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The Role of the Business Environment and Firms' Characteristics

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Abstract

The paper studies the relationship between innovation efforts, innovation outputs, and productivity, using firm-level data from six East Asian countries. Firms are more likely to invest in innovation when they use technology licensed by a foreign company, are part of a large group, and have a more educated workforce. Investment in research and development can significantly boost both product and process innovation. Product innovation yields significant productivity gains. However, productivity gains from process innovation are not detectable in the sample.

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The Returns to Innovation in East Asia: The Role of the Business Environment and Firms' Characteristics

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1. Introduction

Does innovation spur productivity? Griliches (1986) famously argued that innovation accounts for a sizeable portion of productivity growth, as changes in capital and labor alone can explain only half of it. By introducing new products, processes, or managerial practices, innovation would lead to improved uses of capital and labor, enabling firms to enter new markets and grow. Indeed, Porter and Millar (1985) argue that information and communication technology (ICT) may improve the accuracy and efficiency of production and help upgrade operational and production processes. Yet not everyone agrees with this view. Robert Solow coined the term "productivity paradox" in reference to the lack of apparent productivity gains when ICT technologies were largely adopted in the 1970s and 1980s.[2]

These apparent contradictions are reconciled by Cirera and Maloney (2017). They document that the "innovation paradox" can be explained by the fact that complementary physical and human capital factors, chiefly firm managerial capabilities, are critical to reap the returns to innovation investments. This empirical evidence echoes insights from Acemoglu et al. (2006): limited firms' capabilities and distance from the technological frontier can explain low incentives to adopt innovation and weak productivity growth.

Also, timing issues may affect the ability to uncover the positive impact of innovation on productivity. There may be a delay between the introduction of new technologies and the realization of productivity improvements. From a within-firm perspective, Brynjolfsson et al. (2019) argue that adapting pre-existing production processes to new technologies is not necessarily smooth and quick. Technology adoption in developing countries may require substantial re-organization of production, hence it is slow and its contribution to productivity requires time to realize (Juhász et al.,2020). From an economy-wide perspective, Gort and Klepper (1982) postulate that rapid product innovation yields a surge in entry, a period of significant experimentation followed by a shakeout period when unsuccessful enterprises wither and exit while successful developers and firms grow. Pioneering a new methodology, Foster et al. (2018) provide some empirical support to this hypothesis for the U.S.[3]

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[2] In a 1987 interview by the New York Times, Solow is quoted saying: "[...] what everyone feels to have been a technological revolution, a drastic change in our productive lives, has been accompanied everywhere, including Japan, by a slowing-down of productivity growth, not by a step up. You can see the computer age everywhere but in the productivity statistics." (New York Times, July 12, 1987, p. 36)

[3] The authors use low-frequency firm-level data for the entire U.S. private sector and infer whether innovation took place by looking at firms' entry dynamics. Building on Gort and Klepper (1982), spikes in entry could be interpreted as proxy of innovation in the previous period. Foster et al. (2018) document that a surge in productivity in high-tech sectors in the late 1990s is a strong contributor of the increased within-industry covariance between market share and productivity (i.e., firms whose productivity has grown in previous period gain market share). This surge in productivity is associated with higher entry and within-industry productivity dispersion, and high productivity growth in high-tech sectors, all elements that could be reconciled with an increase in innovation. In line with the Gort and Klepper (1982) hypothesis, they also find that the post-2000s period has seen a decline in entry and a high-tech productivity slowdown driven by lower within-firm productivity growth and smaller covariance between market share and productivity. In contrast with Gort and Klepper (1982), they also find increased within-industry productivity dispersion, which is even greater for young (instead of mature) firms.

The type of innovation introduced is also expected to matter. When "low-hanging fruits" technologies have been already adopted, the remaining innovations may be expected to yield lower returns (Gordon 2012; Gordon and Sayed 2019).

Understanding the returns to innovation is thus an empirical question. This question has received considerable attention in developed countries, where data are more likely to be available. Evidence from advanced economies, mostly in Europe, points to a positive, albeit somewhat noisy, relationship between (primarily product) innovation and (levels/growth of) productivity (see Hall, 2011 for a review). Evidence from developing countries is more limited and not as conclusive - despite some positive association documented for newly industrialized countries such as the Republic of Korea (Lee and Kang 2007), Malaysia (Hegde and Shapira 2007), and China (Fisher-Vanden et al., 2006). Leveraging cross-country data from East Asia, we want to fill this gap in the literature and offer a consistent assessment of the interaction between productivity and innovation, exploring the complementary role played by the business environment and firms' characteristics.

A variety of methodologies have emerged to link productivity with innovation, despite limited data on technology adoption at the firm level. For example, some researchers resort to randomized control trials (RCTs) to generate first-hand data on technology adoption and productivity. But their data are of relatively small size and time range making generalization of their analyses difficult (Bloom et al., 2013; Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen, 2017; Hardy and McCasland, 2016). Another approach that has gained popularity is to check the effects of innovation on the full-range firm productivity distribution. (Syverson, 2011; Juhász et al.,2020). The firm dynamics embodied in the distribution are critical for understanding differences in productivity across sectors (Hsieh and Klenow, 2009). Yet this method imposes a demanding data requirement for cross-country analyses.

