable (L)	0.090*** (0.024)			0.262** (0.122)	0.219** (0.095)			0.060* (0.031)		
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes
Year effects	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
No. of obs.	12,409	18,538	18,538	917	916	3,790	3,790	9,276	12,667	12,667

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The pooled sample comprises firms in emerging market and developing economies, including African countries. Other controls include manager experience, affiliation to a large firm, and capacity utilization.

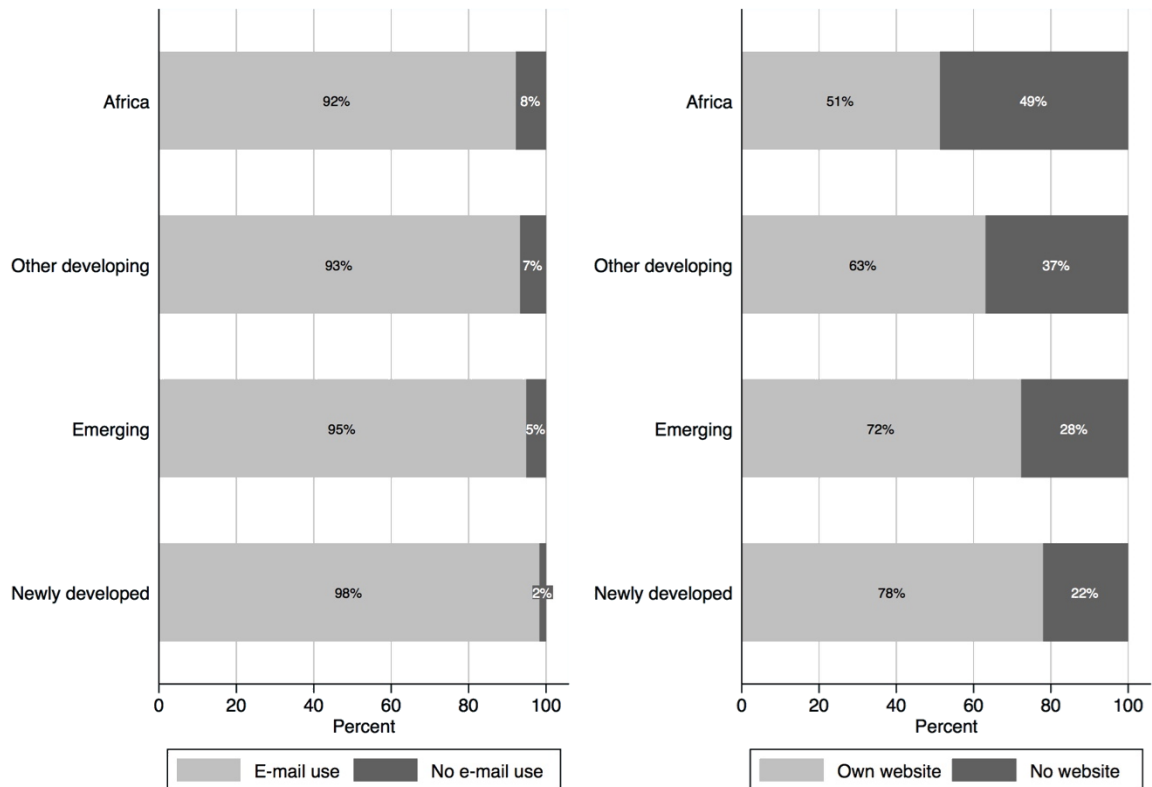
Source: Authors' calculations.

Figure 1: Firms' access to broadband internet connection



Source: Authors' calculations based on ES data.

Figure 2: ICT adoption by firms with access to broadband internet connection



Source: Authors' calculations based on ES data.

