RESEARCH ARTICLE

Nexus of Innovation and Firm-Level Productivity: Evidence from Philippine Manufacturing Firms

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We examine firms' propensity to engage in innovation activities and the impact of innovation on firm-level productivity in the Philippine manufacturing firms using comprehensive firm-level data from the 2015 World Bank Enterprise Survey. We use two main specifications: the probit model to assess firms' propensity to innovate, and endogenous switching regression to evaluate the impact of innovation on productivity and address endogeneity issues. Our empirical findings suggest that the propensity of firms to engage in innovation is low and negatively affected by R&D intensity and capital intensity. We find evidence of beneficial effects for both product and process innovations on firm-level productivity for firms that innovate compared to firms that chose not to innovate at all.

Keywords: Firm-level Productivity, Product and Process Innovation, Endogenous switching regression

JEL Classification: C34, D24, L60, O31, O32,

Interest in productivity, both economy-wide and industry-level, have increased globally due to the association between productivity and economic growth (Mairesse et al., 2005). The total factor productivity (TFP) drives economic growth and firms' output. The TFP growth in the Philippines analyzed at the country and industry levels showed negative growth of 0.4% from 1960 to 1996 and managed to rebound by almost 0.3% from 1996 to 1999 upon implementation of trade and liberalization policies (Austria, 1998). Since 2017, the Philippines' aggregate productivity growth has been mainly driven by within-sector yield through resource allocation activities which boost firm-level productivity (World Bank, 2018). According to Kim and Loayza (2019), the key determinants of productivity can be associated with factors that include innovation, market efficiency, education, infrastructure, and institutions.

Firm-specific factors such as firm size, capital intensity, export participation, R&D intensity, industry classification, and country-specific factors such as geographical location and government subsidies all have a significant effect on firms' propensity to innovate and productivity (Crepon et al., 1998; Griffith et al., 2006; Mairesse et al., 2005). The contribution of R&D spending and embodied technology to firms' engagement in innovation affects firm-level productivity directly and indirectly (Hall et al., 2013).

Other studies have shown that process innovation has a significant effect on firm-level productivity through investments in new equipment and machinery that reduce production costs (Hall et al., 2008; Masso & Vahter, 2008; Parisi et al., 2006). In the case of emerging markets such as Southeast Asian countries, Na and Kang (2019) found that product innovation has a positive effect on productivity as measured by sales growth, whereas process innovation has a negative effect on productivity because the adaptation process may take longer and employees must be familiarized with the new production methods.

Despite studies at the level of manufacturing firms in selected Southeast Asian countries, the fundamental question of whether process or product innovation drives productivity is still open. Another question that emerges is whether all innovating firms benefit from productivity and whether non-innovating firms are better off not innovating. Our study attempts to fill the gap in the literature by specifically addressing the following questions: (1) what factors affect firms' decisions to engage in product innovation and process innovation, and (2) how does the decision to innovate or not to innovate impact the productivity of both innovating and non-innovating firms?

Literature Review

Two strands of literature guide our analysis. First, firms' innovation propensity, and second, the relationship between innovation and firm-level productivity.

Literature on innovation is broad: reasons why firms innovate, obstacles encountered in innovating, sources of information relevant to innovation, and interpretation of the relationships between R&D intensity, innovation inputs and outputs, and productivity performance (Crepon et al., 1998; Mairesse et al., 2005; Mohnen & Röller, 2005). Our focus in the first strand of literature is on the firm's propensity to innovate. Mohnen and Röller (2005) investigated the existence of complementarities in the intensity and inclination of businesses to innovate. Findings indicate that innovation intensity and propensity to innovate complement innovation policy which is evident in all types of inventions (Fazlıoğlu et al., 2019). Another study highlighted that innovation might be linked to variables such as human capital, innovation effort, capital intensity, and company size, which vary according to the typologies of innovation (Crowley & McCann, 2015).