Given the nature of our data, a more suitable empirical strategy is to rely on the Crépon, Duguet, Mairessec (1998, henceforth CDM for short) model which exploits cross-sectional variations and tends to abstract from issues related to the timing of innovation and its contribution to productivity. The CDM model is articulated in three parts and explores: (i) whether and to what extent a firm undertakes R&D investment, as a function of the firm and industry characteristics; (ii) what type of innovation outcomes take place as a function of R&D intensity and other firm and industry characteristics; and (iii) whether and to what extent innovation outcomes affect productivity. The CDM model offers a way to deal with issues related to selection bias (focusing on the few firms reporting positive investments in innovation would skew the sample and possibly bias the results) and endogeneity in the functions of innovation and productivity (due to measurement error or unobservable factors that affect both the productivity of the firms and the choice of inputs used).

We build on the CDM model and explore whether the effects of innovation investments on productivity are heterogeneous and whether there is evidence of spillovers from innovation on productivity. In estimating the relationship between innovation and productivity, we explore the role of other (complementary) factors, including firm-specific factors (e.g., management capabilities, foreign ownership) or business-environment characteristics (e.g., sector financial dependence and availability of financial services). In particular, we want to study which complementary factors can facilitate the return of innovation on productivity, based on the Hendry and Krolzig's (2004) -general to specific or GETS- method.

We present the data in Section 2, discuss the empirical strategy and results in Section 3, and conclude in Section 4.

2. Data

The analysis presented is based on the most recent Enterprise Surveys data available from East Asian countries. They are China (2012), Indonesia (2015), Malaysia (2015), Philippines (2015), Thailand (2016), and Vietnam (2015).[4] The surveys provide data on a representative sample of formal firms operating in non-agricultural sectors. We exclude from the analysis micro-enterprises, firms with fewer than 5 full-time employees, such as self-employed entrepreneurs and micro firms, and sectors with fewer than 4 firms for each country and survey year.

We report in Table 1 the definition of the variables used in the analysis. They can be broadly put in these categories: (i) innovation measures, (ii) firm performance, (iii) internal capabilities, (iv) access to external knowledge, and (v) demand-pull, and a final miscellanea category. We selected these categories based on evidence from the existing literature, the choice of the specific variable considered is then dictated by data availability.

Table 1 Variables definition

Innovation	
Innovation	(0/1) if a firm introduces a product or process innovation
Product innovation	(0/1) if a firm introduces a product innovation
Process innovation	(0/1) if a firm introduces a process innovation
Performance	
Labor productivity	Log (constant US$) sales per full-time worker
R&D per worker	Log (constant US$) R&D expenditures per full-time worker
Fixed investment	Log (constant US$) fixed investment per full-time worker
R&D dummy	(0/1) if a firm has invested in R&D
Employment	Log full-time employment (headcount)
Internal capabilities	
Age	(years) firm age
Human capital	The average number of years of education for the typical worker
Group	(0/1) if a firm is part of a large group
FDI	(0/1) if a firm has 10 % or more foreign ownership
Diversification index	Diversification index (% of sales of main product)
Manager experience	(years) experience of the manager in the sector of the firm
Access to external knowledge	
Cooperation	% of firms that cooperate for innovation activities in the same sector (at 2-digit ISIC level) and country for each survey year
Large city	(0/1) if a firm is in a city with more than 1 million population
Licenses	(0/1) if a firm uses technology licensed from a foreign-owned company
Demand-pull	

[4] For Myanmar the data available are from 2016 but the large number of missing values for the core variables severely affects the quality of the analysis and therefore we opt not to include the country in the sample.

Competitors 1	(0/1) if a firm faces 0 competitors in the main market
Competitors 2	(0/1) if a firm faces 1 competitor in the main market
Competitors 3	(0/1) if a firm faces 2 to 5 competitors in the main market
Competitors 4	(0/1) if a firm faces more than 5 competitors in the main market
International market	% of firms whose direct exports consist of more than 50% of total sales by sector (at 2-digit ISIC level) and country for each survey year
Other	
Materials	Log (constant US$) raw materials and intermediate goods per full-time worker

Nominal variables such as labor productivity, R&D per worker, fixed investment, and materials are deflated using weighted GDP deflators from WDI. The GDP deflators are weighted based on the closing month of each firm's last completed fiscal year. For example, if a firm's last complete fiscal year spans July 2015 through June 2016, then relevant deflator corresponds to $\frac{6}{12} deflator_{2015} + \frac{6}{12} deflator_{2016}$. Since these variables are expressed in local currency (LCU), we convert them into USD using weighted exchange rates.

When the closing/starting month data of the last completed fiscal year is missing, we assume the start month to be 1 if the last completed fiscal year spans only one year (i.e., 2014) and 7 if the last completed fiscal year spans two years (i.e., 2013-2014). If the last completed fiscal year variable is missing, we assume it as survey-year minus 1 or refer to the corresponding questionnaires if they indicated the actual last completed fiscal year. We use the sampling weight according to median eligibility from WBES. To avoid biases from extreme values, we censor the age of the firm at 100 and the years of managerial experience in a sector at 35.[5]

Half of the firms in our sample perform some kind of innovation (Table 2). Process innovation is more widely adopted (40% of firms) than product innovation (20% of firms). Only 10% of firms invest in R&D. Similarly, the use of technologies licensed by foreign-owned companies is limited: only10% of firms do it. Firms tend to be small, located in cities with at least 1 million people. Concerning internal capabilities, firms are relatively young and on average 14 years old. The typical worker has 10 years of education (human capital). Only 10% of firms belong to a large group and receive 10% or more foreign ownership (FDI), respectively. Diversification of own products is also quite low as about three-quarters of firms have more than 90% of their sales come from their main products (diversification index).