Appendix A: List of included countries

Africa	Other developing	Emerging	(Newly) developed
Burundi	Afghanistan	Argentina	Cyprus
DRC	Bolivia	Bangladesh	Czech Republic
Ethiopia	Cambodia	Chile	Estonia
Ghana	Costa Rica	China	Israel
Kenya	Dominican Republic	Colombia	Latvia
Malawi	Ecuador	India	Lithuania
Mauritania	El Salvador	Indonesia	Malta
Namibia	Guatemala	Malaysia	Slovak Republic
Nigeria	Honduras	Mexico	Slovenia
Senegal	Jamaica	Pakistan	Sweden
South Sudan	Lao PDR	Peru	
Sudan	Myanmar	Philippines	
Tanzania	Nepal	Thailand	
Uganda	Nicaragua	Venezuela	
Zambia	Panama	Vietnam	
	Papua New Guinea		
	Paraguay		
	Solomon Islands		
	Sri Lanka		
	Timor-Leste		
	Trinidad and Tobago		
	Uruguay		

Appendix B: GSEM estimates by firm size

Table B.1: GSEM estimates of knowledge generation (R&D) equation by firm size

R&D	Small		Medium		Large	
	FIML (1)	LIML (2)	FIML (3)	LIML (4)	FIML (5)	LIML (6)
Internal capabilities						
Firm size: Employment	0.663*** (0.168)	0.356*** (0.048)	0.228** (0.098)	0.099*** (0.034)	0.091 (0.068)	0.109*** (0.023)
Human capital: High-school completion	0.006*** (0.002)	0.005*** (0.001)	0.009*** (0.001)	0.007*** (0.001)	0.008*** (0.002)	0.006*** (0.001)
Human capital: Skillfulness	0.010*** (0.003)	0.002*** (0.001)	0.001 (0.002)	0.002*** (0.001)	-0.010*** (0.002)	-0.001 (0.001)
Human capital: Manager experience	-0.015* (0.008)	-0.001 (0.002)	-0.007 (0.006)	0.001 (0.002)	-0.001 (0.006)	-0.005** (0.002)
Foreign ownership	0.008 (0.005)	0.002 (0.001)	-0.002 (0.003)	0.000 (0.001)	-0.004 (0.002)	-0.000 (0.001)
State ownership	-0.018 (0.019)	-0.004 (0.005)	-0.027*** (0.007)	-0.013*** (0.004)	-0.001 (0.005)	-0.005** (0.002)
Firm age	0.072 (0.106)	0.049* (0.030)	-0.057 (0.077)	-0.025 (0.026)	-0.042 (0.089)	0.076*** (0.029)
Product concentration	0.001 (0.003)	-0.002 (0.001)	0.008*** (0.003)	-0.000 (0.001)	-0.004 (0.003)	-0.001 (0.001)
Access to external knowledge						
Location in a capital city	-0.031 (0.161)	0.208*** (0.048)	0.330*** (0.115)	0.332*** (0.041)	0.010 (0.131)	0.112** (0.049)
Affiliation to a large firm	0.562** (0.236)	0.336*** (0.064)	0.372*** (0.143)	0.198*** (0.046)	0.605*** (0.126)	0.374*** (0.042)
Demand-pull factors						
Export orientation	0.659* (0.349)	0.495*** (0.091)	0.712*** (0.173)	0.448*** (0.059)	0.778*** (0.157)	0.274*** (0.050)
International competition	-0.749 (0.459)	-0.131* (0.071)	-0.537*** (0.203)	-0.071 (0.067)	-0.486*** (0.174)	-0.110** (0.051)
Outstanding barriers						
Firm has access to finance	0.323** (0.145)	0.145*** (0.055)	0.784*** (0.096)	0.279*** (0.035)	0.864*** (0.112)	0.238*** (0.040)
Inadequate education (Ref: No obstacle)						
Minor	0.708*** (0.167)	0.096* (0.050)	0.755*** (0.121)	0.113*** (0.041)	0.232 (0.148)	0.103** (0.047)
Moderate	0.996*** (0.180)	0.288*** (0.055)	1.324*** (0.131)	0.344*** (0.046)	0.817*** (0.153)	0.324*** (0.054)
Major	0.435* (0.248)	0.056 (0.076)	0.819*** (0.170)	0.201*** (0.059)	0.488** (0.195)	0.262*** (0.070)
Very severe	0.352 (0.376)	0.008 (0.119)	0.358 (0.313)	-0.068 (0.103)	0.519* (0.312)	0.304*** (0.110)
Latent variable (L)	1.000		1.000		1.000	
	Constr(d)		Constr(d)		Constr(d)	
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	No	No	No	No	No
Year effects	No	Yes	No	Yes	No	Yes
No. of obs.	3,844	6,331	5,099	7,305	3,466	4,902