Other studies have linked the intensity of innovation and R&D to the technological environment. Major increases in R&D intensity, market concentration, and export intensity may result in innovation in high-tech sectors and businesses utilizing low-technology (Bhattacharya & Bloch, 2004). Hall et al. (2013) showed evidence that R&D and ICT increase the likelihood to innovate, with R&D having a greater effect. Surprisingly, despite the link between R&D and the likelihood to innovate, R&D intensity did not significantly affect firm productivity (Parisi et al., 2006). Other evidence shows that firms' participation in various forms of innovation activities is associated with firm-specific factors such as human capital, innovation effort, capital intensity, and company size (Crowley & McCann, 2015; Fazlıoğlu et al., 2019). Other factors such as supplementary labor skills and export capacity increase firms' likelihood to engage in product and process innovations (Chudnovsky et al., 2006). Firms' decision to innovate is complex involving both short-run and long-run considerations. Evidence has shown that the multiplier effects derived from factors such as a firm's size, R&D activities driven by demand-pull and technological push variables adjusted for labor skill specifications and capital intensity, and investments may explain businesses' decisions to invest in product and process innovations (Crepon et al., 1998; Hall et al., 2008).

In the second strand, we focus on two types of innovation: product and process, and their impact on productivity. Product innovation is concerned with new or significant enhancements to products or services. It can be subdivided into innovations in new to market or new to the firm, which might be dramatic or incremental in character (Crowley & McCann, 2015; Fazlıoğlu et al., 2019). Process innovation is described as activities implemented through a new or enhanced manufacturing process, distribution system, or support activity for goods and services to achieve cost-effectiveness in production quality and delivery (Fazlıoğlu et al., 2019).

Numerous studies have investigated the effects of new product introduction, manufacturing improvements, and acceptance of current technology on firm productivity (Dabla-Norris et al., 2010; Satpathy et al., 2017). Empirical findings revealed a long-run cointegrating relationship between innovation and total factor productivity (Saleem et al., 2019). Other studies have shown that both product and process innovation affect productivity. Arza and López (2010) highlighted the significant contribution of both product and process innovation in productivity growth. Both quantitative and qualitative evaluations have shown evidence that innovation activities have a considerable impact on productivity (Hong et al., 2012).

Compared with product innovation, process innovation has consistently shown an influence on worker productivity (Parisi et al., 2006; Masso & Vahter, 2008). When companies increase investments in new machinery and R&D, they directly impact process innovation due to advanced technologies embodied in newer equipment. Investment in new equipment and machinery improves efficiency, especially production-related costs (Hall et al., 2008). Conversely, product innovation was found to have a significant impact on productivity which has been linked directly to in-house activities, including information gathered from consumers (Mairesse & Robin, 2009; Arza & López, 2010; Fazlıoğlu et al., 2019).

In summary, there is little evidence to show that innovation impacts the productivity of all firms equally, so the real question of whether non-innovating firms are necessarily worse off has not been addressed. Although existing studies reviewed point to a link between firm-specific factors and the propensity to innovate, it leaves open the possibility that this may depend on the type of innovation.

Methodology

Data Sources and Description

This study drew on cross-sectional data from the 2015 World Bank Enterprise Survey (http://www.enterprisesurveys.org) collected from the Philippines' manufacturing sector. This enterprise survey included 731 manufacturing businesses that participated in face-to-face interviews. Our measure of productivity is the annual real sales in the logarithmic form of innovating and non-innovating manufacturing firms. Access to finance is proxied by overdraft facilities and credit loans, and firm size is measured in terms of the number of employees. Firm-specific factor such as R&D intensity is measured as the ratio of R&D expenditures over annual sales; human capital intensity is the percentage of full-time permanent workers who have completed secondary school; capital intensity is measured as the net book value of assets over sales; and export intensity is measured as the percentage of the establishment's sales from direct exports were included as exogenous variables used for the econometric models.

Based on the descriptive statistics in Table 1, the majority of the participating manufacturing firms did not engage in product innovation (62.95% versus 37.05%) and process innovation (62.65% versus 37.35%) within their individual organizations.