Table 2 Weighted summary statistics of the estimation sample of the first stage of our CDM model

	N	Mean	SD	Min	p25	p75	Max
Innovation	321997	0.5	0.5	0.0	0.0	1.0	1.0
Product innovation	323101	0.2	0.4	0.0	0.0	0.0	1.0
Process innovation	322932	0.4	0.5	0.0	0.0	1.0	1.0
Labor productivity	323587	10.1	1.3	2.7	9.3	11.0	17.1
R&D expenses per worker (log constant US$)	33919	7.5	2.0	-13.3	6.5	8.8	21.8

[5] Additional data cleaning included dropping firms with inconsistent answers on innovation investments. Specifically, we drop firms that state not to have invested in R&D, but then report the amount of R&D expenditure.

R&D, dummy	324413	0.1	0.3	0.0	0.0	0.0	1.0
Fixed invest	242997	8.9	1.8	-4.5	7.8	10.2	17.8
Employment (log number of full-time workers)	324413	3.4	1.2	1.6	2.5	4.2	10.3
Firm age	324413	13.9	8.2	0.0	8.0	17.0	100.0
Human capital	324413	10.2	3.2	0.0	9.0	12.0	100.0
Part of a group, dummy	324413	0.1	0.3	0.0	0.0	0.0	1.0
FDI	324413	0.1	0.2	0.0	0.0	0.0	1.0
Diversification index	324413	93.2	13.6	3.0	90.0	100.0	100.0
Manager experience	324413	15.8	7.4	1.0	10.0	20.0	35.0
Cooperation	324413	46.8	16.3	0.0	45.9	54.9	100.0
Large city	324413	0.9	0.3	0.0	1.0	1.0	1.0
Licenses	324413	0.1	0.3	0.0	0.0	0.0	1.0
Competitors 1	324413	0.0	0.1	0.0	0.0	0.0	1.0
Competitors 2	324413	0.0	0.0	0.0	0.0	0.0	1.0
Competitors 3	324413	0.1	0.3	0.0	0.0	0.0	1.0
Competitors 4	324413	0.9	0.3	0.0	1.0	1.0	1.0
International market	324413	7.9	5.7	0.0	4.6	10.0	75.0
Materials	302761	8.9	1.6	-7.3	8.0	9.9	16.0

3. Empirical results

The CDM model allows us to explore the relationships between innovation efforts, innovation outputs, and productivity while dealing with issues related to selectivity bias (only a few firms report positive investment in R&D at any given time) and endogeneity (due to measurement error or unobservable factors that affect both productivity and the choice of inputs/innovation inputs). This approach has been widely used in the literature (Lööf et al., 2017) as it allows to unpack the relationship between innovation input and productivity by considering the innovation output.

Our work is closely related to Crespi et al. (2016). Both studies rely on data from World Bank Enterprise Survey: ours focuses on East Asia, while theirs on Latin America.

3.1 What are the determinants of innovation investments?

The first stage of the CDM model seeks to estimate how firms decide whether and how much to invest in R&D. The firm's innovative effort is assumed to be a latent variable that could be (imperfectly) observed when firms report positive R&D expenditures. We thus apply a generalized Tobit model estimated by maximum likelihood, considering the following potential determinants:

- **Internal capabilities.** Proxies include (i) the firm age which captures the tacit knowledge accumulated through experience and learning by doing; (ii) human capital which reflects the cognitive skills needed to absorb new knowledge and develop new technologies (Acemoglu et al., 2006); (iii) a group dummy which identifies whether the firm is part of a large group or a subsidiary of a multinational which in turn may imply easier access to more sophisticated knowledge (Girma and Gorg, 2007) and/or human capital (Kumar and Aggarwal, 2005); (iv) FDI; (v) sales diversification is an indicator of the scope of the firm's productive capabilities and the extent to which the firm's knowledge base is focused on narrow/specialized sectors or can apply to different sectors; (vi) manager experience is associated with the decision to innovate and the share of new-product sales (Barker and Mueller, 2002; Balsmeier and Czarnitzki, 2013; Galasso and Simcoe, 2011).

- **Access to external knowledge.** Cooperation (the share of firms that cooperate for innovation activities in the same 2-digit sector-country pair) in principle has an ambiguous effect on innovation investments. On the one hand, it can stimulate innovation investments by allowing to share costs and internalize spillovers. On the other hand, collaboration may curb the need to expand investments by increasing access to R&D activities. To deal with this potential endogeneity, instead of relying on the amount of collaboration reported by the firm and use instead of the average of collaboration activities reported by firms operating in the same 2-digit sector and country.[6] Being located in a large city (>1 million population) can facilitate exploiting agglomeration effects that can positively affect innovation. Firms can more easily access specialized resources (mostly human capital) and services providers, as argued by Moretti (2004). Expenditure on licensing is associated with high rates of return (twice as large as investments in physical capital), as shown by Álvarez et al. (2002).
- **Demand-pull factors.** Facing a larger number of competitors (competitors1, competitors2, competitors3, and competitors4[7]) can provide a stronger incentive to innovate, as argued by Aghion et al. (2005), firms in highly competitive sectors may be encouraged to innovate to escape competition. Exposure to international markets[8] may facilitate innovation, especially when firms already have a certain level of technological skills.

