World Development 146 (2021) 105619

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Innovation, gender, and labour productivity: Small and medium enterprises in Vietnam

Ngoc Hoang, Daehoon Nahm, Michael Dobbie *

Macquarie Business School, Macquarie University, Australia

ARTICLE INFO

Article history:
Accepted 25 June 2021
Available online 5 July 2021

Keywords:
Innovation
Gender
Productivity
SME
Endogenous switching model
Oaxaca decomposition

ABSTRACT

This study undertakes an empirical analysis of the links between gender, innovation and firm labour productivity in Vietnamese Small and Medium Enterprises (SMEs). Specifically, we analyse whether female-controlled firms are more or less productive, than male-controlled firms. We also analyse whether female-controlled firms are more or less innovative than male-controlled firms. The present study goes further than most others in this area by allowing for endogenous selection into innovation, and by decomposing the productivity differential between innovators and non-innovators into the parts due to the differences in endowments and in technology. We show that while female-controlled firms are less likely to innovate, they are not less productive than male-controlled firms, once the role of innovation is controlled for. We also show that innovators are about 23% more productive than non-innovators, with over three quarters of this gap being due to innovators possessing better technology. An important contribution of our analysis is therefore to show that innovators are more productive than non-innovators mainly due to the use of different technology, not because they have better endowments. As the number of females starting or running new businesses is higher than males in developing countries, including in Vietnam, it follows that female entrepreneurship plays an important role in economic growth in emerging economies. Our analysis of the gender gap in business performance and innovation provides insights that assist with formulating entrepreneurship-related polices to assist this economic growth.

1. Introduction

Innovation is a key factor in economic development. It affects productivity and competitive advantage and helps frame innovation-oriented policies at both the national and firm level. Evidence for the positive influence of innovation on firm performance is found in many studies (Coad & Rao, 2008; Crowley & McCann, 2018; Friesenbichler & Peneder, 2016; Griffith et al., 2006; Hall & Kramarz, 1998; Hall et al., 2009; Parisi et al., 2006; Wadho & Chaudhry, 2018). These studies confirm that innovation and R&D lead to increased productivity and this impact is found in many countries at both the firm and national level. While some studies suggest that firm innovation and productivity are driven by male entrepreneurs (Fairlie & Robb, 2009; Loscocco & Robinson, 1991; Marvel et al., 2015; Strohmeyer et al., 2017; Watson & Robinson, 2003), other studies find mixed results on the link between gender and firm performance/innovativeness (Brush, 1992; Eagly et al., 1995; Lee & Marvel, 2014; Rosa et al., 1996). In addition, it should be noted that the number of females starting or running new businesses is higher than males in developing countries, with the biggest difference seen in Vietnam (GEM, 2017). Therefore, female entrepreneurship plays an important role in enhancing economic growth in emerging economies, including Vietnam. Analyzing the gender gap in business performance and innovation activities could deepen our understanding of female entrepreneurship and innovativeness, and provide some useful suggestions for formulating entrepreneurship-related polices.

The purpose of the study is to provide additional insights into the link between innovation and firm labour productivity. In addition, the study examines how gender impacts firm productivity and firm innovativeness. We use panel data for SMEs in manufacturing sector in Vietnam 2009–2015. We draw on Nahm et al. (2017) who employed a variant of the endogenous switching regression model and the Blinder-Oaxaca decomposition method to analyse union wage effects. Our study is one of small number

* Corresponding author at: Macquarie Business School, 4 Eastern Road, Macquarie University, NSW 2109, Australia.

E-mail addresses: annie.hoang@mq.edu.au (N. Hoang), daehoon.nahm@mq.edu.au (D. Nahm), michael.dobbie@mq.edu.au (M. Dobbie).

https://doi.org/10.1016/j.worlddev.2021.105619
0305-750X/

of studies, including Crowley and McCann (2015, 2018), that employ the endogenous switching regression model to examine the relationship between innovation and firm performance. However, instead of using cross sectional data as in Crowley and McCann (2015, 2018), we utilized panel data in order to gain more insights into the analysis of innovation, gender, and firm productivity over time. Our model accounts for endogenous selection for innovation and firm-specific heterogeneity. This study is part of a small body of research on SMEs that analyses the link between gender, innovation, and firm labour productivity in emerging countries.

The remainder of the article has the following structure. Section 2 discusses the literature on the relationship between innovation and firm productivity, the link between gender and firm productivity, and the impact of gender on the firm's decision to innovate. Section 3 outlines the modified endogenous regression model and Oaxaca decomposition. Section 4 describes the data and the results are presented in section 5. The final section provides some brief conclusions and policy implications. We find that innovation boosts firm labour productivity. Although the gender gap in innovativeness favours male owners/managers, this gap is narrow, and female-controlled firms are not significantly less productive than male-controlled firms once its impact on innovation is controlled for.

2. Literature review

2.1. Innovation: Definition and measurement

A business innovation is defined as "a new or improved product or business process (or combination thereof) that differs significantly from the firm's previous products or business processes and that has been introduced on the market or brought into use by the firm." (OECD, 2018). In the literature on innovation, most data from innovation surveys follow the Oslo Manual (OECD, 2005) that provides the guidelines for measuring, collecting, and interpreting data on innovation activities. However, the only available innovation measures are dichotomous variables for both product and process innovation (Mohnen & Hall, 2013). Despite this limitation of the measures, they can still provide some useful insights into the differential effects of different types of innovation on firm productivity.

2.2. Measuring firm performance

In studying the effect of innovation on firms' productivity, the method used to measure productivity is important. Most studies in the literature use either labour productivity (i.e. output per one unit of labour input) or total factor productivity (TFP) that is represented by an index. Use of each of these two measures has both advantages and disadvantages. TFP is conceptually superior in the sense that innovation can affect capital productivity as well as labour productivity. However, its main disadvantage is that it is not directly observed and hence it needs to be estimated via an aggregation method, such as the Malmquist index. On the other hand, labour productivity can be directly measured by dividing total output by the number of units of labour input. Although it does not include the effect of innovation on capital productivity, the effect can be effectively controlled for in the regression analysis. This may be the reason that a large majority of studies in the literature use labour productivity (eg., *inter alia*, Coad et al., 2015; Crowley & McCann, 2018; Griffith et al., 2006; Hall et al., 2009; Hashi & Stojčić, 2013; and Raffo et al., 2008) compared with those that use TFP (Huergo & Moreno, 2011; Parisi et al., 2006). The present study analyses the effect on labour productivity, which is measured as real value added per employee.[1]

2.3. Sources of innovation

The sources of innovation are varied, but there are some commonalities such as research and development (R&D), investment in physical assets, firm size and age, ownership structure, percentage of staff who are professionals and geographic location of firms. R&D is widely considered as a crucial factor affecting innovation decisions. R&D intensity leads to an increase in the probability of engaging in product and process innovations (Crépon et al., 1998; Griffith et al., 2006; Hall et al., 2009; Huergo & Moreno, 2011). R&D creates, utilizes, and translates new knowledge into the introduction of new products and processes (Landry et al., 2002; Sternberg & Arndt, 2001). R&D also improves a firm's ability to recognize new external information, absorb and then transform it into innovative activities (Cohen & Levinthal, 1990). The importance of fixed investment in enhancing the likelihood of engaging in both product and process innovations is consistently shown in empirical studies (Crowley & McCann, 2018; Hall et al., 2009; Parisi et al., 2006).

There are mixed results about the impact of firm size on innovation decisions. There is much evidence to show that larger firms spend a substantial amount on R&D and hence have a higher innovation propensity (Cohen & Klepper, 1996; Friesenbichler & Peneder, 2016; Hall et al., 2009; Hashi & Stojčić, 2013; Wadho & Chaudhry, 2018). However, Acs and Audretsch (1987) suggest that the debate on whether small firms or large firms are more conducive to innovation depends on the circumstances of specific industries. Large firms are more likely to innovate in capital-intensive industries while small firms have relative advantages in industries that require a substantial component of skilled labour.

The evidence on the role of firm age in relation to innovation is mixed. Some studies indicate that older firms are more innovative than younger ones (Cohen & Klepper, 1996; Friesenbichler & Peneder, 2016; Sorensen & Stuart, 2000). On the other hand, Crowley and McCann (2018) and Roper et al. (2008) find either insignificant or negative relationships. Firms that are located in big cities and clustered regions have advantages such as easy access to skilled labour, developed infrastructure, and technological spillovers. These benefits yield stronger firm innovation propensity (Baptista & Swann, 1998; McCann & Folta, 2011) and firm performance (Chung & Kalnins, 2001; Gilbert et al., 2008; Lee & Marvel, 2014). Firms in developing countries encounter obstacles to setting up and maintaining innovative networks that could help them to engage in R&D and innovation activities (Raffo et al., 2008).