Table 2 reveals the means of our sample. The mean of TFP in our sample is 7.92 for product-innovating firms and 7.88 for process-innovating firms. Strikingly, these averages are way above the national average, indicating that productivity has been a source of growth in the Philippines. There is considerably less reliance on investments in R&D by firms: product innovating mean value is 0.01, and a mean value of 0.02 for process-innovating firms. Furthermore, liquidity, as reflected by the capital intensity of product-innovating

Table 1. *Product and Process Innovating Firms*

Variable	Product innovation		Process innovation	
	Frequency	Percentage	Frequency	Percentage
No	209	62.95	208	62.65
Yes	123	37.05	124	37.35
Total	332	100.00	332	100.00

Note: The data were gathered from the Enterprise surveys (http://www.enterprisesurveys.org), The World Bank.

firms, accounted, on average, 0.54 and 0.59 for process-innovating. The percentage of full-time permanent workers who have completed secondary school for product-innovating firms is 90%, and 89% for process-innovating firms. In terms of export intensity, product-innovating firms recorded a mean value of 0.14 and 0.16 for process-innovating firms indicating lower gains from sales generated from direct exports.

Model Specifications

Endogenous Switching Regression (ESR)

The econometric challenge of estimating the impact of innovation on productivity outcomes is derived from the fact that innovation and selection of innovators are not purely random. Firms that choose to innovate and firms that do not innovate may differ in terms of unobserved and observed characteristics, which simultaneously impact the decision to innovate and productivity. For example, innovators may inherently have the inclination for productivity-inducing attributes than non-innovators. This selection bias would require a special econometric model, ESR, which allows for a two-stage process: model innovation behavior in the first stage, and in the second stage, estimate productivity equations separately for innovators and non-innovators conditional on a specific innovation criterion. The following is the model equation (Greene, 2012; Di Falco et al., 2011):

$$I_i = 1 \; if \; \alpha \, Z_i + aE_i^* + \eta_i > 0, \tag{1}$$

$$I_i = 0 \; if \; \alpha \, Z_i + aE_i^* + \eta_i \leq 0, \tag{2}$$

Equations 1 and 2 showed the probit model, which measures the underlying propensity of firms to engage in innovation activities based on utility associated with the decision to innovate. Z_i represents firm-specific factors such as capital intensity, R&D intensity, human capital, and export intensity (Crepon

Table 2. *Descriptive Statistics of Manufacturing Firms*

Variable	Product innovating	Non-product innovating	Process innovating	Non-process innovating
	Mean	Mean	Mean	Mean
Productivity	7.92	7.60	7.88	7.62
	(0.88)	(0.93)	(0.93)	(0.91)
R&D intensity	0.01	0.00	0.02	0.00
	(0.12)	(0.01)	(0.12)	(0.00)
Capital intensity	0.54	0.94	0.59	0.92
	(0.78)	(2.29)	(0.95)	(2.26)
Human capital intensity	0.90	0.89	0.89	0.89
	(0.21)	(0.25)	(0.24)	(0.23)
Export intensity	0.14	0.18	0.16	0.17
	(0.30)	(0.36)	(0.33)	(0.35)
Firm size				
Small (5-19)	[32.52]	[35.41]	[36.29]	[33.17]
Medium (20-99)	[39.02]	[38.28]	[33.06]	[41.83]
Large (100 or more)	[28.46]	[26.32]	[30.65]	[25.00]
Access to finance				
Overdraft facilities				
Subscribed	[13.82]	[8.61]	[19.35]	[5.29]
Unsubscribed	[86.18]	[91.39]	[80.65]	[94.71]
Credit loan				
Subscribed	[53.66]	[35.41]	[52.42]	[36.06]
Unsubscribed	[46.34]	[64.59]	[47.58]	[63.94]

Note: The data were gathered from the Enterprise surveys (http://www.enterprisesurveys.org), The World Bank. The corresponding standard deviation values of each indicator are shown in parenthesis, while percentage values are in square brackets.

et al., 1998; Parisi et al., 2006; Masso & Vahter, 2008; Hall et al., 2008; Satpathy et al., 2017). E_i represents instruments such as access to finance and firm size, η_i is the random disturbance error term, and I_i represents a latent variable that describes engagement or not in product or process innovations. The instruments have been introduced to help reduce correlations between the error term and independent variables. The latent variable is unobservable; however, it becomes observable when it takes a value of 1 or zero (0).