We control for the firm size (ln (full-time employment (headcount))) in the estimation of the decision to invest but not for the intensity of R&D investment. This approach is suggested by the findings in Cohen and Klepper (1996) where large firms appear to invest more in R&D, but not differentially so once the decision to invest is accounted for.

Table 3 The determinants of R&D investment in China and ASEAN5

	Decision to invest	**R&D per worker**
Firm age	-0.00113*	-0.0507**
	(0.000664)	(0.0250)
Human capital	0.00151	0.147**
	(0.00128)	(0.0609)
Group	0.00368	1.361**
	(0.00966)	(0.554)
FDI	-0.00887	-0.828
	(0.00903)	(0.657)
Diversification	-0.000263	-0.0240**
	(0.000292)	(0.0107)
Manager experience	0.000810*	0.0295
	(0.000439)	(0.0308)
Cooperation	0.000130	0.0225
	(0.000254)	(0.0194)

[6] Cooperation is measured as the share of firms that cooperate on innovation activities (either process or product) in the same sector and country.

[7] Competitors# is a dummy variable that refers to the number of competitors faced by the firm in the main market (as reported by the firm itself). Specifically, competitors1(2/3/4) is equal to one if the firm faces 0(1/2-5/>5) competitors in the main market.

[8] As a proxy for the exposure to international markets we use the share of firms in a sector-country pair that directly export at least 50% of their sales.

Large city	0.0158	0.716
	(0.0161)	(0.922)
Licenses	0.0284***	0.983**
	(0.00913)	(0.483)
Competitors2	0.0108	1.667*
	(0.0266)	(0.953)
Competitors3	0.0131	0.599
	(0.0176)	(0.912)
Competitors4	-0.00846	0.164
	(0.0160)	(0.779)
International market	-0.000746	0.00731
	(0.000598)	(0.0328)
Employment	0.00856***	
	(0.00205)	
N	3,136	3,136
*** p<0.01, ** p<0.05, * p<0.1. Generalized Tobit model estimated by maximum likelihood. Marginal effects are reported, i.e., the coefficients predict (i) the expenditures in R&D and (ii) the likelihood of investing in R&D. Robust standard errors in parentheses. The sample includes data from these surveys: China (2012), Indonesia (2015), Malaysia (2015), Philippines (2015), Thailand (2016), Vietnam (2015).		

The decision to invest in R&D appears strongly correlated with using technology licensed by a foreign-owned company: licenses are associated with a 2.8 percentage points higher likelihood to invest in R&D. Also, larger firms appear more likely to invest in R&D. Younger firms or firms led by managers with more experience in the sector are also marginally (statistically) more likely to invest in R&D.

The intensity of R&D investment is associated with being part of a large group and with using technology licensed by a foreign-owned firm. Facing one competitor in the main market is also associated with higher R&D intensity, but the result is noisy. Other factors matter, though to a smaller extent. Having a more educated workforce and more diversified sales, as well as being younger are all associated with higher R&D intensity.

Interestingly, we do not find evidence of agglomeration economies, or that the exposure to international markets or FDI matters. A possible interpretation is that multinationals would not invest in R&D locally if the market size is not sufficiently large or the national academic attractiveness is limited in technologically lagging countries. This would be consistent with the evidence from Latin America discussed in Crespi et al. (2016).

Accounting for this investment in R&D allows us to then estimate the knowledge (technology) production function, which is the second stage of the CDM model. We thus investigate the determinants of (overall) innovation (Table 4; column 1), distinguishing between innovation in product/service (Table 4; column 2) or innovation in process (Table 4; column 3).[9]

Having invested in R&D is associated with more innovation, a 10% increase in R&D spending (log constant US$) translates into a 5 percentage points increase in the probability of innovation.

[9] For brevity, throughout the text we refer to product innovation. The measure is actually broader and encompasses the introduction of new or significantly improved products or services.

Being the recipient of FDI does not correlate with the decision/intensity of innovation (Table 3) but it does with innovation outputs, especially product innovation, suggesting that firms' innovation outcome may benefit from technology developed abroad. The level of fixed investments and the size of the firm are positively correlated with innovation outputs, be it innovation in product or process.

Some results are counterintuitive. Firms innovate less when they have more educated workers, they are part of a large group, their manager has more experience in the sector, they face more cooperation in innovation, they locate at a large city, and they use technology licensed by a foreign-owned company (licenses). These results appear not to be driven by innovation in product or process. Yet, some of these counterintuitive findings are not peculiar to East Asia. Crespi et al. (2016) document similar findings regarding human capital for firms in Latin America. They argue that firms with a higher share of skilled workers may be operating in more complex markets and may lack the capabilities needed to introduce new products or processes in these markets. Similarly, one could argue that firms may be cooperating in product innovation precisely because it is harder to succeed in that particular field.