The impact of legal status and ownership structure on innovation propensity has been studied in the literature, with mixed results reported. Some studies, for instance, find that foreign ownership impacts positively on innovation propensity (see Ayyagari et al., 2011; and Love et al., 1996) while others find the effect of foreign ownership to be statistically insignificant (Bishop & Wiseman, 1999; Friesenbichler & Peneder, 2016). Ayyagari et al. (2011), Friesenbichler and Peneder (2016) and Wadho and Chaudhry (2018) find that state ownership has a negative or statistically insignificant impact on innovation. There is also evidence that the percentage of staff who are professionals positively impacts the likelihood of a firm engaging in innovation, (Ayyagari et al., 2011; Crowley & McCann, 2018).

[1] Using a measure of TFP produces very similar empirical results to those reported in the current article. A short note on the methodology of estimating TFP and estimation results are available on request.

2.4. Innovation and firm performance

Most studies confirm that innovation has a positive effect on firm performance (Coad & Rao, 2008; Crowley & McCann, 2018; Friesenbichler & Peneder, 2016; Griffith et al., 2006; Hall & Kramarz, 1998; Hall et al., 2009; Parisi et al., 2006; Wadho & Chaudhry, 2018). However, there are some divergent views. Crowley and McCann (2018) found that innovation is associated with negative firm value added per employee in transition economies. Similarly, Griffith et al. (2006) and Raffo et al. (2008) also found a negative influence of innovation on firm labour productivity in Germany and Argentina, respectively. The same effect of innovation on firm productivity was found in Ireland (Roper et al., 2008). Roper et al. (2008) suggest these negative effects result from the disruptive effects of innovation, and of its effect on the product-life cycle. A new product may disrupt production and hence diminish firm productivity. In the product-life cycle scenario, the product may take time to be produced efficiently before it improves firm productivity. Similarly, Coad and Rao (2008) suggest that there may be considerable time delays to turn an innovation into economic performance. It is also costly and time consuming to transform a product idea into efficient manufacturing routines and procedures.

It should be noted that these studies on innovation and firm productivity addressed the potential endogeneity of innovation using a simultaneous equation system proposed by Crépon et al. (1998). However, they did not specify separate production or productivity equations for innovators and non-innovators. Two studies by Crowley and McCann (2015, 2018) are the only studies that accounted for the self-selection problem by employing an endogenous-switching model with cross sectional data for European firms, which allows separate productivity equations for innovators and non-innovators. For the identification of an endogenous-switching model, some variables that are included in the self-selection equation need to be excluded in the productivity equations. Although these variables are supposed to be those that are important for the decision to innovate, but not for productivity once the effect of innovation is controlled for, there does not seem to be a consensus on the variables in the literature. For example, out of the only two studies that employ an endogenous-switching model, Crowley and McCann (2015) excludes public support dummies, percentage of workforce in the professional category, and market environment dummies from the productivity equations, while Crowley and McCann (2018) excludes R&D efforts and market environment dummies.

2.5. Gender and firm productivity

Being an entrepreneur or upper-level manager are commonly believed to be jobs for males, and this gender stereotype implicitly devalues female performance (Heilman, 2001). Numerous studies have attempted to explain why female-owned businesses might underperform. Domestic responsibilities compel women to strive for a work-life balance that leads to modest expectations about the future of their firms (Lee-Gosselin & Grisé, 1990). The same domestic responsibilities may reduce the time and focus that women can devote to running the business effectively. Women may also lack management and industry specific experience. All this can result in women tending to move into business sectors that are unattractive to men (Loscocco & Robinson, 1991). This also contributes to female-controlled firms having slower growth, smaller size and lower profitability and productivity (Fischer et al., 1993; Rosa et al., 1996; Watson & Robinson, 2003).

On the other hand, many women have no other option than to start a business to support their families. This necessity motive is reported as being 20% higher for women than men (GEM, 2017). Additional evidence for this necessity motive comes from Thébaud (2015) who suggested that women are less likely to choose starting a business as a fallback employment strategy if there exist supporting policies such as paid leave and publicly subsidized childcare.

Fairlie and Robb (2009) suggest that if women participate in a business start-up out of necessity, they are more likely to experience difficulties in obtaining start-up capital, and are less likely to have relevant prior work experience in a similar business. These types of difficulties could negatively impact the performance of female-owned firms. The existence of a gender-gap in relation to access to finance has seen significant research in recent years, and increasingly in relation to developing economies. The results are mixed, for instance, Presbitero et al. (2014) find evidence for such a gap in Barbados, Jamaica and Trinidad and Tobago. Hansen and Rand (2013) on the other hand, find against the idea of a gender-gap in relation to access to finance in 16 sub-Saharan African countries. If women experience difficulties accessing loans this could negatively impact the performance of their firms.

Notwithstanding all the above, there is a body of evidence that does not support the existence of a gender gap in firm performance, and indeed some studies find that female-controlled firms outperform male-controlled firms. In an early study, Kalleberg and Leicht (1991) indicated that small firms owned by women were not less successful than those owned by men, including in terms of survival. In addition, Brush (1992) argued that business performance should not only be evaluated by financial measures but other criteria such as employee satisfaction, effectiveness, and social contribution. Female performance therefore could be assessed more adequately.

Eagly et al. (1995) suggested that overall male and female leaders are equally effective. Men are seen to be more effective in more masculine roles while women are more effective in less masculine roles. In addition, studies show no difference in the quality of decision-making between male and female managers (Johnson & Powell, 1994). For instance, Watson and Robinson (2003) found less variation in profits for female-controlled SMEs even though these firms generated significantly lower profits than male-controlled SMEs. After modulating the risk (standard deviation of profits) by using the ratio of profit over its standard deviation to measure firm performance, the authors concluded there was no significant gap between male and female-controlled firms. A similar finding in SMEs was revealed by Johnsen and McMahon (2005). They found no evidence supporting poorer performance in female-owned businesses in terms of financial performance (return on equity/assets) and firm growth. In addition, evidence from Chen et al. (2018) suggests that female representation on a company board actually enhanced firm performance, especially in innovation-intensive industries.

2.6. Gender and firm innovation activities

A substantial number of studies suggest that innovation is strongly gender-biased toward males. Females are considered to be more risk averse than males (Croson & Gneezy, 2009; Dohmen & Falk, 2011; Dohmen et al., 2011). Hence, females are seen as less likely to take risky actions such as producing new products and using new technologies (Carter et al., 2003). In addition, gender has indirect effects on innovation activities through the effect of formal education and the location of businesses. Formal education is positively associated with generating innovative products/services (Fischer et al., 1993; Marvel & Lumpkin, 2007) and it helps owners/managers assess and seize on potential business and innovation opportunities. This effect of formal education is especially true for engineering or natural science majors since it equips owners/managers with technical skills that better assist innovation than do less technical majors (Marvel et al., 2015). Female entrepreneurs are less likely to complete degrees in engineering or natural science than their male counterparts (Marvel et al., 2015; Strohmeyer et al., 2017). In addition, locating the business in cities or industry clusters can produce advantages such as access to skilled labour, local business networks, and technology spillovers that encourage firm to be involved in innovation activities (Baptista & Swann, 1998). Despite those potential benefits women are more likely to locate their businesses far from the clustered regions due to family commitments. This reduces the likelihood of females participating in innovation activities compared to men (Marvel et al., 2015; Rosenthal & Strange, 2012).

Some studies considered other explanations for the firm innovation gender gap. Firstly, women are more likely to start a business, and consequently innovate, in the service rather than the manufacturing sector (Blake & Hanson, 2005). Measuring and collecting data on innovation activities in services industries is more difficult, and this may make women less visible innovators. Secondly, gender stereotypes and organizational practices perceive men as dominant decision-makers. Hence, ideas proposed by women may not be encouraged in the first place (Cooper, 2012). For the same reasons, even if their ideas are heard, they are less likely to be acted upon (Foss et al., 2013). Finally, Miller and Del Carmen Triana (2009) and Chen et al. (2018) argue that gender diversity on company boards facilitates innovation. The research reported in these studies suggests the underlying mechanism by which this occurs operates through resolving agency problems and by creating cognitive conflict that is conducive to innovation. This group of explanations emphasize that it is not that women are less innovative than men, but that a number of factors, including gender stereotypes impede the innovation activities of women and or make them less visible.

Only the current study and that of Crowley and McCann (2018) have explicitly dealt with the self-selection issue in the innovation decision, with the current study doing so using an endogenous-switching approach. While Crowley and McCann (2018) use cross sectional data on European firms in 2005, this study provides more understanding of the link between innovation and firm productivity over time by utilizing panel data on Vietnamese SMEs 2009–2015.