We represent productivity as two switching regimes: regime 1, when a firm chooses to innovate, and regime 2, when a firm chooses not to innovate at all. In this model, X_{1i} and X_{2i} are vectors of the firm's characteristics affecting the outcome of their decision. Then, E_i^* represents the instruments, whereas β_i and β_o are the parameters to be estimated and ε_{1i} and ε_{2i} are the error terms.

$$Regime\ 1 = Prod_{1i} = \beta_{1i}X_{1i} + \alpha E_i^* + \varepsilon_{1i} \quad \text{when a firm innovates } (I_i = 1) \tag{3}$$

and

$$Regime\ 2 = Prod_{2i} = \beta_{2i}X_{2i} + \alpha E_i^* + \varepsilon_{2i} \quad \text{when a firm does not innovate } (I_i = 0) \tag{4}$$

Some estimation issues may occur when error terms ε_{1i} and ε_{2i} are found to be correlated across the productivity equation shown in Equations 3 and 4. As a result, biased estimates β_i will potentially affect firms' propensity to innovate and productivity. The error terms of two regimes, as illustrated in Equations 3 and 4 and the selection model shown in Equations 1 and 2, follow a tri-variate normal distribution, with zero mean and covariance matrix Ω, that is, $(\varepsilon_{1i}\ \varepsilon_{2i}\ \eta_1)$ N (0 Ω):

$$\Omega = \begin{bmatrix} \sigma_1^2 & . & \sigma_{1\eta} \\ . & \sigma_2^2 & \sigma_{2\eta} \\ . & . & \sigma_\eta^2 \end{bmatrix},$$

where σ^2_η is the variance of the error term in the selection equations and assumed to be scaled to factor 1, σ^2_1 and σ^2_2 are the variances of the error terms in the regime Equations (3) and (4) respectively (Lokshin & Sajaia 2004). The $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i}. From the covariance matrix, $\sigma_{1\eta}$ is the covariance of η_i and ε_{1i}, and $\sigma_{2\eta}$ is the covariance of η_i and ε_{2i}. This covariance association is the primary justification for estimating selection and regime equations concurrently. From the regime equations, a firm can only be observed in one state (i.e., innovating = 1, or non-innovating = 0) and cannot be observed simultaneously, which indicates that the covariance between ε_{1i} and ε_{2i} is undefined (Maddala 1983; Lokshin & Sajaia, 2004, 2011). Following the literature, the expected values of error terms ε_{1i} and ε_{2i} conditional on the sample selection are nonzero (Di Falco et al., 2011; Greene, 2012; Ahmed & Mesfin, 2017):

$$E[\varepsilon_{1i}|A_i = 1] = E[\varepsilon_{1i}|\eta_i > 0 - Z_i\alpha] = \sigma_{1\eta}\frac{\varphi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{1\eta}\lambda_{1i} \tag{4a}$$

$$E[\varepsilon_{2i}|A_i = 0] = E[\varepsilon_{2i}|\eta_i \le 0 - Z_i\alpha] = -\sigma_{2\eta}\frac{\varphi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} = \sigma_{2\eta}\lambda_{2i} \tag{4b}$$

Equations 4a and 4b are expressions of the expected productivity (y_i) for innovators and non-innovators, respectively. The φ(.) describes the standard normal probability density function, Φ(.), the standard normal cumulative density function, and $Zi\alpha = Xi\beta_i$. Following Maddala and Nelson (1975) and Di Falco et al. (2011), endogenous switching can be verified as follows:

$$\lambda_{1i} = \frac{\varphi(Z_i\alpha)}{\Phi(Z_i\alpha)} \ ; \ \lambda_{2i} = -\frac{\varphi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} \tag{4c}$$