Table 4 The determinants of innovation outputs in China and ASEAN5

	(1) Innovation	**(2) Product innovation**	**(3) Process innovation**
R&D per worker (predicted)	0.485***	0.203*	0.217*
	(0.116)	(0.104)	(0.111)
Firm age	0.0126**	0.00482	-0.000401
	(0.00600)	(0.00625)	(0.00570)
Human capital	-0.0604***	-0.0273*	-0.0208
	(0.0188)	(0.0155)	(0.0166)
Group	-0.461***	-0.0629	-0.169
	(0.164)	(0.157)	(0.155)
FDI	0.441***	0.284**	0.101
	(0.111)	(0.113)	(0.107)
Diversification	0.00483	-0.00209	-0.000554
	(0.00332)	(0.00257)	(0.00319)
Manager experience	-0.00716*	-0.00403	0.000918
	(0.00375)	(0.00359)	(0.00385)
Cooperation	-0.00625**	-0.00837***	0.00103
	(0.00300)	(0.00292)	(0.00276)
Large city	-0.285*	-0.157*	-0.107
	(0.160)	(0.0927)	(0.160)
Licenses	-0.182*	-0.0289	0.107
	(0.110)	(0.129)	(0.0940)
Fixed invest	0.0494***	0.0305***	0.0438***
	(0.0104)	(0.00917)	(0.00954)
Employment	0.0509***	0.0278***	0.0707***
	(0.0127)	(0.00966)	(0.0151)
N	2,716	2,718	2,716
*** p<0.01, ** p<0.05, * p<0.1. Probit model. Marginal effects are reported, i.e., the coefficients predict the likelihood of introducing product or process innovation. The sample includes data from these surveys: China (2012), Indonesia (2015), Malaysia (2015), Philippines (2015), Thailand (2016), Vietnam (2015).			

3.2 What are the impacts of innovation outputs on productivity?

The third, and final, stage of the CDM model addresses the key question: the relationship between innovation (output) and productivity. To this end, we estimate the impacts of innovation on productivity controlling for firm characteristics, including physical and human capital and input costs. Innovation measures are based on the innovation outputs predicted from the second step (Table 4), to address endogeneity concerns. In Table 5 column 1, we control for overall innovation, whereas in column 2 we control for both product and process innovation but distinguish between the two, to capture any heterogeneous effects. In columns 3 and 4, we separately control for product and process innovation.

The results suggest that innovation has a positive impact on productivity. Firms that produce innovation generate 37% more output per worker than non-innovative firms (Column 1), and 27% more if we only look at product innovation (Column 3).[10] However, the association between innovation and productivity is not significant if we restrict the estimation to process innovation only (Column 4) or together with product innovation (Column 2). These findings for East Asia are in line with those for Latin America documented in Crespi et al. (2016) and Europe (Hall, 2011).

Table 5 The impact of innovation on labor productivity in China and ASEAN5

	Labor productivity			
	(1)	**(2)**	**(3)**	**(4)**
Materials	0.537***	0.540***	0.540***	0.541***
	(0.0243)	(0.0240)	(0.0192)	(0.0237)
Capital	0.0826***	0.0860***	0.0872***	0.0846***
	(0.0125)	(0.0129)	(0.0146)	(0.0126)
Human capital	0.00700	0.00836	0.00865	0.00810
	(0.00610)	(0.00611)	(0.00626)	(0.00631)
Employment	0.0219	0.0268	0.0291	0.0247
	(0.0167)	(0.0193)	(0.0194)	(0.0198)
Manager experience	-0.0261***	-0.0253***	-0.0251***	-0.0258***
	(0.00259)	(0.00272)	(0.00254)	(0.00266)
Firm age	0.0211***	0.0195***	0.0192***	0.0199***
	(0.00322)	(0.00321)	(0.00274)	(0.00325)
Innovation	0.314**			
	(0.146)			
Product innovation		0.194	0.240*	
		(0.215)	(0.135)	
Process innovation		0.0628		0.220
		(0.228)		(0.170)
N	2,607	2,607	2,609	2,607
*** p<0.01, ** p<0.05, * p<0.1. Ordinary least squares. Bootstrapped standard errors in parentheses. The sample includes data from these surveys: China (2012), Indonesia (2015), Malaysia (2015), Philippines (2015), Thailand (2016), Vietnam (2015).				

[10] These results are robust if we measure labor productivity using total factor productivity (TFPR) estimated based on the approach put forward by De Loecker (2013).

3.3 Is there any evidence of spillovers that could guide policy design and analysis?

Knowledge is a public good (Nelson, 1959 and Arrow, 1962): for it is non-rival as more than one person can use it at once and non-exclusive as it can potentially be shared easily, and preventing free-riders access can be challenging. The possible free-riding may disincentivize private investment in knowledge production, especially basic research. However, not all knowledge is equally affected. The public good rationale may apply to basic but not specific or technological knowledge: basic knowledge can be the product of public institutions, such as universities and research centers, while applied knowledge tends to be the product of targeted R&D investment that happens at the firm level. Moreover, the extent to which intellectual property rights and data policies are protected may vary across jurisdictions and over time, affecting the ability to defend private investment against the misappropriation of the associated returns. These differences in turn affect the likelihood of knowledge spillovers.

We explore whether the productivity of a given firm is related to the spillovers from the innovation (and the type of innovation) generated by other firms, controlling for the standard elements of a Cobb-Douglas production function. Innovation spillovers are defined as the average of the innovation propensities at the sector and country level, assuming that spillovers are the product of within-sector and within-country knowledge flows. As shown in Table 6, we only find a significant impact of product innovation's spillover on productivity, with process innovation and its externality controlled (Column 2). While own product innovation boosts productivity, innovation by others is negatively correlated with own productivity. Such a negative coefficient may be observed when firms are technologically distant, or when competition effects dominate, and therefore innovation by others widens the gap in productivity as laggards or less competitive firms are unable to keep up.

