How Do Credit Constraints Impact Innovation?[1]

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Abstract

This study provides an analysis of the impact of credit constraints on innovation at the firm level by using panel data from the Survey of Manufacturing Small and Medium Scale Enterprises in Vietnam in the period 2005–2013. We apply the two-stage econometric strategy to address the endogeneity issue between credit constraints and innovation arisen from unobserved heterogeneity factors and reverse causality. By categorising credit constraints into three levels, we obtain intriguing findings that, in Vietnam, the impacts of credit constraints on firm-level innovation vary by the level of constraints. Specifically, innovation is fostered by partial constraint but hampered by full constraint. All in all, constrained firms are more likely to start up new projects in future. Policy implications are discussed.

Keywords: Innovation, credit constraints, credit market, SMEs

1. Introduction

The purpose of this study is to address the research question as: How do credit constraints affect innovation and innovation plans at the firm level? In order to provide a relevant answer, this study aims to examine the following sub-questions: How does partial constraint affect innovation? Is there any significant linkage between full constraint and innovation? How do partial and full constraints affect innovation plans of firms? Do parametric approach and non-parametric approach yield consistent results regarding credit constraints vis-à-vis innovation relationship?

The rapid increase of globalisation and economic integration has presented both opportunities and challenges for enterprises, particularly for the small and medium sized (SMEs) (Madrid-Guijarro et al., 2009). This sector has been viewed as a crucial ingredient of national economic growth and employment generation. The process of globalisation provides SMEs with opportunities to operate independently, adopt new technology, or have a better use of transport-communication technologies and business networking (Cam and Palaz, 2016). However, challenges arise from the increased competition with larger enterprises who are able to expand capacity through investment mobility (Forth et al., 2006). In the context of globalisation, innovation is a must-do strategy for SMEs to become internationally competitive and resilient

(ADB, 2015). Innovation enables them to take full advantage of market opportunities by adopting new technology in the process of internationalisation.

Innovation has been broadly acknowledged as a crucial factor in the competitiveness, long-term survival, and economic growth of firms and countries (Gorodnichenko and Schnitzer, 2013; Wan et al., 2005). SMEs engaging in innovation perform better than those that did not (McAdam et al., 2004). Along with competitiveness, firms' success and survival mainly rely on the extent to which they incorporate innovation into their business strategy, especially in the context of global competition (Madrid-Guijarro et al., 2009). However, financing innovation appears to remain challenging because risks and uncertainty from taking innovative projects might raise conflicts of funders (Freel, 2000). In addition, SMEs are subject to experience more barriers to innovation than their large counterparts because of the shortage of internal sources, such as human capital and financing (Hadjimanolis, 1999). Due to their small scale, SMEs are less advantageous in the markets and subject to remain a lack of resources[2], higher transaction costs, higher market completion, and limited investment in research and development (R&D).

It appears that SMEs are required to overcome barriers to innovation. Lack of access to credit remains one of the most severe obstacles to firm's innovation and thereby a country's economic growth and development (Madrid-Guijarro et al., 2009). From the supplier's perspective, capital markets can be far from providing SMEs with sufficient debt and equity financing (ADB, 2015). Market imperfections with higher transaction costs as well as lack of transparency and credit expertise in screening SMEs' loan applications make these firms less favourable in the lending portfolios of commercial banks. Yet, from the borrower's perspective, a majority of SMEs are unable to submit a bankable business plan, which does not satisfy banks' credit requirements. They are also limited in showing standard financial reports and information disclosure practices, thus making them more difficult to access credit. Consequently, SMEs tend to face more constraints than their larger counterparts in doing innovation.

While literature tends to mostly indicate a negative relationship, some studies also find that lack of external credit may not necessarily impede innovation and productivity. For example, Mohnen et al. (2008) and Ferrando and Ruggieri (2018) find that credit constraints highly impede innovation and productivity, while Hewitt-Dundas (2006) and Avarmaa et al. (2013) argue that this may not necessarily be true. All in all, results are mixed, at best. Further, earlier studies have often tended to involve developed countries, such as the Netherlands, France, Italy, Spain, Sweden (i.e., Efthyvoulou and Vahter, 2016; Ferrando and Ruggieri, 2018; Mohnen et al., 2008; Musso and Schiavo, 2008; Savignac, 2008). Little is known about the linkage between credit constraints

[2] Resources include finance, skilled labour, technology, information, networks, etc.

and innovation at the firm level in developing economies like Vietnam. The foregoing—that the credit constraints vis-à-vis innovation results are mixed and studies have tended to concentrate on developed economies—motivate us to conduct the present study.