whereas $\boldsymbol{\lambda}_i$ is the inverse Mills ratio (lambda) which is evaluated at the level of $Xi\beta_i$ and represents the probability that a firm decides to innovate over the cumulative probability of the decision not to innovate. The estimated lambda controls for endogeneity show that part of the error term that is attributed to the effect of a decision to innovate and productivity (Paltasingh & Goyari, 2018). If the decision to innovate and productivity are correlated, the estimated covariance of $\sigma_{1\eta}$ and $\sigma_{2\eta}$ will show statistical significance, which confirms selection bias and justifies endogenous switching regression (Maddala & Nelson, 1975; Di Falco et al., 2011). To put this in context, it implies that innovation (product and process) and productivity are linked together.

The econometric issues associated with selection bias are the reasons for using an estimation process that can handle simultaneous equations, specifically, estimating jointly Equations 1, 2, 3, and 4. Following previous studies (e.g., Lokshin, & Sajaia, 2004, 2011; Di Falco et al., 2011, Maddala, 1983), we specify the full information maximum likelihood (FIML) as follows:

$$InL = \sum_i \begin{pmatrix} A_i \left[In\{\Phi(\psi_{1i})\} + In\left\{ \frac{\varphi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right)}{\sigma_1} \right\} \right] + \\ (1-A_i)[In\{1-\Phi(\psi_{2i})\} + In\{\varphi(\varepsilon_{2i}/\sigma_2)\}] \end{pmatrix} \quad (5)$$

whereas,

$$\psi_{ji} = \frac{(Z_i\alpha + \rho_j \varepsilon_{ji}/\sigma_j)}{\sqrt{1-\rho_j^2}}, j = 1,2,$$

ρ_{ji} are the correlation coefficients between the error terms of the selection equations (1 & 2) and the error terms ε_{ji} of the productivity equations (3 & 4). For the estimation of parameters, Lokshin and Sajaia (2004) published a detailed Stata command, "movestay," used to implement the FIML. Following Lokshin and Sajaia (2004) and Di Falco et al. (2011), the parameters estimate of endogenous switching regression can be used to construct conditional expectations or anticipated outcomes as follows.

For firms that utilized either product or process innovations:

$$E(y_{1i}|A_i = 1) = X_{1i}\beta_1 + \sigma_{1\eta}\lambda_{1i} \quad (6)$$

For firms that did not utilize neither product nor process innovations:

$$E(y_{2i}|A_i = 0) = X_{2i}\beta_2 + \sigma_{2\eta}\lambda_{2i} \quad (7)$$

For firms that employed either product or process innovations had they decided not to innovate (counterfactual):

$$E(y_{2i}|A_i = 1) = X_{1i}\beta_2 + \sigma_{2\eta}\lambda_{1i} \quad (8)$$

For firms that did not engage neither in product nor process innovations had they decided to innovate (counterfactual):

$$E(y_{1i}|A_i = 0) = X_{2i}\beta_1 + \sigma_{1\eta}\lambda_{2i} \quad (9)$$

Equations 6 and 7 are the actual outcome expectations of the outcome observed from the sample and Equations 8 and 9 are the counterfactual outcomes. Following Heckman et al. (2001) and Di Falco et al. (2011), the treatment effect on the treated (TT) and the treatment on the untreated (TU) can be calculated as follows:

$$\begin{aligned} TT &= E(y_{1i}|A_i = 1) - E(y_{2i}|A_i = 1) \\ &= X_{1i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} \end{aligned} \quad (10)$$

Equation 10 calculates the productivity differences between firms that innovated (on either product or process) and firms that did not innovate at all. To put it differently, the treatment (innovation) on the treated (firms that innovated) is calculated as the difference between Equations 6 and 8.

$$\begin{aligned} TU &= E(y_{1i}|A_i = 0) - E(y_{2i}|A_i = 0) \\ &= X_{2i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i} \end{aligned} \quad (11)$$

Equation 11 calculates the effect of not innovating on the productivity of firms that did not innovate as the difference between Equations 9 and 7.