3. The model and the estimation method

3.1. Endogenous switching model

The present study attempts to examine the difference in performance between firms that innovate and those which do not by analysing how innovation affects their production technology. The production functions for innovators and non-innovators are assumed to exhibit constant returns to scale (CRS) and they are given by

$$Y_{it} = A^{j}(X_{it}^{*})F^{j}(K_{it}, L_{it}) \quad \text{for j} = \text{innovator, non} - \text{innovator}$$

where Y_{it} is real value-added (output), K_{it} is capital stock, and L_{it} is the number of employees for firm i in period t; A(.) is TFP that is a function of various factors included in the vector X_{it}^{*}; and F(.) is the production function that represents the maximum output a firm can produce given K and L under the technology available to innovators or non-innovators. Under the assumption of CRS, dividing both sides by L_{it} and taking the natural logs gives

$$lny_{it} = lnA^{j}(X_{it}^{*}) + lnf^{j}(k_{it}) \tag{2}$$

where y_{it} is output per employee, k_{it} is capital intensity, and f(.) is F(.,1). A Taylor expansion of this function enables one to approximate lny_{it} as a linear function of X_{it}^{*} and k_{it}. The regression models for innovators and non-innovators represent these linear approximations of the productivity functions.[2]

In the present study, firms are assumed to self-select into the decision to innovate. This implies that inferences based on a model that does not account for this issue could suffer from a selection bias. To address this issue, we employ the endogenous switching model (Lee, 1978; Maddala, 1983). An additional benefit of using this model is that it also allows us to explicitly analyse how the decision to self-select is made. Following Nahm et al. (2017), this study utilizes the approach introduced by Mundlak (1978) and Chamberlain (1980) to make the endogenous switching model suitable for panel data. The model is defined as

$$lny_{1,it} = \alpha_1 Female_{it} + \beta_1^{'} X_{it} + h_{1,i} + e_{1,it}$$

$$lny_{0,it} = \alpha_0 Female_{it} + \beta_0^{'} X_{it} + h_{0,i} + e_{0,it} \tag{3}$$

$$I_{it}^{*} = \delta E(lny_{1,it} - lny_{0,it}) + \alpha_s Female_{it} + \beta_s^{'} Z_{it} + h_{s,i} + e_{s,it} \tag{4}$$

where $Female_{it}$ takes on value one if firm *i* in year *t* is controlled by a female owner or manager and zero otherwise; X_{it} and Z_{it} are vectors of the other firm characteristics that affect labour productivity and the firm's decision to innovate, respectively; α's are the scalar coefficients for the female dummy while β's are the coefficient vectors for the explanatory variables other than the female dummy; h_i are individual firm heterogeneity and e_{it} are idiosyncratic errors; the subscripts 1, 0, and s denote innovators, non-innovators, and selection, respectively; and E(.) is the expectations operator. All the factors in X_{it}^{*} and capital intensity are included in X_{it}, but female dummy is separately presented to highlight its importance in the current study. Equation (4) is the index equation for the selection model, where I_{it}^{*} is the latent variable underlying the decision to innovate. It is assumed to be a function of the expected differential in the productivity between the two regimes. The random error terms are assumed to follow a trivariate normal distribution with the variance for $e_{s,it}$ being normalized to unity so that the selection model is probit. Endogenous switching between the two regimes, namely innovators and non-innovators, implies that the idiosyncratic error terms in the productivity equations (i.e. $e_{1,it}$ and $e_{0,it}$) are contemporaneously correlated with the error term in the probit model (i.e. $e_{s,it}$). As the two regimes are mutually exclusive, the correlation between $e_{1,it}$ and $e_{0,it}$ cannot be measured.

The productivity equations for both innovators and non-innovators have the same set of explanatory variables. However, the selection model has a different set of explanatory variables, although it shares a subset of variables with the productivity equations. The common set of explanatory variables in X_{it} and Z_{it} are log of firm age, log of capital intensity, interest-to-sales ratio, and dummies for female owner/manager, government assistance, firm size, populous city, high-tech industry, household business, outsource, growth constraint, informal loan, sale via e-trade, and years. The subset of explanatory variables that are unique to Z_{it} are owner's age, percentage of professional staff, and dummies for owner's education level, industry-zone location, and whether the firm/business is the main source of income.[3] These variables are believed to affect the decision to innovate, but they are unlikely

[2] Although the production function presented in (1) implies that the technological change induced by innovation is Hicks neutral, the same regression models can be deduced under the alternative assumption of Harrod-neutral technological change. In the latter case, technological change must be labour-augmenting implying that the production function is given by $Y_{it} = F^{j}\left[K_{it}, A^{j}(X_{it}^{*})L_{it}\right]$; see Barro and Sala-i-Martin (2004). Dividing both sides of this by L_{it} and taking a linear Taylor expansion of the natural log of y_{it} results in the same regression model.

[3] Detailed definitions of these variables are provided in Table A1 in the appendix.

to have significant (direct) effects on firm performance once the effect of innovation is controlled for. Although the selection of these variables for exclusion in the productivity equations is subjective to a certain degree, the key results reported in the next section are robust to changes to this set of variables.[4] Crowley and McCann (2015, 2018), which are the only studies in the literature that employ endogenous-switching models, also take a similar approach.

Allowing for random effects is likely to result in inconsistent estimates because some explanatory variables such as firm size, firm age and owner's education are highly likely to be correlated with time-invariant unobservable heterogeneity. The alternative fixed-effects approach avoids this problem, but it entails the incidental-parameter problem (Lancaster, 2000; Wooldridge, 1995) because the model is nonlinear. To overcome this problem, we employ the approach introduced by Mundlak (1978) and replace the heterogeneity terms (h_i) with the group-means of explanatory variables (i.e.$\overline{X}_i$ and $\overline{Z}_i$) in equations (3) and (4) to control for firm-specific heterogeneity. The model is then estimated using the pooled data.

The model is estimated in two stages: in the first stage, the productivity equations are simultaneously estimated with the reduced-form selection model by the full-information maximum likelihood (FIML) method.; and in the second stage, the structural probit model is then estimated incorporating the predicted differential in the productivity between innovators and non-innovators.[5] The normality assumption implies that the conditional expectations of firm productivity are given as by Lokshin and Sajaia (2004):

$$E\left(lnY_{1,it}|I=1, Female_{it}, X_{it}, \overline{X}_i, \overline{Z}_i\right) = \alpha_1 Female_{it} + \beta_1' X_{it} + \gamma_1' \overline{X}_i + \sigma_{1s}\frac{\phi(\pi' W_{it})}{\Phi(\pi' W_{it})} \tag{5}$$

$$E\left(lnY_{1,it}|I=0, Female_{it}, X_{it}, \overline{X}_i, \overline{Z}_i\right) = \alpha_1 Female_{it} + \beta_1' X_{it} + \gamma_1' \overline{X}_i - \sigma_{1s}\frac{\phi(\pi' W_{it})}{1-\Phi(\pi' W_{it})} \tag{6}$$

$$E\left(lnY_{0,it}|I=1, Female_{it}, X_{it}, \overline{X}_i, \overline{Z}_i\right) = \alpha_0 Female_{it} + \beta_0' X_{it} + \gamma_0' \overline{X}_i + \sigma_{0s}\frac{\phi(\pi' W_{it})}{\Phi(\pi' W_{it})} \tag{7}$$

$$E\left(lnY_{0,it}|I=0, Female_{it}, X_{it}, \overline{X}_i, \overline{Z}_i\right) = \alpha_0 Female_{it} + \beta_0' X_{it} + \gamma_0' \overline{X}_i - \sigma_{0s}\frac{\phi(\pi' W_{it})}{1-\Phi(\pi' W_{it})} \tag{8}$$

where σ_{1s} and σ_{0s} are the covariance between $e_{1,it}$ and $e_{s,it}$ and the covariance between $e_{0,it}$ and $e_{s,it}$, respectively; $\phi(.)$ and $\Phi(.)$ are the p.d.f. and the c.d.f. for the standardized normal distribution respectively; W_{it} is a vector that includes all the explanatory variables in the union set of $female_{it}$, X_{it}, Z_{it}, $\overline{X}_i$, and$\overline{Z}_i$; and π is its coefficient vector in the reduced-form probit model.

Equation (5) defines the expected productivity for innovators when they select to innovate, while equation (8) defines the expected productivity for non-innovators when they choose not to innovate. Eqs. (6) and (7) are the expected productivities for innovators and non-innovators, respectively, under the counterfactual situations. The selectivity terms, namely the last terms in the above equations, correct for the effect of the unobservable traits of innovators and non-innovators on the firm productivity. If either or both of σ_{1s} and σ_{0s} is non-zero, the selection into innovation is endogenous. For the estimation of the structural probit model, (4), the difference between the estimated values of (5) and (8) is used.[6]

[4] For example, estimating the model without excluding any variables from the productivity equations, which forces the model to be identified through non-linearity of the selection term, leaves the signs and significance of the key variables largely unchanged. These results are available on request.

[5] The FIML estimation in the first stage has been carried out using the *movestay* routine for Stata by Lokshin and Sajaia (2004). Maximum Likelihood Estimation of Endogenous Switching Regression Models. *The Stata Journal: Promoting communications on statistics and Stata*, *4*(3), 282-289. https://doi.org/10.1177/1536867X0400400306.