This paper endeavours to contribute to the literature by testing, to the best of my knowledge, for the first time, the credit constraint vis-à-vis innovation relationship in Vietnam, a developing economy and a new economic dragon in the Southeast Asian region. The economic reforms initiated in Vietnam in 1986 "*Doi Moi*" (Renovation) have created a socialist-oriented market economy, leading to the most outstanding socio-economic changes in Vietnam. GDP growth rate in 2017 reached 6.8% (ADB, 2018). Average per capita GDP growth rate during the period 1990–2015 was 5.5% (World Bank, 2016). This achievement yields a 3.5-fold increase in average income. Proportion of population living below the national poverty line remarkably dropped from 58% in the early 1990s to 7% in 2015. Apparently, the growth of Vietnamese economy since the early 1990s has been among the fastest in the world, and its pace of poverty reduction has been unprecedented.

This study uses data from the Survey of Small and Medium Manufacturing Enterprises in Vietnam in the period 2005–2013, conducted jointly under the collaboration between Vietnam and Denmark. This biennial survey covered 10 of the 64 provinces across Vietnam with more than 2,500 SMEs in each survey round. This study is the first to employ this longitudinal dataset that spans nearly a decade to provide a comprehensive picture of credit constraints and innovation of SMEs in Vietnam.

A major concern when examining the association between credit constraints and innovation is the presence of endogeneity (e.g., Gorodnichenko and Schnitzer, 2013). This issue arises from unobserved heterogeneity factors that affect the probability of being constrained and the propensity to innovate—such as the hesitation of the outputs generated from innovative projects, or the confidentiality of innovative projects—as well as from the decision to innovate and the likelihood to be credit constrained that jointly depend on unknown factors captured in the error term. To address endogeneity, a parametric approach of two stages is applied, in which credit constraints are regressed on a set of factors and instrumental variables in the reduced-form equation (the first stage), hence predicted values of credit constraints is obtained and used in the structural equation (the second stage). This econometric strategy enables the study to avoid biased estimates of credit constraint vis-à-vis innovation relationship arisen from endogeneity issues. Further, in order to address a selection bias of the key independent variable, which is credit constraints, and avoid specification of the functional form, this paper introduces an alternative method by applying the propensity score matching (non-parametric) approach that controls for initial conditions of both treated (constrained firms) and control (unconstrained firms) groups. This technique then matches the treatment with the controls based on their propensity scores. PSM has been proven to yield relevant estimates to those yielded from other parametric techniques (e.g., Dehejia and Wahba, 2002).

Once endogeneity and selection bias issues are corrected, this study performs intriguing findings. It is found that, in Vietnam, the impacts of credit constraints on firm-level innovation vary by the type of constraints. Particularly, partial constraint increases innovation; however, full constraint hampers firms from innovating, though the coefficient remains insignificant. These differences are explained by the unique characteristics of both groups of firms. All in all, constrained firms—either partially or fully—are necessary to start up new projects in the future. Thus, in the long term, formal credit should be the dominant financing source for SMEs' innovation, particularly those with limited internal credit. The government may take reforms in the banking and finance into account, so that SMEs likely have better credit access. Technological supports from the government and associations are needed to enhance SMEs' capacity.

The contributions of this paper are threefold. First, this study develops a three-level concept of credit constraints, including non-constraint, partial constraint, and full constraint, then further examines the impacts of constraint levels on innovation and innovation plans. This classification helps to avoid the misleading results imposed on the middle class of constraint if partially and fully constrained firms are merged. Second, not only does this study analyse the linkage between credit constraints and the probability of firms to innovate but it also examines how constraints affect innovation plans in the future. Third, this is the first to apply both parametric and non-parametric approaches on a panel dataset to investigate the effects of partial constraint as well as full constraint on innovation and innovation plans. These techniques enable the study to eliminate the irrelevant influences arisen from endogeneity and selection bias problems, thus leading to more consistent and relevant estimates.

The remaining of this study is organised as follows. Section 2 provides literature review and research hypothesis on credit constraints and innovation. Section 3 presents data sources and selection of variables, while research methods are provided in Section 4. Empirical results and discussion are shown in Section 5, followed by conclusion in Section 6.