Heterogeneity effects (BH_1=1 or innovators; and BH_2=0; non-innovators) and transitional heterogeneity (TH) provide additional information in impact analysis and can easily be calculated from the expected outcomes of Equations 6, 7, 8, and 9. Following Carter and Milon (2005) and Di Falco et al. (2011), the base heterogeneity effect, BH_1, is the difference between Equations 6 and 9, whereas BH_2 is calculated as the difference between Equations 8 and 7; and TH is simply the difference between Equations 10 and 11. The intuition behind base heterogeneity is to understand the possibility that firms that innovated could have done better productivity-wise regardless of innovating (Di Falco et al. 2011). On the other hand, transitional heterogeneity provides the size of productivity change due to innovation or potential effects on non-innovators as if they innovated (counterfactual scenario).

Results and Discussion

Manufacturing Firms' Propensity to Innovate

First, we examine the firms' propensity to engage in innovation activities. In this stage, the maximum likelihood estimators were used to measure predicted probabilities of firms' engagement in product and process innovation activities. This includes firm-specific factors such as R&D intensity, capital intensity, human capital intensity, and export intensity which served as predictors for firms' engagement in innovation alongside the control variable, size.

Probit Model Results Showing Firms Propensity to Engage in Innovation Activities

Empirical results in Table 3 imply that R&D intensity negatively decreases firms' likelihood to engage in product and process innovations. The basic difference between product innovating and process innovating firms is that as R&D expenditures increase, the firm's decision to engage in product innovation decreases by almost 0.76 percentage points and approximately 1.07 percentage points for process innovating firms. Prior studies are mixed: results are inconsistent with Hall et al. (2008, 2013), wherein R&D was found to positively affect product and process innovations. However, the results are consistent with the findings of Cohen and Klepper (1996), which explained that an increase in R&D spending might lessen firms' investment in new products. Capital intensity negatively affects the likelihood of firms to engage in product and process innovations by approximately 0.146 percentage points for product innovating and by 0.127 percentage points for process innovating firms. The results are inconsistent with the findings of Crowley and McCann (2015), showing that capital intensity might enable innovation intensity which may vary depending on the types of innovation that firms decide to engage in.

Endogenous Switching Method for Product Innovation and Firm-Level Productivity

To examine the effects of both product and process innovations on firms' productivity, we estimated the ESR approach using full information maximum likelihood estimation. Table 6 shows the endogeneity between product innovation and productivity, as evidenced by the likelihood ratio test for independent equations (chi-square statistic of 10.10). The ρ_1 and $\boldsymbol{\rho}_2$ covariance in Table 6 also show self-selection. The coefficients alternate in signs, which conform to theoretical expectations and imply a deliberate decision by firms to innovate or not based on perceived benefits (Lokshin & Sajaia, 2004). Capital intensity is negatively related to productivity for both product-innovating and non-product-innovating firms. However, an increase in capital outlays will reduce productivity by almost

Table 3. *Firms' Propensity to Engage in Product and Process Innovations*

VARIABLES	Product innovation	Process innovation
R&D intensity	-0.761***	-1.074***
	(0.182)	(0.245)
Capital intensity	-0.146***	-0.127**
	(0.060)	(0.056)
Human capital intensity	0.083	-0.148
	(0.306)	(0.310)
Export intensity	-0.195	0.030
	(0.212)	(0.214)
Constant	-0.369	-0.214
	(0.284)	(0.287)
Observations	332	332
Log likelihood	-205.115	-200.307
Wald chi2(6)	20.52	21.93
Prob > chi2	0.0004	0.0002
Pseudo R2	0.0628	0.0869

*Note: All of the given variables are computed based on log form. Estimations used maximum likelihood estimators. First indicated values represented the indicators' coefficients, whereas the robust standard errors are shown in parentheses. P-values significance levels were presented with *** p<0.01, ** p<0.05, * p<0.1. The data were gathered from the Enterprise surveys (http://www.enterprisesurveys.org), The World Bank.*