Table 1
Correlation Between the Key Variables.

Variable	Productivity	Product innovation	Female
Productivity	1.0000		
Product innovation	0.1391***	1.0000	
Female	−0.0065	−0.0569***	1.0000

***: significant at 1%.

3.2. Decomposition of productivity differential

To gain deeper understanding of the impact of innovation on firm performance, we use the Blinder-Oaxaca decomposition method (Blinder, 1973; Oaxaca, 1973). The difference in productivity between innovators and non-innovators is decomposed into one part that is due to the difference in the firm characteristics (endowments effect) and the other part that is due to the difference in the production technology (coefficients effect). The decomposition is based on the following equality:

$$\widehat{\beta}_1'\overline{X}_1 - \widehat{\beta}_0'\overline{X}_0 = \frac{1}{2}\left(\widehat{\beta}_1 + \widehat{\beta}_0\right)'\left(\overline{X}_1 - \overline{X}_0\right) + \frac{1}{2}\left(\widehat{\beta}_1 - \widehat{\beta}_0\right)'\left(\overline{X}_1 + \overline{X}_0\right) \tag{9}$$

where subscripts 1 and 0 denote innovators and non-innovators, respectively; $\overline{X}$ are the sample means of all the explanatory variables in the productivity equations, including female dummy, and $\widehat{\beta}$ are estimated coefficients. The first term in the right-hand side represents the endowments effect evaluated at the average production technology, while the second term measures the coefficients effect evaluated at the mean levels of endowments.

4. Description of data

The data used in this study is from four biennial surveys of manufacturing SMEs in Vietnam that cover four waves between 2009 and 2015 (CIEM, 2015). The surveys were a joint effort between the Ministry of Labour, Invalids and Social Affairs in Vietnam and the University of Copenhagen in Denmark. After clearing invalid observations and extreme outliers, the final sample is an unbalanced panel data set containing 3,589 firm-wave observations.

In the surveys, firms are asked two questions about innovation: whether they introduced new products or improved existing products, and whether they introduced new production processes/technology in the previous two years. However, as the number of firms who reported process innovations is negligible, we use only a binary variable for product innovations as a measure of innovation. Productivity is defined as the log of value-added per employee, which is commonly used in the literature. Detailed definitions of the explanatory variables are provided in Table A1. The correlation matrix between the key variables is reported in Table 1. The simple

[6] It is interesting to note that the actual difference in the expected productivity when the firm switches the regime is (5)–(7) for innovators and (8)–(6) for non-innovators. However, the factual difference (5)–(8) is more relevant for the decision to innovate because it is what firms observe. They are unable to distinguish the difference due to different production functions from the difference due to different innovator/non-innovator traits.

Table 2
Number of Observations and Proportion of Innovators (in parentheses) by Firm Size and Gender.

	2009		2011		2013		2015		Total	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Micro firms	197 (28.9%)	478 (40.6%)	228 (29.4%)	469 (38.0%)	247 (11.7%)	458 (19.4%)	255 (28.6%)	465 (39.8%)	927 (24.4%)	1,870 (34.6%)
Small firms	66 (72.7%)	120 (63.3%)	65 (50.8%)	99 (44.4%)	61 (31.2%)	104 (34.6%)	74 (47.3%)	76 (32.9%)	266 (50.8%)	399 (45.4%)
Medium firms	8 (75.0%)	29 (62.1%)	14 (78.6%)	22 (68.2%)	18 (33.3%)	10 (40.0%)	14 (50.0%)	12 (33.3%)	54 (55.6%)	73 (56.2%)
Total	271 (41.0%)	627 (45.9%)	307 (36.2%)	590 (40.2%)	326 (16.6%)	572 (22.6%)	343 (33.5%)	553 (38.7%)	1,247 (31.4%)	2,342 (37.1%)

Table 3
Sample Means of the Variables.

	Product innovator	Product non-innovator	Female owner/manger	Male owner/manager
Log value-added per labour	3.88***	3.67	3.74	3.75
Product innovation	–	–	0.31	0.37***
Female owner/manager	0.31	0.37***	–	–
Government assistance	0.23***	0.15	0.18	0.18
Capital intensity	71.08	73.46	84.44**	66.33
Firm age	20.41	22.01***	21.72	21.39
Micro-sized firms	0.69	0.83***	0.74	0.80***
Small-sized firms	0.25***	0.15	0.21***	0.17
Medium-sized firms	0.06***	0.02	0.04**	0.03
Interest-to-sales	0.01***	0.01	0.01	0.01
Outsource	0.08***	0.03	0.04	0.05*
Informal loan	0.60***	0.56	0.57	0.58
Growth constraint	0.89***	0.83	0.84	0.86
Populous city	0.47**	0.43	0.43	0.45
E-trading	0.08***	0.03	0.06	0.04
Household business	0.67	0.79***	0.71	0.77***
High-tech industry	0.06**	0.05	0.06***	0.04
Industrial zone	0.07***	0.03	0.04	0.04
College degree or higher	0.26***	0.17	0.23***	0.19
Owner/manager's age	53.34	54.84***	52.45	55.31***
Main income from the firm	0.88	0.87	0.80	0.91***
% professional	0.03***	0.02	0.03***	0.02

*, ** and ***: significantly larger than the other (i.e. innovators vs. non-innovators and female vs. male) at 10%, 5% and 1%, respectively. The means of binary variables are proportions.

correlation coefficients indicate that productivity and innovation are positively correlated, and innovation and female dummy are negatively correlated. The correlation between productivity and female dummy is negative, but it is statistically insignificant.

Table 2 shows that the total number of male-controlled firms is almost twice the number of female-controlled firms (2,342 vs. 1,247). However, as far as the proportion of product innovators is concerned, there exists only a small difference between male-controlled firms (37.1%) and female-controlled firms (31.4%). The proportion of female innovators is lower in micro and medium-sized firms but higher in small-sized firms. The overall proportion of innovators had been decreasing over the period from 2009 to 2013 before slightly improving in 2015. The global financial crisis in 2008 appears to be the main contributor to the slowdown of innovation activities in the first three waves in the sample. As a result of the financial crisis, the Vietnamese economy suffered from high inflation, stock market and real-estate market crashes in 2009, and the tightening of banking credits, depressing innovation activities.

Table 3 reports the sample means of the variables by the innovation status and by the gender of the owner/manager. Innovators are more productive than non-innovators by about 23%.[7] This difference will later be decomposed into the parts due to endowments and the technology that converts them into productivity. The difference in productivity between male-controlled and female-controlled firms is insignificant. On average, male-controlled firms are more likely to introduce product innovations than female-controlled firms, which is consistent with the earlier observation. Innovators and male-controlled firms have higher productivity than non-innovators and female-controlled firms, respectively, on average. Innovators have significantly higher interest payments over sales, have more professional staff, and they are also significantly younger than non-innovators, on average. Innovator firms are more likely to obtain government assistance, be located in a populous city or industrial zone, use e-trade, and have informal loans, while they are less likely to be micro-sized. Female owners/managers are more likely to be younger and have a college or higher degree than male owners/managers. Female-controlled firms tend to be more capital intensive, use more professional staff, and more likely to operate in a high-tech industry compared to male-controlled firms, on average. Although these differences are statistically significant at 5%, they do not represent causal relationships. The partial effects of these characteristic variables on productivity and the decision to innovate are analysed in the next section.

5. Empirical results

5.1. Productivity models

The productivity equations given by (3) are estimated by the fixed-effects method as well as by the FIML method as the endogenous switching model to see the effects of selectivity bias. The first

[7] This is $e^{(3.88-3.67)} - 1$.