2. Related literature and research hypothesis

This section provides review of related literature on credit constraints vis-à-vis innovation linkage, thus developing a research hypothesis. While Section 2.1 highlights the extant literature, Section 2.2 discusses the presence of endogeneity of credit constraints. A research hypothesis is stated.

2.1. Related literature on the linkage between credit constraints and innovation

Credit constraint is regarded as a key determinant of the propensity that a firm makes innovation (e.g., Efthyvoulou and Vahter (2016); Gorodnichenko and Schnitzer, 2013). Literature has shown that credit constrained firms are less likely to innovate due to their limited capacity arisen from the shortage of capital spending in innovative projects as well as in research and development activities (Silva and Carreira, 2012). Maskus et al. (2012) emphasise that firms prefer first using internal funding to implement their innovations. Because of their further credit demands for R&D investment, firms seek external financing first from banks and formal credit institutions, then from equity markets, such as on stock markets and private bond-market capitalisation. Empirical evidence of the impact of credit constraints on innovation has provided mixed results.

Credit constraints have been shown to negatively affect firm-level innovation. Aghion et al. (2012) show that firms facing credit constraints are less likely to invest in innovative projects due to their sensitivity to long-term exogenous shocks. Similarly, Silva and Carreira (2012) find a negative relationship between credit constraints and innovation in the sense that firm's R&D investment is hampered due to limited credit. Lorenz (2014) finds that financial constrained firms are less likely to perform innovation, measured by new products, services and/or methods to the firm and/or to the market. This finding is affirmed by Lööf and Nabavi (2016) who emphasise that credit constrained firms, particularly those in high-tech sector, are less likely to invest in patent applications. This implies a lower probability of doing innovation in constrained firms as compared to unconstrained firms. In the same vein, Madrid-Guijarro et al. (2016) show a negative effect of credit constraints on both product and process innovation, consistent with Canepa and Stoneman (2007) who find that firm's innovative activity is significantly and negatively influenced by financial constraints, particularly for those operating in high-tech industry and those in small size. Their study emphasises that the high financial expenses prevent firms from innovating, causing their postponement of innovative projects. Studies by Mohnen et al. (2008) and Hottenrott and Peters (2012) have asserted that innovation is negatively affected by firm's financial constraints since the shortage of capital is one of the biggest obstacles for firms to invest in R&D activity and implement innovative projects. This is explained that firms in unhealthy financial conditions must hold back their innovative investment and inventory accumulation due to their inability to mobilise external funding at higher costs (Guariglia and Liu, 2014).

In the same vein, studies by Gorodnichenko and Schnitzer (2013) and Efthyvoulou and Vahter (2016) have demonstrated that capital constraints are strongly and negatively associated with firm's innovative endeavours due to limited internal financing. Apparently, firms with better access to credit are more likely to demonstrate their innovation activities than those without credit access. As a result, this group of firms tend to yield a higher level of development of new goods, technologies, and practices. It is noted that high interest rates of external credit due to market imperfections arisen from information asymmetry concerns are a crucial factor that detrimentally affects the technological frontier convergence. On one hand, compared to outsiders, innovative firms hold more information on the potential growth of their innovative projects, especially the probability of success and estimated returns. However, these firms are unwilling to disclose their plans and strategies in order to mitigate competition in the market. On the other hand, lenders, due to their limited information on firm's repayment capability, require a higher rate of returns, which turns the credit equilibrium at the interest rate unachievable.

Studies by Caggese and Cuñat (2013) and Altomonte et al. (2016) document that innovation is negatively and indirectly affected by financial constraints through a decline of entry, competition as well as incentives to make innovation. The underlying reason has been shown that credit markets appear not to foster innovation of firms operating in industries that are more independent of internal finance. Limited price signals make banks continue financing firm's projects, even including those with negative expected returns (Rajan and Zingales, 2001). This phenomenon, originally driven by the financial systems in the formal credit markets, causes an inefficient flow of external funding to innovative projects (Beck and Levine, 2002). Further, from inside of firms, those doing innovation are less likely to maintain stable amounts of internal cash flows to meet their debt demands (Brown et al., 2012). These innovative firms also face difficulties in seeking capital from banks due to their low rate of physical assets. Brown et al. (2009) document that banks give their priority to lend firms having a high rate of physical assets to mitigate the risk. Therefore, firms appear to encounter financing struggles in credit markets for their innovations.