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.2: GSEM estimates of innovation output equation by firm size

Innovation output	Small		Medium		Large	
	FIML (1)	LIML (2)	FIML (3)	LIML (4)	FIML (5)	LIML (6)
R&D	4.509*** (0.474)	1.158*** (0.023)	3.358*** (0.634)	1.009*** (0.147)	3.216*** (0.623)	1.117*** (0.148)
Internal capabilities						
Firm size: Employment	0.152 (0.174)	-0.335*** (0.067)	-0.313*** (0.108)	-0.189*** (0.054)	-0.063 (0.074)	-0.100** (0.041)
Human capital: High-school completion	0.001 (0.002)	-0.004*** (0.001)	-0.004*** (0.002)	-0.004** (0.001)	-0.010*** (0.002)	-0.005*** (0.002)
Human capital: Skillfulness	-0.002 (0.003)	-0.003*** (0.001)	0.001 (0.002)	-0.001 (0.001)	-0.001 (0.002)	-0.002 (0.001)
Human capital: Manager experience	0.019** (0.008)	0.005 (0.003)	0.011** (0.005)	0.009*** (0.003)	-0.003 (0.007)	0.006* (0.003)
Human capital: Employee training	0.889*** (0.204)	0.174** (0.073)	0.436*** (0.107)	0.187*** (0.051)	0.507*** (0.141)	0.228*** (0.064)
Physical capital	-0.036 (0.028)	0.001 (0.005)	-0.049*** (0.019)	-0.005 (0.010)	-0.029 (0.024)	0.014 (0.010)
Foreign ownership	0.008 (0.006)	-0.001 (0.002)	0.003 (0.003)	0.001 (0.001)	-0.004 (0.002)	0.002 (0.001)
State ownership	-0.036*** (0.011)	-0.002 (0.007)	-0.024*** (0.006)	-0.005 (0.005)	-0.015*** (0.005)	-0.004 (0.003)
Firm age	-0.054 (0.111)	-0.081** (0.038)	-0.044 (0.078)	-0.063 (0.041)	0.313*** (0.099)	0.042 (0.053)
Product concentration	-0.027*** (0.004)	-0.002 (0.002)	-0.015*** (0.003)	-0.005*** (0.002)	-0.022*** (0.004)	-0.009*** (0.002)
Access to external knowledge						
Foreign-technology adoption	1.099*** (0.309)	0.267** (0.116)	0.778*** (0.161)	0.399*** (0.077)	0.781*** (0.162)	0.387*** (0.075)
ICT adoption	1.124*** (0.183)	0.217** (0.087)	0.610*** (0.133)	0.336*** (0.062)	1.075*** (0.291)	0.449*** (0.131)
Location in a capital city	0.188 (0.181)	-0.138** (0.069)	0.122 (0.112)	-0.051 (0.086)	0.161 (0.138)	0.166* (0.092)
Affiliation to a large firm	0.742** (0.317)	-0.152 (0.122)	0.038 (0.148)	0.007 (0.085)	0.073 (0.139)	-0.228** (0.101)
Demand-pull factors						
Export orientation	0.156 (0.389)	-0.385*** (0.119)	-0.193 (0.151)	-0.205* (0.105)	0.050 (0.134)	-0.078 (0.085)
Outstanding barriers						
Inadequate education (Ref: No obstacle)						
Minor	0.586*** (0.176)	-0.011 (0.072)	0.643*** (0.114)	0.219*** (0.068)	0.962*** (0.165)	0.332*** (0.092)
Moderate	0.821*** (0.209)	-0.203** (0.085)	0.775*** (0.127)	0.099 (0.101)	1.112*** (0.181)	0.212 (0.134)
Major	0.986*** (0.264)	0.055 (0.105)	0.554*** (0.163)	0.083 (0.100)	1.090*** (0.216)	0.264* (0.144)
Very severe / Major or very severe	2.391*** (0.490)	0.373* (0.208)	1.307*** (0.315)	0.539*** (0.164)	0.928*** (0.316)	0.153 (0.200)
Latent variable (L)	-2.044*** (0.236)		-0.886* (0.455)		-0.733 (0.479)	
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	Yes	No	Yes	No	Yes
Year effects	No	Yes	No	Yes	No	Yes
No. of obs.	3,844	6,331	5,099	7,305	3,466	4,902