Table 6 The relation between innovation spillovers on productivity: evidence from China and ASEAN countries

	Labor productivity			
	(1)	(2)	(3)	(4)
Materials	0.537***	0.539***	0.540***	0.541***
	(0.0243)	(0.0240)	(0.0190)	(0.0237)
Capital	0.0827***	0.0904***	0.0874***	0.0849***
	(0.0125)	(0.0132)	(0.0145)	(0.0127)
Human capital	0.00670	0.00973	0.00926	0.00805
	(0.00622)	(0.00605)	(0.00611)	(0.00639)
Firm size	0.0223	0.0332*	0.0279	0.0255
	(0.0167)	(0.0196)	(0.0191)	(0.0201)
Manager experience	-0.0258***	-0.0243***	-0.0252***	-0.0257***
	(0.0026)	(0.0026)	(0.0025)	(0.0027)
Firm age	0.0208***	0.0185***	0.0193***	0.0198***
	(0.0033)	(0.0032)	(0.0028)	(0.0034)
Innovation (Predicted)	0.2.82*			
	(0.148)			
Innovation spillovers	0.582			
	(0.648)			
Product innovation (Predicted)		0.454**	0.291**	
		(0.216)	(0.133)	
Product innovation spillover		-1.181**	-0.796	

		(0.592)	(0.610)	
Process innovation (Predicted)		-0.201		0.202
		(0.232)		(0.179)
Process innovation spillover		0.858		0.222
		(0.577)		(0.566)
N	2,607	2,607	2,609	2,607
*** p<0.01, ** p<0.05, * p<0.1. Ordinary least squares. Bootstrapped standard errors in parentheses.				

We also explore whether the strengths of innovation spillovers vary depending on the extent to which a firm innovates, as shown in Table 7. We add a dummy variable that takes value 1 for firms with above-average propensity to innovate and the interaction of such dummy with innovation spillovers. A positive interaction coefficient suggests that a firm's productivity benefits from innovation spillovers when the firm's propensity to innovate is above the sectoral average. We find some evidence of this for innovation (Column 1) and process innovation when product innovation and its spillover are controlled (Column 2), but not for product innovation.

Table 7 The relation between innovation spillovers on productivity: robustness check

	China and ASEAN countries			
	(1)	**(2)**	**(3)**	**(4)**
Materials	0.538***	0.540***	0.540***	0.541***
	(0.0244)	(0.0244)	(0.0186)	(0.0240)
Capital	0.0811***	0.0862***	0.0884***	0.0841***
	(0.0122)	(0.0135)	(0.0142)	(0.0127)
Human capital	0.00646	0.00947	0.00905	0.00867
	(0.00601)	(0.00601)	(0.00599)	(0.00630)
Firm size	0.0201	0.0201	0.0257	0.0246
	(0.0165)	(0.0194)	(0.0187)	(0.0201)
Manager experience	-0.0261***	-0.0261***	-0.0260***	-0.0256***
	(0.00270)	(0.00274)	(0.00244)	(0.00274)
Age	0.0202***	0.0198***	0.0200***	0.0193***
	(0.00328)	(0.00345)	(0.00282)	(0.00349)
Innovation	0.170			
	(0.217)			
Innovation spillover	0.449			
	(0.657)			
Dummy of innovation > sect. avg.? (Yes=1)	-0.294*			
	(0.166)			
(Innovation spillover) x (Dummy of Innovation > sect. avg.?)	0.569**			
	(0.234)			
Product innovation		0.887***	0.699***	
		(0.268)	(0.204)	
Product innovation spillover		-1.462**	-1.158*	
		(0.706)	(0.687)	
Dummy of product innovation > sect. avg.? (Yes=1)		-0.0529	-0.104	
		(0.148)	(0.110)	
(Product innovation spillover) x (Dummy of product innovation > sect. avg.?)		-0.455	-0.103	
		(0.377)	(0.284)	
Process innovation		-0.357		0.00418
		(0.279)		(0.246)
Process innovation spillover		0.915		0.295
		(0.622)		(0.639)

Dummy of process innovation > sect. avg.? (Yes=1)		-0.0858		-0.0755
		(0.115)		(0.135)
(Process innovation spillover) x (Dummy of process innovation > sect. avg.?)		0.450**		0.277
		(0.195)		(0.214)
N	2,607	2,607	2,609	2,607
*** p<0.01, ** p<0.05, * p<0.1. Ordinary least squares. Bootstrapped standard errors in parentheses				

3.4 What factors facilitate higher returns?

Innovation does not happen in a vacuum but hinges on the availability and the adequacy of a broad range of factors. Cirera and Maloney (2017) note that supply,[11] demand[12] as well as accumulation and allocation[13] factors play an important role in the diffusion and adoption of innovation. We thus want to understand which of these complementary factors play a more significant role and whether any differential effect emerges for innovative versus non-innovative firms.[14] To this end, we rely on the general to specific (GETS) method (Hendry and Krolzig, 2004, and Hoover and Perez, 1999) to identify which factors are associated with productivity. The idea is to first consider a large set of variables and then select the explanatory variables through a series of statistical tests, based on the relevance and power of these variables to explain the dependent variable. Hoover and Perez (1999) show that this technique performs well in recovering the true data-generating process in Monte Carlo simulations. We believe this could be a fruitful approach to identify complementary factors -theoretically, a large number of factors can support the innovation-productivity relationship; hence we allow for statistical models to pin down the most relevant for East Asian economies.