Table 4. *ESM Results for Product Innovation and Productivity*

VARIABLES	Productivity with product innovation	Productivity without product innovation
Capital intensity	-0.244**	-0.062**
	(0.096)	(0.030)
Human capital intensity	1.032***	0.708***
	(0.347)	(0.264)
Export intensity	-0.104	0.646***
	(0.251)	(0.180)
Constant	7.036***	6.579***
	(0.379)	(0.256)
Observations	332	332
	0.144 (0.282)	-0.678 (0.125)***
Log likelihood	-601.659	
Wald X^2 (7)	16.06***	
LR test of independent equations X^2 (1)	10.10 ***	

*Note: All of the given variables are computed based on log form. First indicated values represented the indicators' coefficients, whereas the robust standard errors are shown in parentheses. P-values significance levels were presented with *** p<0.01, ** p<0.05, * p<0.1. The data were gathered from the Enterprise surveys (http://www.enterprisesurveys.org), The World Bank.*

0.244 percentage points for firms engaging in product innovation and 0.062 percentage points for product non-innovating firms. The negative contribution of capital intensity to productivity is more evident for product-innovating firms than non-innovating ones. This may be explained by different firms' capacity to absorb both labor and capital jointly (Table 4).

Furthermore, an increase in human capital intensity enhances firm-level productivity by roughly 1.03 percentage points for firms that engaged in product innovation. However, product non-innovating firms experienced only 0.708 percentage points boost in productivity. These results are consistent with other studies on the role of education and human capital development in firm-level productivity growth (Liu & Bi, 2019; Park, 2012; Botrić et al., 2017; Satpathy et al., 2017). On the other hand, a one percentage point increase in export intensity enhances firm productivity by 0.646 percentage points for product non-innovating firms. The no effect of export intensity on productivity for product innovating firms may be related to the demand structure of the foreign market when export is unrelated to productivity (Baldwin & Harrigan, 2011; Table 4).

As shown in Table 5, the expected firm-level productivity of firms that engaged in product innovation is 7.921 and 7.642 for product non-innovating firms. In counterfactual scenario, productivity gains for product innovating firms would have been less at 7.606 had they not innovated. On the other hand, productivity gain for product non-innovating firms would have been less at 6.699 if they innovated.

As shown in Table 5, engaging in product innovation increases productivity by 0.315 percentage points. Product innovation is significantly higher for firms that implemented product innovation than for firms that did not innovate by as much as 1.258 percentage points. These findings are consistent with empirical studies (Janz et al., 2004; Mairesse & Robin, 2009; Dabla-Norris et al., 2010; Hall, 2011; Antonietti & Cainelli, 2011; Saleem et al., 2019; Na & Kang, 2019).

Table 6 confirms endogeneity between process innovation and productivity based on the likelihood ratio test for independent equations (chi-square statistic

Table 5. *Conditional Expectations, Treatment, and Heterogeneity Effects of Product Innovation to Firm-Level Productivity*

Subsamples	Decision Stage		
	To Innovate	**Not to Innovate**	**Treatment Effects**
Firms that innovated	(a) 7.921	(c) 7.606	$TT = 0.315$
Firms that did not innovate	(d) 6.699	(b) 7.642	$TU = -0.943$
Heterogeneity Effects	$BH_1 = 1.222$	$BH_2 = -0.036$	$TH = 1.258$

Note: (a) and (b) depict the actual observed expectation samples, whereas (c) and (d) are the outcomes that are counterfactual. This modified method is anchored with Lokshin and Sajaia's (2004) endogenous switching approach and aligned with the methods of Dutoit (2007) and Fazlıoğlu et al. (2019).