In another aspect, literature has shown a positive effect of credit constraints on firm-level innovation. For example, Hewitt-Dundas (2006) provides evidence that capital constrained firms tend to report their innovation performances in both product development and business strategy better than unconstrained firms, implying a positive effect of constraints on innovation. However, financial constraints might turn their influence to the other way round, particularly for small firms, in the long run. This finding is affirmed by Savignac (2008) who shows a positive linkage between financial constraints and innovation in the absence of endogeneity.

Once endogeneity is taken into account, financial constraints tend to do more harm than good to innovation. Additionally, financial constraints are shown to have no significant relationship with innovation (Galia and Legros, 2004). This finding is consistent with Bhagat and Welch (1995) who provide no significant evidence of the linkage between financing constraints and R&D investments of firms in developed countries. In the same vein, studies by Bond et al. (2005) and Chen and Chen (2011) shows that capital constraints are unimportant to R&D activities due to the absence of cash-flow sensitivity to innovation. Accordingly, innovative investments are less sensitive to cash flows, thus making unconstrained firms self-selected their innovative implementation.

2.2. Endogeneity of credit constraints

An important concern about the linkage between credit constraints and innovation is of endogeneity. Some key points are noted. First, some common factors of unobserved heterogeneity could significantly affect the probability of being constrained and the inclination to innovate (Aghion et al., 2012; Efthyvoulou and Vahter, 2016; Savignac, 2008). Accordingly, in the structural equation where innovation is regressed on credit constraints and other explanatory variables, the endogenous independent variable *credit constraints* is associated with unobserved factors captured in the error term. Other unobserved factors in the error term might include the quality of innovative projects, and/or elements that might cause or worsen credit constraints of firms because risk and borrowing might be inversely related, and/or managerial skills and experience that might reduce the likelihood of a firm being credit constrained and, at the same time, enhance profits and/or productivity (Musso and Schiavo, 2008; Rizov, 2004). Therefore, the estimates will be biased if endogeneity of credit constraints caused by the correlation with unobserved elements is not addressed.

Second, the decision to engage in innovative projects and the probability of being credit constrained are considered as simultaneous equation models (Mairesse and Mohnen, 2010; Savignac, 2008). In particular, the decision to innovate and the likelihood to be credit constrained are determined simultaneously and jointly depend on other unobserved or unknown factors captured in the error term. Accordingly, innovation and credit constraints are determined within the system of equations. Savignac (2008) finds that the presence of financial constraints significantly decreases the propensity to innovate in the case of French manufacturing firms. In an adverse direction, firms with innovation activities might demand more external financing, which results in a higher likelihood of facing financial obstacles (Canepa and Stoneman, 2007). Further, firms making innovation, such as those with high R&D expenses, are more likely to perceive a low rate of tangible assets that can act as collateral (Brown et al., 2009). Basically, R&D expenses are mostly allocated to human-capital investments, particularly salaries and wages for scientists, which might potentially impossible work as collateral. Hence, this implies a higher probability of innovative firms to be credit constrained as they appear not to satisfy the borrowing requirements.

Third, the measure of credit constraints based on self-reported information may be subject to potential measurement error due to cultural biases (Gorodnichenko and Schnitzer, 2013). Responses to questions on whether a firm experienced any problems getting the loan, or whether a firm is in need of a loan, or why a firm had not applied for formal loans since the last survey round can be distorted by personal or cultural biases. However, the direct measure of credit constraints based on self-reported information is preferred compared to using the measure by actual use of external financing for investment (Gorodnichenko and Schnitzer, 2013). Survey-based information exactly reflects the method to finance innovative projects as it provides specific responses on credit constraints of firms without particular assumptions about their investment behaviour (Efthyvoulou and Vahter, 2016). This is consistent with Campello et al. (2010) with regard to the use of a direct measure to identify financially constrained firms based on survey data. In sum, the two cases of time span and self-report can result in measurement errors and make credit constraints endogenous[3].