We consider the following set of variables[15]:

i. **Firm choices:** whether at least 10% of a firm belongs to a foreign company, % of firm owned by the largest owner(s), whether a firm provides internal training to its employees, average years of education of typical worker, whether at least 10% of its total sales are from firm's direct exports, whether a firm uses foreign production technology, whether the firm owns or shares a generator, whether the firm has an ISO quality certification, whether the firm is externally audited, and whether the firm uses a webpage to communicate with clients.
ii. **Policy variables:** whether a firm has access to a credit line, % of total manager's time spent dealing with bureaucracy, whether a firm dealt with informal competitors last year, % of sales spent on informal payments to govt officials, the average number of days to get electricity connection, whether the firm experienced power outages during the last year, whether the firm experienced

[11] Supply factors considered by Cirera and Maloney (2017) include: human capital, support to firm capability upgrading, domestic science and technology system, and international NIS.

[12] Demand factors considered by Cirera and Maloney (2017) include: incentives to accumulate (macro context, competitive structure, trade regime and international networks) and firm capabilities (core competencies, production systems, and technological absorption and production).

[13] Cirera and Maloney (2017) distinguish between barriers to all accumulation (credit, entry/exit barriers, business and regulatory climate, rule of the law) and barriers to knowledge accumulation (rigidities for example in the labor market, seed and venture capital, innovation externalities).

[14] Firms are considered innovative if they have introduced a new or significantly improved product, service or process.

[15] The selection of the variables considered is influenced by data availability (number of missing values in measures that are omitted above).

water outages during the last year, whether a firm uses its security system, whether the firm experienced a criminal attempt during the last year, % of sales lost due to criminal activity, % of the value of merchandise lost during transit.

iii. **Controls:** age of the firms in years, % of capacity used in production, whether a firm was formally registered at birth, whether the firm is a shareholding company, whether the firm is part of a larger group.

We estimate the model for the whole sample as well as on the subsample of innovating firms. Comparing the results across specifications enables us to understand which factor matter more for which type of firm in which country. As shown in Table 8, we find that a few elements are correlated with productivity for both innovative and non-innovative firms. Having an ISO quality certification, and, surprisingly, the time to get an electricity connection is positively correlated with productivity, for both types of firms. Other characteristics matter for either innovative or non-innovative firms. For innovative firms, productivity is also associated with being an exporter, being externally audited, and having a more educated workforce, spending less time dealing with red tape and bureaucracy. For non-innovative firms, a wider set of characteristics appear relevant. Productivity is expected to improve with having access to a credit line, having a shareholding structure, owning or sharing a generator, experiencing fewer water outages, and having a web page all contribute to higher productivity. Besides, productivity is higher if there is more exposure to informal competition.

Table 8 What affects labor productivity? Focus on the manufacturing sector

	Full sample	**Innovative firms**	**Non-innovative firms**
Access to a credit line?			0.283**
			(0.144)
Own or share a generator?			0.555***
			(0.203)
Water outages during the last year?			-0.845**
			(0.377)
Days needed to get an electricity connection	0.0159***	0.0162***	0.0220***
	(0.00144)	(0.00169)	(0.00182)
Dealt with informal competitors last year?			0.273**
			(0.120)
% of sales spent on informal payments to govt officials			0.0107***
			(0.00392)
% of capacity used in production		-0.00770***	0.00879**
		(0.00291)	(0.00399)
Shareholding company?			0.860***
			(0.184)
Have ISO quality certification?	0.409***	0.346***	0.284**
	(0.0879)	(0.0980)	(0.122)
Use a web page to communicate with its clients?	0.341***		0.374***
	(0.0960)		(0.115)
Directly export at least 10% of sales	0.335***	0.273***	
	(0.106)	(0.0981)	
Average years of education of the typical worker		0.0330**	
		(0.0163)	
% management's time spent on bureaucracy	-0.0135***	-0.0217***	

	(0.00330)	(0.00730)	
Externally audited?		0.266***	
		(0.0914)	
Power outages during the last year?	-0.183**		
	(0.0791)		
N	5,629	2,307	1,814
R-squared	0.275	0.225	0.378
*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses			

As a robustness test, we also run country-level regressions. These uncover substantial cross-country heterogeneity. Not only the most important productivity correlates vary between innovative and non-innovative firms, as suggested by the difference in estimates for the full (Table 9) versus innovative-only sample (Table 8). But the same correlate may have opposite effects on productivity across countries.[16] For example, higher average education years contribute to higher productivity of the Chinese innovative firms but not for all the Chinese firms (Table 9). Additionally, the higher percentage of sales spent on informal payments to government officials hurt the productivity of firms in Malaysia but not in Vietnam (Table 9).