Table 4
Fixed Effects and Endogenous Switching Models for Productivity[a]

	Fixed Effects		**Endogenous switching**[e]	
	(Product) Innovator	Non-innovator	(Product) Innovator	Non-innovator
Female owner/manager	−0.020 (0.073)[b]	0.030 (0.040)	−0.002 (0.053)	0.004 (0.035)
Government assistance	0.108 (0.050)**[c]	−0.008 (0.039)	−0.024 (0.058)	−0.030 (0.039)
Capital intensity (log)	0.091 (0.029)***	0.097 (0.022)***	0.131 (0.025)***	0.079 (0.021)***
Firm age (log)	0.644 (0.809)	0.168 (0.563)	1.585 (0.803)**	0.476 (0.561)
Firm size (base: micro size)				
Small-sized firms	0.033 (0.096)	−0.244 (0.062)***	−0.156 (0.078)**	−0.237 (0.066)***
Medium-sized firms	−0.327 (0.188)*	−0.397 (0.198)**	−0.317 (0.149)**	−0.531 (0.163)***
Interest-to-sales	−1.357 (1.129)	−2.187 (0.609)***	−1.598 (1.102)	−2.567 (0.661)***
Outsource	0.059 (0.077)	0.214 (0.137)	−0.095 (0.104)	0.182 (0.110)*
Informal loan	0.038 (0.049)	0.057 (0.031)*	0.121 (0.038)***	0.076 (0.029)**
Growth constraint	0.002 (0.073)	0.033 (0.035)	−0.033 (0.073)	0.005 (0.038)
Populous city	-[d]	–	0.348 (0.039)***	0.202 (0.039)***
E-trading	0.121 (0.117)	0.012 (0.140)	−0.011 (0.088)	−0.060 (0.081)
Household business	−0.206 (0.133)	0.017 (0.077)	−0.187 (0.057)***	−0.163 (0.059)***
High-tech industry	0.062 (0.132)	0.196 (0.185)	−0.036 (0.081)	0.028 (0.081)
Year (base: 2009)				
Year 2011	0.206 (0.069)***	0.277 (0.047)***	0.132 (0.062)**	0.265 (0.048)***
Year 2013	−0.013 (0.108)	0.081 (0.069)	0.048 (0.124)	0.178 (0.069)**
Year 2015	0.151 (0.142)	0.103 (0.100)	−0.044 (0.133)	0.124 (0.098)
Selectivity and other parameters				
R^2 (within)	0.115	0.099		
S.D. of the productivity equation (σ_j)			0.630 (0.115)**	0.660 (0.037)***
Correlation with probit error (ρ_j)			−0.590 (0.328)	−0.537 (0.123)***
Covariance with probit error (σ_{js})			−0.372	−0.354
Wald test $\chi^2(2)$			27.43 (p-value = 0.000)	
Log likelihood			−5,328.52	
Number of observations	1,259	2,330	3,589	

a: The dependent variable is the log of real value added per employee.
b: Standard errors in parentheses.
c: *, **, *** imply that the coefficients are significant at 10%, 5%, and 1%, respectively.
d: Populous city is omitted in the fixed-effects models due to collinearity.
e: Group means are included but not presented in the table.

two columns of Table 4 present the fixed-effects estimates and the last two columns report the ML estimates of the endogenous switching model. In general, the coefficients in the fixed-effects model are less significant than those in the endogenous switching model, implying that controlling for selectivity led to more efficient estimates. However, all the coefficients that are significant at 5% in both models have the same sign in both models. These are the coefficients for capital intensity, size dummies and interest-to-sales ratio for non-innovators, and the dummy variable for year 2011. The magnitudes of those coefficients are also very similar in both models. For instance, both models predict that an increase in interest payments by 1% of sales lowers productivity of non-innovators by more than 2%, ceteris paribus. However, despite this consistency between the two subsets of estimates, a Chi-square test (27.43) strongly rejects the null hypothesis that the selectivity terms in the two productivity equations are jointly unimportant, with a p-value much lower than 0.01. This implies that the fixed-effects estimates, which are based on the assumption that selection into innovation is exogenous, are inconsistent.

According to the estimation results of the endogenous switching model, the effects on productivity of the gender of the owner/-manager and government assistance are statistically insignificant.[8] Female owners/managers of a business may be regarded as having a different leadership style than male owners, but there doesn't seem to be significant evidence that such difference affects the productivity of employees of SMEs in Vietnam once its impact on innovativeness is controlled for. This result is consistent with a majority of findings in the literature. For example, Johnsen and McMahon (2005) find no significant evidence of a gender gap in the financial and growth performance of SMEs in Australia. Watson and Robinson (2003) also find that there is no significant difference in performance, measured by sales and profit between male-controlled SMEs and female-controlled SMEs, once the risk factor is controlled for. The coefficient for government assistance is also insignificant for both groups, implying that government programs are ineffective in helping firms enhance productivity. Although there could be several different reasons for this, such as a failure in finding and matching the right targets with the right programs, and inefficient methods of implementation of the programs, pinpointing the exact reason is beyond the scope of the current study. The insignificant roles of gender and government assistance for productivity are in contrast with what we will observe in regard to the factors that affect the decision to innovate, where both variables have significant effects.

As one would expect, capital intensity has a significantly positive effect on labour productivity for both innovators and non-innovators. It is, however, much more effective for innovators than for non-innovators, by about 5.2 percentage points, in improving productivity. This accords with our intuition that the effect of an increase in capital intensity would be greater when it is applied to innovated products. It is interesting to note that the age of a firm is not important for non-innovators, but it is an important positive factor for innovators. A firm's age is associated with the accumulation of business and technological knowhow. Both innovators and non-innovators may have accumulated knowledge, but it can only contribute toward improvement of productivity when it is applied to innovative activities. The coefficients for the dummies for small and medium sized firms are negative for both innovators and non-

[8] It was suspected that changes in the gender of the owner/manager would rarely occur and hence the female dummy variable's collinearity with heterogeneity could have made it difficult to obtain a significant estimate of its coefficient. However, an examination of the data reveals that changes in the gender of owner/manager occurred quite frequently, in more than 18% of observations.

innovators, implying that their productivities are lower than the micro-sized firms, on average, ceteris paribus. Furthermore, the absolute size of the coefficient for medium size firms is larger than that for small size firms, implying that the coefficient decreases monotonically with size. This means that the elasticity of output (i.e. real value added) with respect to labour input is inelastic. This result is consistent with the law of diminishing marginal output of labour as the coefficient represents a partial effect when all the other factors, including capital intensity, are fixed.

The effect of an increase in the ratio of interest payments to sales is negative for both innovators and non-innovators, but it is only statistically significant for non-innovators. This difference may be closely related to the purpose of loans. It is more likely that money borrowed by innovators is used for productive purposes such as applying innovations to the production process so that the negative effect of interest expenses is mitigated by an increase in output. On the other hand, money borrowed by non-innovators is less likely to be used for productive purposes and hence interest expenses are not sufficiently covered by an increase in output, leading to lower productivity. The coefficients for the dummy variable indicating whether the firm received a loan through an informal channel are significantly positive for both innovators and non-innovators. The result appears to reflect the importance of informal loans as a funding channel for those who find it difficult to access bank loans, especially during the sample period, which saw tight monetary policies limiting bank credit growth and hence access to bank loans by small businesses.

The significantly positive coefficients for populous city are in line with our intuition and also with the findings in the literature; see, for example, Chung and Kalnins (2001), Gilbert et al. (2008), and Lee and Marvel (2014). Big cities provide firms advantages such as more access to leading techniques and technology, specialized labour markets, and heightened demand. These benefits would easily outweigh the potentially negative effects of higher competition in big cities. The magnitudes of the coefficients imply that the benefit of being based in a big city is higher for innovators than for non-innovators by almost 75%. Irrespective of innovation decisions, although household businesses account for around two-third of the SME sample, they significantly underperform compared with other legal statuses including private proprietorship, collective /cooperative, limited liability company, and joint stock company without state ownership. This is in line with our intuition considering that household businesses are less organized and staff time is less likely to be used efficiently. Also, informal firms[9] represent 36% of the sub-sample of household businesses. The existence of the informal sector is very common in developing economies like Vietnam. The number of informal businesses drastically reduced to only one firm in 2015. This was due to the introduction of the new Enterprise Law 2014 which contained policies that encouraged informal firms to become formal. Another interesting observation is that 28% of informal household businesses are female-controlled firms. In other words, male-controlled firms, rather than female counterparts, dominate in the informal sector. Our data do not support the common phenomenon observed in some emerging markets where women tend to operate in the informal sector. The significantly positive coefficients for the dummy for the year 2011 appear to reflect the economy-wide recovery from the global financial crisis in 2008–2009.

It is surprising that utilizing modern business tools, such as outsourcing and e-trade, does not improve productivity according to our results. However, one should not accept this at face value given that each of these tools was used by less than 5% of the sample.

5.2. Effects of selectivity

Table 4 shows that the correlation coefficients ρ_1 and ρ_0 are both negative, but only ρ_0, which represents the correlation between the error terms of the productivity model for non-innovators and the selection model, is statistically significant at 1%. As mentioned above, the joint hypothesis of no selection bias is strongly rejected ($\chi^2(2)$ = 27.43, p-value = 0.000), meaning that the decision to innovate is endogenous. Note that the estimates of the covariances, σ_{1s} and σ_{0s}, which are also the coefficients for the selectivity terms in equations (5)-(8), are the products of the correlation coefficient (ρ_j) and the standard deviation (σ_j). In light of the conditional expectation given by (8), the negative estimate of σ_{0s} implies that the expected productivity of non-innovator firms is higher than the productivity a randomly selected firm is expected to achieve under the non-innovator regime. When substituted into (7), it also implies that innovators would perform worse than a randomly selected firm if they used the technology of non-innovators. This difference is statistically significant. On the other hand, the negative estimate of ρ_1 implies that the expected productivity of innovator firms is lower than the productivity that a randomly selected firm is expected to achieve under the regime of innovators. This implies that there exist some unobservable characteristics of innovators that hinder them from achieving higher productivity. This effect, however, is statistically insignificant.