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.3: GSEM estimates of firm performance equation by firm size

	Small			Medium			Large		
	TFP	TFP	Labor productivity	TFP	TFP	Labor productivity	TFP	TFP	Labor productivity
	FIML	LIML	LIML	FIML	LIML	LIML	FIML	LIML	LIML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Innovation (process/product)	0.047 (0.042)	0.513** (0.216)	1.313*** (0.562)	0.107*** (0.038)	0.236*** (0.058)	1.480*** (0.156)	0.110** (0.054)	0.048 (0.052)	0.337*** (0.081)
Employment	0.029 (0.042)	-0.082 (0.058)	0.134** (0.067)	0.062* (0.034)	0.072* (0.044)	0.153* (0.080)	-0.035 (0.023)	-0.038 (0.028)	-0.204*** (0.032)
High-school completion	0.003*** (0.000)	0.002*** (0.001)	-0.001 (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.001 (0.001)	0.004*** (0.001)	0.003*** (0.001)	0.001 (0.001)
Skillfulness	-0.001* (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.001* (0.001)	-0.000 (0.001)	-0.004*** (0.001)	-0.001** (0.001)	-0.001 (0.001)	0.002* (0.001)
Physical capital	-0.016** (0.007)	-0.015* (0.009)	0.106*** (0.010)	-0.017*** (0.007)	-0.027*** (0.009)	0.118*** (0.015)	-0.025*** (0.007)	-0.030*** (0.009)	0.147*** (0.010)
Foreign ownership	0.003** (0.001)	0.003* (0.002)	0.002 (0.002)	0.002* (0.001)	0.002* (0.001)	0.004* (0.002)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
State ownership	0.009*** (0.002)	0.009* (0.005)	0.021*** (0.006)	0.010*** (0.002)	0.010*** (0.003)	0.025*** (0.007)	0.006*** (0.002)	0.005** (0.002)	0.003 (0.002)
Firm age	-0.011 (0.026)	0.030 (0.035)	0.020 (0.038)	0.002 (0.027)	0.082** (0.035)	0.004 (0.062)	0.005 (0.027)	0.085** (0.037)	0.046 (0.039)
Fuel intensity	-0.003*** (0.001)	-0.003*** (0.001)	-0.000 (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.001 (0.001)
Latent variable (L)	0.087** (0.038)			0.058 (0.043)			0.175*** (0.055)		
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	No	No	No	No	No	No	No	No	No
Year effects	No	Yes	No	No	Yes	No	No	Yes	No
No. of obs.	3,844	6,331	6,331	5,099	7,305	7,305	3,466	4,902	4,902

Note: (Robust) standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Other controls include manager experience, affiliation to a large firm, and capacity utilization.