Table 9 What affects labor productivity? Focus on the manufacturing sector in each country (innovative and non-innovative firms)

	China	**Indonesia**	**Malaysia**	**Philippines**	**Vietnam**
Directly export at least 10% of sales		2.354***			
		(0.606)			
Use foreign technology in production?		1.598***		0.470***	
		(0.513)		(0.146)	
Average years of education of the typical worker					0.0817***
					(0.0288)
Own or share a generator?				0.445***	-3.262***
				(0.141)	(0.504)
Water outages during the last year?				0.577**	-1.639***
				(0.229)	(0.389)
Own security system?				0.614***	
				(0.143)	
% management's time spent on bureaucracy		-0.0302			-0.0143***
		(0.0235)			(0.00323)
Dealt with informal competitors last year?		0.746***			
		(0.258)			
% of sales spent on informal payments to govt officials			-0.0364***		0.249***
			(0.00963)		(0.0510)
% of capacity used in production				0.0113***	
				(0.00304)	
Externally audited?				0.649***	
				(0.216)	
Power outages during the last year?	-0.271***				0.957***
	(0.0935)				(0.338)
Have ISO quality certification?	0.414***	0.987**		0.353**	0.913***
	(0.101)	(0.439)		(0.171)	(0.298)

[16] Surprisingly, having access to finance is negatively associated with productivity in Thailand, as if the investments in R&D are detrimental on average.

Shareholding company?		2.025***			1.804***
		(0.647)			(0.294)
Access to a credit line?			0.651**	0.316**	0.0456
			(0.326)	(0.127)	(0.257)
Part of a larger group?					1.383***
					(0.313)
Experience a criminal attempt last year?				-0.374**	
				(0.169)	
Age				0.0105**	
				(0.00502)	
% of firm owned by the largest owner(s)					0.0212***
					(0.00493)
N	1,669	971	285	541	378
R-squared	0.072	0.371	0.253	0.344	0.558
*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Showing results only for countries for which a sufficiently large sample of innovative firms is available.					

Restricting to the innovative firms, less managerial time spent with bureaucracy, not belonging to a foreign company, and access to credit lines are the main labor-productivity correlates shared by innovative firms across the examined EAP sample (Table 10).

Table 10 What affects labor productivity? Focus on the manufacturing sector in each country, innovative firms

	China	**Indonesia**	**Malaysia**	**Philippines**	**Vietnam**
Average years of education of the typical worker	0.0642***				
	(0.0218)				
Power outages during the last year?	-0.334***				0.447
	(0.0886)				(0.410)
% management's time spent on bureaucracy	-0.0365**				-0.0272***
	(0.0142)				(0.00865)
% of capacity used in production	-0.00839**			0.00996***	0.0172*
	(0.00367)			(0.00356)	(0.00914)
Have ISO quality certification?	0.220**				
	(0.105)				
Belong to a foreign company?			-1.655**		-0.976**
			(0.824)		(0.397)
Access to a credit line?			1.129**		0.578*
			(0.439)		(0.329)
% of sales spent on informal payments to govt officials			-0.0504***		0.0518*
			(0.0152)		(0.0300)
Age			-0.0159		
			(0.0155)		
% of firm owned by the largest owner(s)			-0.00599		
			(0.0105)		
Use foreign technology in production?					1.354***
					(0.338)
Water outages during the last year?					-0.356
					(0.400)
Shareholding company?				0.597***	
				(0.169)	

Part of a larger group?					2.165**
					(0.989)
Own security system?				0.673***	
				(0.157)	
Experience a criminal attempt last year?				-0.303	
				(0.235)	
Externally audited?				0.895***	
				(0.231)	
N	1,081	216	127	419	56
R-squared	0.124	0.000	0.531	0.244	0.514
*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Showing results only for countries for which a sufficiently large sample of innovative firms is available.					

4. Conclusions

We study the link between innovation and productivity in major developing East Asian countries (China and ASEAN 5), highlighting the role of the complementary business environment and firm characteristics.

We investigate the determinants of R&D investments, the returns of R&D investment on innovation outcome, and the association between innovation and productivity. Our main findings are threefold. First, elements that contribute to R&D investments are using technology licensed by a foreign company, having higher human capital at work, and being associated with a large group, for example, being a subsidiary of a multinational with easier access to and absorption of new and sophisticated knowledge. Second, R&D investment can significantly boost innovation, be it product or process innovation. Among other complementary factors, FDI is the most critical determinant for overall and product innovation, though not for process innovation. Third, significant productivity gains arise from overall innovation and product innovation alone, but not from process innovation; a finding also documented for Latin America in Crespi et al. (2016) and Europe in Hall (2011).

To gain a deeper understanding of the innovation-productivity link, we rely on Hendry and Krolzig's (2004) GETS method to select significant determinants of productivity from a full range of complementary factors ranging from management capabilities to foreign ownership to availability of financial services. The results show substantial heterogeneity by innovative and non-innovative firms and across countries. Critical productivity correlates vary greatly between innovative and noninnovative firms. Moreover, the same correlates may have opposite effects on productivity across countries. Nevertheless, despite this heterogeneity, some stylized facts emerge. Having ISO quality certification is the most common determinant of higher productivity across the selected EAP countries for both innovative and non-innovative firms. We do not claim causality, rather investing in quality control may signal ability/willingness to participate in higher-value value chains that require higher standards.

Our findings suggest three policy implications. First, policies for boosting innovation should focus on human capital accumulation and factors facilitating exposure to external resources, especially foreign technology licenses and investment. Second, policies should target product and process innovation differentially, given their heterogeneous linkages with R&D investment and productivity. Future research may further advance this line of work, by decomposing process innovation as innovations that feature automation in the production process and other types of process innovation building also on Cirera and Sabetti (2019). Third, innovation policies should be tailored to country-specific contexts in that different complementary features of firms and the business environment are at work in driving innovation and productivity across countries.

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