5.3. Probit model for innovation

Table 5 reports the marginal effect of each determinant on the probability of innovating at the sample mean values of the variables. Overall, estimates are highly significant. The marginal effect of the expected productivity differential term is significant and of the correct positive sign, implying that higher productivity expected for innovators is an important factor for the likelihood of innovation. The estimate indicates that an increase in the productivity differential by 1% would increase the probability of innovation by 1.6 percentage points on average when the other factors remain the same. The significantly positive effect of productivity on a firm's decision to innovate is consistent with other studies; see, for example, Coad and Rao (2008), Crowley and McCann (2018), Friesenbichler and Peneder (2016), Griffith et al. (2006), Hall and Kramarz (1998), Hall et al. (2009), Parisi et al. (2006), and Wadho and Chaudhry (2018).

Unlike the productivity models, the female dummy variable has a significantly negative effect on the probability of innovation, implying that female-controlled firms are less likely to innovate, ceteris paribus. Females are considered to be more risk averse than males (Croson & Gneezy, 2009), hence they are less likely to make a risky decision such as to innovate (Carter et al., 2003). In developing economies like Vietnam, women are likely to hold more domestic responsibilities than males. With more domestic responsibilities, female owners/managers tend to be even more risk averse in order to achieve a balance between work and family life. Furthermore, women in developing countries are likely to start a business to make a living rather than to pursue a managerial career, making them less likely to take risks. The magnitude of the gender gap is a relatively small four percentage points, but the estimate is statistically significant at 5%. The coefficient for government assistance is significantly positive. This implies that although government assistance is ineffective in enhancing labour productivity for SMEs, it is effective in encouraging innovation.

An increase in capital intensity has a significantly negative effect on the probability of innovation. The result that capital intensity does not have a positive effect on product innovation is

[9] Unregistered at the District Business Register Office

Table 5
Structural Probit Model for (Product) Innovation Decision.

	Marginal effect[a,b]
Log difference in value-added per employee	1.607 (0.459)***c,d
Female owner/manager	−0.040 (0.020)**
Government assistance	0.055 (0.023)**
Capital intensity (log)	−0.076 (0.027)***
Firm age (log)	−2.714 (0.598)***
Small-sized firms	−0.066 (0.056)
Medium-sized firms	−0.268 (0.125)**
Interest-to-sales	−1.447 (0.674)**
Outsource	0.647 (0.132)***
Informal loan	−0.075 (0.027)***
Growth constraint	0.109 (0.026)***
Populous city	−0.243 (0.069)***
E-trading	−0.024 (0.046)
Household business	0.037 (0.032)
High-tech industry	0.117 (0.049)**
Industrial zone	0.103 (0.044)**
College degree or higher	−0.006 (0.024)
Owner/manager's age (log)	−0.016 (0.079)
Main income is from the firm	−0.029 (0.028)
% professional	0.235 (0.199)
Year 2011	0.240 (0.069)***
Year 2013	0.161 (0.095)*
Year 2015	0.380 (0.098)***
Log likelihood	−2,136.565
Number of observations	3,589
Pseudo R2	0.081

a: Marginal effects are evaluated at the sample mean values of the variables.
b: For dummy variables, the effects are the discrete changes from the base level.
c: The standard errors are based on the delta method.
d: *, ** and ***: significant at 10%, 5% and 1%, respectively.

somewhat consistent with the findings in the literature. Parisi et al. (2006) found that spending on fixed capital increases the probability of *process* innovation but not the probability of *product* innovation. Hall et al. (2009) also excludes capital intensity in the model for the probability of product innovation. Crowley and McCann (2015) find that capital intensity has a positive, but insignificant, effect on product innovation at 5%. The significantly negative estimate of the coefficient for capital intensity in the present result appears to be related to the difference in the number of employees, relative to the difference in capital, between innovators and non-innovators. The number of employees is controlled for in the model via the two size dummies. However, variations within each class are not controlled for and would influence the effect of capital intensity, which is the ratio of capital to the number of employees. A brief examination of the data reveals that innovators have larger capital than non-innovators by 52.8%, on average, but they also have a workforce that is 71.5% bigger. This results in innovators having lower capital intensity than non-innovators by 3.3%, on average, leading to a negative coefficient for capital intensity. More than 80% of the firms in the sample have capital less than one billion Vietnamese dongs, which is equivalent to about 51,000 in 2010 US dollars.[10] For firms with this level of capital, an increase in capital alone would hardly enhance the likelihood of innovation. On the other hand, an increase in the number of employees seems to have a negative effect on the probability of innovation, as noted by Crowley and McCann (2015) and the negative and monotonically decreasing coefficients for the size dummies in the present study.

Younger and smaller firms have a higher likelihood of innovation. When the other factors including capital intensity are controlled for, medium-sized firms are less likely to innovate than micro-sized firms by 27 percentage points, on average. Smaller firms are more able to adapt to changes in the market, and hence facilitate innovations faster. A large amount of interest expense relative to sales appears to lower the likelihood of innovation. An increase in interest-to-sales ratio by 1% is associated with a decrease in probability of innovation by 1.45 percentage points. Similarly, firms with informal loans have lower propensity to innovate. Although informal loans provide an extra channel for funding which may improve productivity, they may also indicate that the firm is under financial stress. If this is so, the present result implies that firms under financial stress are less likely to make risky decisions such as innovation. Alternatively, the presence of informal loans might imply an inability to gain access to credit through more formal channels. Ayyagari et al. (2011) found, using data from the World Bank Enterprise Surveys of 19,000 firms for 2002–4, that access to external funding (mainly bank loans) contributed positively to the innovation activity in SMEs across 47 emerging economies.

Outsourcing, high-tech industry, and location in an industry zone have significantly positive impacts on the probability of innovation. Interestingly, firms that feel they have constraints for growth have a higher tendency to innovate products. Challenges seem to spur innovations. Although being located in a populous city helps improve productivity, it lowers the probability of innovation when the effects of other factors, especially being located in an industry zone and high-tech industry, are controlled for. Owner's education and age, selling through e-trade, and the proportion of professional staff do not have a significant effect on the probability of innovation.

5.4. Decomposition of productivity differential

To gain insight into the sources of the difference in productivity between innovators and non-innovators, the predicted productivity differential at the sample mean values of the variables is decomposed into the parts that are due to the difference in the endowments and the difference in the coefficients. These reflect the technology of converting the endowments into productivity. Table 6 indicates that the total difference in the predicted productivity, 0.209, is similar to the difference in the average productivity that was observed above. This difference is significant at 1%. The decomposition shows that more than 78% of the difference is due to the difference in the technology, and the part attributable to the difference in endowments accounts for a mere 22%. The differences in both components are, however, significant at 5%. In terms of value-added per employee, these figures convert to 23% total, 5% endowments, and 18% technology differentials between innovators and non-innovators, in favour of the former[11].

6. Conclusions and policy implications

This paper attempts to identify and measure the effects of innovation on productivity, and to measure the role that gender plays in this relationship for SMEs in Vietnam. The findings largely support the conclusions made by previous studies on SMEs in the literature. Namely, innovation significantly enhances productivity. Further, having a female owner/manager does not significantly affect the productivity of an SME, but it significantly reduces the likelihood of innovation. The present study goes further than most others and allows endogenous selection into innovation in measuring the effects of innovation on productivity, and decomposes the productivity differential between innovators and non-innovators into the parts due to the differences in endowments and in technology. The study finds that innovators are about 23% more productive than non-innovators, of which more than three quarters is attributable to the difference in technology between innovators

[10] One US dollar was worth about 19,000 Vietnamese dongs in 2010.

[11] $e^{0.209} - 1 = 0.232$, $e^{0.045} - 1 = 0.046$, and $e^{0.164} - 1 = 0.178$.

Table 6
Blinder-Oaxaca Decomposition of the Differential in Predicted Productivity[a.]

Comparison	Reference	Total	Endowments	Coefficients[b]
Product innovator	Non-innovator	0.209***[c] (0.025) [0.16 0.26][d]	0.045** (0.037) [0.01 0.19]	0.164** (0.038) [0.03 0.21]

a: Bootstrapped standard errors in parentheses (based on 3,000 resampling).
b: Includes the difference between the selectivity terms.
c: ** and *** indicate that the 95% and 99% confidence intervals, respectively, do not include zero.
d: 95% confidence intervals.

and non-innovators. This implies that innovators are more productive than non-innovators mostly due to a use of different technology in doing their business, not because they have better endowments.

In addition to these findings, it has been found that government assistance has an insignificant effect on productivity once the effect of innovation is controlled for. However, it helps firms enhance productivity indirectly through innovation as it significantly increases the probability of innovation. This result bears important policy implications. It implies that it would be more fruitful if government assistance was targeted towards promoting innovations rather than directly targeted towards enhancing productivity. For example, tax incentives and favourable loans could be linked to innovation activities.