Table 6. *ESM Results for Process Innovation and Productivity*

VARIABLES	Firm productivity with process innovation	Firm productivity without process innovation
Capital intensity	-0.258***	-0.057*
	(0.082)	(0.030)
Human capital intensity	0.989***	0.864***
	(0.325)	(0.278)
Export intensity	0.157	0.452**
	(0.234)	(0.189)
Constant	7.010***	6.441***
ρ_1, ρ_2	(0.344)	(0.271)
Observations	332	332
	0.044 (0.254)	-0.745 (0.103)***
Log likelihood	-604.980	
Wald X^2	21.67***	
LR test of independent equations X^2	12.90 ***	

*Note: All of the given variables are computed based on log form. First indicated values represented the indicators' coefficients, whereas the robust standard errors are shown in parentheses. P-values significance levels were presented with *** p<0.01, ** p<0.05, * p<0.1. The data were gathered from the Enterprise surveys (http://www.enterprisesurveys.org), The World Bank.*

of 12.90). The ρ_1 and $\boldsymbol{\rho}_2$ covariances also indicate self-selection bias. Furthermore, estimation results indicate that capital intensity negatively affects the productivity of process-innovating and non-process-innovating firms. These findings are consistent with the literature (Yasar et al., 2006; Yasar & Paul, 2007; Segarra & Teruel, 2011).

Human capital intensity positively affects productivity for both process-innovating and non-process-innovating firms. These findings are consistent with findings in the literature linking education and human capital development to firm-level productivity growth (Liu & Bi, 2019; Park, 2012; Botrić et al., 2017; Satpathy et al., 2017). Similarly, export intensity positively affects productivity only for process non-innovating firms. This result suggests that productivity linked to process innovating firms is not automatic; process innovation does require activities, as Baldwin & Harrigan (2011) noted that "such as production processing, marketing, logistics, and structure organization" (p.10; see Table 6).

Table 7 shows that the productivity of firms engaged in process innovation is about 7.884 and about 7.755 for process non-innovating firms. Firms that engaged in process innovation would have had productivity gains of only 7.627 if they did not innovate. On the other hand, process non-innovating firms are projected to have a productivity of only 6.601 if they did innovate.

Table 7. *Conditional Expectations, Treatment, and Heterogeneity Effects of Process Innovation on Firm-Level Productivity*

Subsamples	Decision Stage: To Innovate	Decision Stage: Not to Innovate	Treatment Effects
Firms that innovated	(a) 7.884	(c) 7.627	$TT = 0.257$
Firms that did not innovate	(d) 6.601	(b) 7.755	$TU = - 1.154$
Heterogeneity Effects	$BH_1 = 1.283$	$BH_2 = -0.128$	$TH = 1.411$

Note: (a) and (b) depict the actual observed expectation samples, whereas (c) and (d) are the outcomes that are counterfactual. This modified method is anchored with Lokshin and Sajaia's (2004) endogenous switching approach and aligned with the methods of Dutoit (2007) and Fazlıoğlu et al. (2019).

Firms engaged in process innovation have an average productivity gain of about 0.257 percentage points, which implies that engaging in process innovation increases productivity. As shown in the last column of Table 7, the positive productivity effect of 1.411 implies that process-innovating firms are better off innovating. One interesting puzzle emerges: how do we explain that non-innovating firms are better off not innovating? The answer may lie in the ability of firms to exploit best practice techniques in their production operation.

Conclusion and Implications

This paper attempted to analyze the effects of product and process innovations on productivity using ESR to control for endogeneity and selection bias which affect productivity and the decision by firms to innovate or not to innovate. The results conform to ESR theoretical expectations, validating that a firm's decision to innovate and productivity is affected by unobserved factors. Analysis of factors affecting the decision to innovate showed that both capital intensity and R&D negatively influence innovation decisions. This may be explained by the fact that the decision to innovate is complex and is different for firms in different sectors. Human capital intensity has positive effects on productivity for innovating and non-innovating firms, which reinforces the importance of education as a driver of productivity.

Product innovation and process innovation increase productivity for innovating firms more than for non-innovating firms; however, results also showed that innovating firms tend to have above-average productivity irrespective of innovation activities. The counterfactual scenario also highlighted an interesting result: the impact of innovation on productivity is bigger for firms that actually innovated than non-innovating firms in case the non-innovating firms innovated. These results highlight two areas for policy. Programs designed to improve human capital development, particularly education, may help productivity. The results advocate for innovation policies aimed primarily at promoting reasonable access to investments relevant to the adoption of up-to-date technologies for firms.

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