Younger and smaller firms are more likely to innovate and achieve higher productivity. A higher capital intensity improves productivity but reduces the probability of innovation. It has been noted that unimportance of capital intensity for product innovation, as opposed to process innovation, largely accords with the findings in the literature. Location in a populous city is beneficial to productivity, but it lowers the likelihood of innovation.

All these different effects of a factor on productivity and on the likelihood of innovation highlights the importance of the approach that simultaneously analyses productivity and selection into innovation. As innovation has a significant effect on productivity, the simultaneous approach enables us to clearly identify the channels through which important factors have effects on the productivity of SMEs.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to acknowledge the Development Economics Research Group of the Department of Economics, University of Copenhagen for providing the Vietnam SMEs data for our research. We would also like to thank two anonymous reviewers from this journal for their valuable comments.

Appendix

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105619.

Table A1
Definitions of the Variables.

Variable	Definition
Productivity	Natural log of real value-added per employee
Product innovation	= 1 if firm introduced a new product group or improved an existing product in the previous 2 years, 0 otherwise
Female	= 1 if owner/manager is female, 0 if owner/manager is male
Government Assistance	= 1 if firm received any kind of assistance from the government such as tax incentives, favourable loans, human resource training, trade promotion program, and quality and technology improvement program; 0 otherwise
Capital intensity	Natural log of year-end value of buildings, machinery and equipment divided by full-time equivalent number of employees. (1 part-time employee is counted as 0.5 full-time employee)
Firm age in 2018	Years since firm started operation
Firm size dummies	Micro-size: =1 if number of full-time equivalent employees is no more than 10, 0 otherwise Small-size: =1 if number of full-time equivalent employees is between 11 and 50, 0 otherwise Medium-size: number of full-time equivalent employees is between 51 and 300, 0 otherwise
Interest-to-sales ratio	= interest payments/sales
Outsource	= 1 if firm outsourced part of its production, 0 otherwise
Informal loan	= 1 if firm received informal loan (not from banks), 0 otherwise
Growth constraint	= 1 if firm has any constraint to growth, 0 otherwise
Populous city	=1 if firm is located in populous cities such as Ha Noi and Ho Chi Minh, 0 otherwise
E-trading	=1 if firm sold products via e-trading, 0 otherwise
Household business	= 1 if firm's legal status is household business, 0 otherwise (Private proprietorship; Collective /cooperative; Limited liability company; and Joint stock company without state ownership)
High-technology industry	= 1 if firm operates in a high-technology industry (Chemicals and chemical products; Machinery, equipment and electronic products; Motor vehicles; and Other transport equipment), 0 otherwise
Industrial zone	= 1 if firm is located in an industrial zone, high-tech zone, or export processing zone, 0 otherwise
College or higher	Owner/manager's education level is college or higher
Owner/Manager's age	Age of owner/manager in 2018
Main source of income	= 1 if the firm is the main source of income for the household of the owner/manager, 0 otherwise
% Professional	Percentage of professionals (e.g. engineers, accountants, technicians) in the workforce

All monetary values are converted to the constant 2010 prices using GDP deflator.

References

CIEM, ILSSA, UCPH, and UNU-WIDER (2009-2015). Viet Nam SME Survey.

Acs, Z., & Audretsch, D. (1987). Innovation, Market Structure, and Firm Size. *The Review of Economics and Statistics, 69*(4), 567–574. https://doi.org/10.2307/1935950.

Ayyagari, M., Demirgüç-Kunt, A., & Maksimovic, V. (2011). Firm Innovation in Emerging Markets: The Role of Finance, Governance, and Competition. *Journal of Financial and Quantitative Analysis, 46*(6), 1545–1580. https://doi.org/10.1017/S0022109011000378.

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more?. *Research Policy, 27*(5), 525–540.

Barro, R. J., & Sala-i-Martin, X. (2004). *Economic Growth* (2nd ed.). Cambridge: The MIT Press.

Bishop, P., & Wiseman, N. (1999). External ownership and innovation in the United Kingdom. *Applied Economics, 31*(4), 443–450. https://doi.org/10.1080/000368499324156.

Blake, M. K., & Hanson, S. (2005). Rethinking Innovation: Context and Gender. *Environment and Planning A: Economy and Space, 37*(4), 681–701. https://doi.org/10.1068/a3710.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources, 8*(4), 436–455. https://doi.org/10.2307/144855.

Brush, C. G. (1992). Research on Women Business Owners: Past Trends, a New Perspective and Future Directions. *Entrepreneurship Theory and Practice, 16*(4), 5–30. https://doi.org/10.1177/104225879201600401.

Carter, N. M., Gartner, W. B., Shaver, K. G., & Gatewood, E. J. (2003). The career reasons of nascent entrepreneurs. *Journal of Business Venturing, 18*(1), 13–39. https://doi.org/10.1016/s0883-9026(02)00078-2.

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data. *The Review of Economic Studies, 47*(1), 225–238. https://doi.org/10.2307/2297110.

Chen, J., Leung, W. S., & Evans, K. P. (2018). Female board representation, corporate innovation and firm performance. *Journal of Empirical Finance, 48*, 236–254. https://doi.org/10.1016/j.jempfin.2018.07.003.

Chung, W., & Kalnins, A. (2001). Agglomeration effects and performance: A test of the Texas lodging industry. *Strategic Management Journal, 22*(10), 969–988. https://doi.org/10.1002/(ISSN)1097-026610.1002/smj.v22:1010.1002/smj.178.

Coad, A., Pellegrino, G., & Savona, M. (2015). Barriers to innovation and firm productivity. *Economics of Innovation and New Technology, 25*(3), 321–334. https://doi.org/10.1080/10438599.2015.1076193.

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy, 37*(4), 633–648. https://doi.org/10.1016/j.respol.2008.01.003.

Cohen, W. M., & Klepper, S. (1996). A reprise of size and R&D. *Economic Journal, 106*(437), 925–951.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. (Technology, Organizations, and Innovation). *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553.

Cooper, R. (2012). The gender gap in union leadership in Australia: A qualitative study. *Journal of Industrial Relations, 54*(2), 131–146. https://doi.org/10.1177/0022185612437836.

Crepon, B., Duguet, E., & Mairessec, J. (1998). Research, Innovation And Productivity: An Econometric Analysis At The Firm Level. *Economics of Innovation and New Technology, 7*(2), 115–158.

Croson, R., & Gneezy, U. (2009). Gender Differences in Preferences. *Journal of Economic Literature, 47*(2), 448–474. https://doi.org/10.1257/jel.47.2.448.

Crowley, F., & McCann, P. (2015). Innovation and Productivity in Irish Firms. *Spatial Economic Analysis, 10*(2), 181–204. https://doi.org/10.1080/17421772.2015.1023340.

Crowley, F., & McCann, P. (2018). Firm innovation and productivity in Europe: Evidence from innovation-driven and transition-driven economies. *Applied Economics, 50*(11), 1203–1221. https://doi.org/10.1080/00036846.2017.1355543.

Dohmen, T., & Falk, A. (2011). Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender. *American Economic Review, 101*(2), 556–590. https://doi.org/10.1257/aer.101.2.556.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. (2011). Individual risk attitudes measurement, determinats, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x.

Eagly, A. H., Karau, S. J., & Makhijani, M. G. (1995). Gender and the Effectiveness of Leaders: A Meta-Analysis. *Psychological Bulletin, 117*(1), 125–145. https://doi.org/10.1037/0033-2909.117.1.125.

Fairlie, R., & Robb, A. (2009). Gender differences in business performance: Evidence from the Characteristics of Business Owners survey. *An Entrepreneurship Journal, 33*(4), 375–395. https://doi.org/10.1007/s11187-009-9207-5.

Fischer, E. M., Reuber, A. R., & Dyke, L. S. (1993). A theoretical overview and extension of research on sex, gender, and entrepreneurship. *Journal of Business Venturing, 8*(2), 151–168.

Foss, L., Woll, K., & Moilanen, M. (2013). Creativity and implementations of new ideas: do organisational structure, work environment and gender matter? International Journal of Gender and Entrepreneurship, 5(3), 298-322.

Friesenbichler, K., & Peneder, M. (2016). Innovation, competition and productivity firm-level evidence for Eastern Europe and Central Asia. *The Economics of Transition, 24*(3), 535–580. https://doi.org/10.1111/ecot.2016.24.issue-310.1111/ecot.12100.

GEM. (2017). Global Entrepreneurship Monitor 2016/2017 - Report on Women's Entrepreneurship. https://www.gemconsortium.org/report/gem-20162017-womens-entrepreneurship-report.

Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2008). Clusters, knowledge spillovers and new venture performance: An empirical examination. Journal of Business Venturing, 23(4), 405-422. 10.1016/j.jbusvent.2007.04.003

Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and productivity across four European countries. *Oxford Review of Economic Policy, 22*(4), 483–498. https://doi.org/10.1093/oxrep/grj028.

Hall, B. H., & Kramarz, F. (1998). The effects of technology and innovation on firm performance, employment, and wages special issue. *Economics of Innovation and New Technology, 5*(2), 109–343. https://doi.org/10.1080/10438599800000001.

Hall, B. H., Lotti, F., & Mairesse, J. (2009). Innovation and productivity in SMEs: Empirical evidence for Italy. *Small Business Economics, 33*(1), 13–33. https://doi.org/10.1007/s11187-009-9184-8.

Hansen, H., & Rand, J. (2013). The myth of female credit discrimination in african manufacturing. *The Journal of Development Studies, 50*(1), 81–96. https://doi.org/10.1080/00220388.2013.849337.

Hashi, I., & Stojčić, N. (2013). The impact of innovation activities on firm performance using a multi-stage model: Evidence from the Community Innovation Survey 4. *Research Policy, 42*(2), 353–366. https://doi.org/10.1016/j.respol.2012.09.011.

Heilman, M. E. (2001). Description and prescription: How gender stereotypes prevent women's ascent up the organizational ladder. *Journal of Social Issues, 57*(4), 657–674.

Huergo, E., & Moreno, L. (2011). Does history matter for the relationship between R&D, innovation, and productivity? *Industrial and Corporate Change, 20*(5), 1335–1368. https://doi.org/10.1093/icc/dtr019.

Johnsen, G. J., & McMahon, R. G. P. (2005). Owner-manager Gender, Financial Performance and Business Growth amongst SMEs from Australia's Business Longitudinal Survey. *International Small Business Journal, 23*(2), 115–142. https://doi.org/10.1177/0266242605050509.

Johnson, J. E. V., & Powell, P. L. (1994). Decision Making, Risk and Gender: Are Managers Different?. *British Journal of Management, 5*(2), 123–138. https://doi.org/10.1111/j.1467-8551.1994.tb00073.x.

Kalleberg, A., & Leicht, K. (1991). Gender and Organizational Performance: Determinants of Small Business Survival and Success. *Academy of Management Journal, 34*(1), 136–161. https://doi.org/10.2307/256305.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics, 95*(2), 391–413. https://doi.org/10.1016/S0304-4076(99)00044-5.

Landry, R., Amara, N., & Lamari, M. (2002). Does social capital determine innovation? To what extent?. *Technological Forecasting & Social Change, 69*(7), 681–701. https://doi.org/10.1016/S0040-1625(01)00170-6.

Lee-Gosselin, H., & Grisé, J. (1990). Are women owner-managers challenging our definitions of entrepreneurship? An in-depth survey. *Journal of Business Ethics, 9*(4), 423–433. https://doi.org/10.1007/BF00380341.

Lee, I., & Marvel, M. (2014). Revisiting the entrepreneur gender–performance relationship: A firm perspective. *An Entrepreneurship Journal, 42*(4), 769–786. https://doi.org/10.1007/s11187-013-9497-5.

Lee, L.-F. (1978). Unionism and Wage Rates: A Simultaneous Equations Model with Qualitative and Limited Dependent Variables. *International Economic Review, 19*(2), 415–433. https://doi.org/10.2307/2526310.

Lokshin, M., & Sajaia, Z. (2004). Maximum Likelihood Estimation of Endogenous Switching Regression Models. *The Stata Journal: Promoting communications on statistics and Stata, 4*(3), 282–289. https://doi.org/10.1177/1536867X0400400306.

Loscocco, K. A., & Robinson, J. (1991). Barriers to Women's Small-Business Success in the United States. *Gender & Society, 5*(4), 511–532. https://doi.org/10.1177/089124391005004005.

Love, J. H., Ashcroft, B., & Dunlop, S. (1996). Corporate structure, ownership and the likelihood of innovation. *Applied Economics, 28*(6), 737–746. https://doi.org/10.1080/000368496328489.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics*. New York: Cambridge University Press.

Marvel, M. R., Lee, I. H., & Wolfe, M. T. (2015). Entrepreneur Gender and Firm Innovation Activity: A Multilevel Perspective. *IEEE Transactions on Engineering Management, 62*(4), 558–567. https://doi.org/10.1109/TEM.1710.1109/TEM.2015.2454993.

Marvel, M. R., & Lumpkin, G. T. (2007). Technology Entrepreneurs' Human Capital and Its Effects on Innovation Radicalness. *Entrepreneurship Theory and Practice, 31*(6), 807–828. https://doi.org/10.1111/j.1540-6520.2007.00209.x.

McCann, B. T., & Folta, T. B. (2011). Performance differentials within geographic clusters. *Journal of Business Venturing, 26*(1), 104–123. https://doi.org/10.1016/j.jbusvent.2009.04.004.

Miller, T., & Del Carmen Triana, M. (2009). Demographic Diversity in the Boardroom: Mediators of the Board Diversity-Firm Performance Relationship. *Journal of Management Studies, 46*(5), 755–786. https://doi.org/10.1111/j.1467-6486.2009.00839.x.

Mohnen, P., & Hall, B. H. (2013). Innovation and productivity: An update. *Eurasian Business Review, 3*(1), 47–65. https://doi.org/10.14208/BF03353817.
Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: Journal of the Econometric Society, 46*(1), 69–85.
Nahm, D., Dobbie, M., & Macmillan, C. (2017). Union wage effects in Australia: An endogenous switching approach. *Applied Economics, 49*(39), 3927–3942. https://doi.org/10.1080/00036846.2016.1273492.
Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review, 14*(3), 693. https://doi.org/10.2307/2525981.
OECD. (2005). Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data (3rd Edition ed.). OECD Publishing. doi:10.1787/9789264013100-en
OECD. (2018). Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation (4th ed.). OECD Publishing. 10.1787/9789264304604-en
Parisi, M. L., Schiantarelli, F., & Sembenelli, A. (2006). Productivity, innovation and R&D: Micro evidence for Italy. *European Economic Review, 50*(8), 2037–2061. https://doi.org/10.1016/j.euroecorev.2005.08.002.
Presbitero, A. F., Rabellotti, R., & Piras, C. (2014). Barking up the Wrong Tree? Measuring Gender Gaps in Firm's Access to Finance. *The Journal of Development Studies, 50*(10), 1430–1444. https://doi.org/10.1080/00220388.2014.940914.
Raffo, J., Lhuillery, S., & Miotti, L. (2008). Northern and southern innovativity: A comparison across European and Latin American countries. *The European Journal of Development Research, 20*(2), 219–239. https://doi.org/10.1080/09578810802060777.
Roper, S., Du, J., & Love, J. H. (2008). Modelling the innovation value chain. *Research Policy, 37*(6), 961–977. https://doi.org/10.1016/j.respol.2008.04.005.
Rosa, P., Carter, S., & Hamilton, D. (1996). Gender as a determinant of small business performance: Insights from a British study. *An International Journal, 8*(6), 463–478. https://doi.org/10.1007/BF00390031.
Rosenthal, S. S., & Strange, W. C. (2012). Female entrepreneurship, agglomeration, and a new spatial mismatch. *Review of Economics and Statistics, 94*(3), 764–788. https://doi.org/10.1162/REST_a_00193.
Sorensen, J. B., & Stuart, T. E. (2000). Aging, Obsolescence, and Organizational Innovation. *Administrative Science Quarterly, 45*(1), 81–112. https://doi.org/10.2307/2666980.
Sternberg, R., & Arndt, O. (2001). The Firm or the Region: What Determines the Innovation Behavior of European Firms?. *Economic Geography, 77*(4), 364–382. https://doi.org/10.1111/j.1944-8287.2001.tb00170.x.
Strohmeyer, R., Tonoyan, V., & Jennings, J. E. (2017). Jacks-(and Jills)-of-all-trades: On whether, how and why gender influences firm innovativeness. *Journal of Business Venturing, 32*(5), 498–518. https://doi.org/10.1016/j.jbusvent.2017.07.001.
Thébaud, S. (2015). Business as plan B: Institutional foundations of gender inequality in entrepreneurship across 24 industrialized countries. *Administrative Science Quarterly, 60*(4), 671–711. https://doi.org/10.1177/0001839215591627.
Wadho, W., & Chaudhry, A. (2018). Innovation and firm performance in developing countries: The case of Pakistani textile and apparel manufacturers. *Research Policy, 47*(7), 1283–1294. https://doi.org/10.1016/j.respol.2018.04.007.
Watson, J., & Robinson, S. (2003). Adjusting for risk in comparing the performances of male- and female-controlled SMEs. *Journal of Business Venturing, 18*(6), 773–788. https://doi.org/10.1016/S0883-9026(02)00128-3.
Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics, 68*(1), 115–132. https://doi.org/10.1016/0304-4076(94)01645-G.