A number of previous studies have not addressed the endogeneity problem, which could lead to biased or inconsistent estimates (Ayyagari et al., 2011; Canepa and Stoneman, 2007; Madrid-Guijarro et al., 2016). For example, Canepa and Stoneman (2007) use two Community Innovation Surveys in the UK to examine the impact of financial constraints on innovation and by firm sizes and sectors. By applying the ordinal logit model, the authors find a significant influence of financial constraints on innovation and this impact is severer for firms in higher tech sectors and for smaller firms. Likewise, in a study on financing constraints and SME innovation in Spain, Madrid-Guijarro et al. (2016) apply the ordinary least square method and find that financial constraints have a negative and significant effect on product innovation and process innovation. Nonetheless, a major limitation of these studies is their failure to consider endogeneity of financial constraints. In case of other unobserved elements that affect innovation activities and also financial constraints, the estimated results could be biased due to no consideration of endogeneity. Our study is expected to overcome the limitations in previous studies and provide a consistent estimated parameter on the association between credit constraints and innovation.

All in all, most studies on credit constraints and innovation are conducted in developed countries, particularly in Europe. Little is known about financing and innovation in developing countries or Asian countries like Vietnam. Further, existing work when analysing the link

[3] See, for example, Mairesse and Mohnen (2010)

between financing constraints and innovation is limited in short-term data (e.g., Altomonte et al., 2016; Hottenrott and Peters, 2012; Ferreira et al., 2015; Madrid-Guijarro et al., 2016). This limitation may affect the representativeness of the sample as well as be insufficient in providing a view on impacts of credit constraints on innovation in the long run. In addition, most of previous studies have only focused on whether a firm innovates or not, rather than examining how planned the innovation is. This study considers both cases of innovation, including innovation and innovation plans.

For the mentioned justifications, this study aims to provide more evidence of innovation of SMEs in Vietnam by considering the propensity of innovation and innovation plans of new products, new improved products, and new processes that firms have produced or introduced. Credit constraints are expected to have a significant influence on firm-level innovation of SMEs in a developing country like Vietnam. It is hypothesised that:

Hypothesis. *In light of the foregoing, it is expected that the credit constraint vis-à-vis innovation relationship in the case of Vietnam's manufacturing SMEs to be negative.*

3. Data source and variables

3.1. Data source

Data is explored from a national survey of manufacturing SMEs that was conducted biennially between 2005 and 2013 and covered ten of the 64 provinces across the country, including Ha Noi, Phu Tho, Ha Tay, Hai Phong, Nghe An, Quang Nam, Khanh Hoa, Lam Dong, Ho Chi Minh City, and Long An. The survey was joint research efforts among the Central Institute for Economic Management (Vietnam), the Institute of Labour Science and Social Affairs (Vietnam), and the University of Copenhagen (Denmark), funded by the Danish Government. Data and information were collected through face-to-face interviews with firm's representatives with the purpose to provide novel insights into the dynamics and development of private sector in Vietnam as a whole.

The SME survey covered many firm-related aspects, including general characteristics, enterprise history, sales structure and production, indirect costs and materials, investments and financing, taxes and informal payments, employment and networks. The survey rounds relied on two databases from the General Statistics Office of Vietnam, including the Establishment Census and the Industrial Survey, to determine the population of non-state manufacturing SMEs. In order to ensure the representativeness of the private sector in Vietnam, certain criteria were taken into account, such as ownership structure, formality, size, location, etc (see Table 1). Accordingly, in all rounds, the surveyed samples were stratified by ownership structure or legal status so that all non-state firm types were included: household businesses, private firms, partnership or collective, limited liability companies, and joint stock enterprises. Notably, formality is a criterion in the sample selection. As such, both registered (formal) and non-registered (informal) SMEs were included in the survey, which makes the data unique as it covers both formal and part of informal sectors of enteprises in Vietnam. Further, the survey was designed to include micro, small, and medium firms in all manufacturing sectors in the ten selected provinces across Vietnam. More than 2,500 SMEs were surveyed in each round with a response rate of approximate 98%, making the entire sample of over 13,000 observations. After combining five surveyed rounds, the study obtains a balanced panel of 6,075 firm-year observations.

[Insert Table 1 here]

Table 1 also shows that household-owned firms account for the majority of the population with 65.7%, followed by limited liability companies (19.2%). State-owned firms and partnerships remain the lowest proportions with below 5% for each. Regarding formal registration, non-registered firms occupy 59% of the sample, while their counterparts account for 41%. In terms of size, micro firms are the most populated group with the share of nearly 68%, followed by small firms and medium firms whose proportions account for 31.2% and 0.9% respectively.

3.2. Variable selection

This section provides justifications for variable selection, including dependent variable, independent variable, and instrumental variable. The key independent variable—credit constraints—is grouped into three categories, including non-constraint, partial constraint, and full constraint.

3.2.1. Dependent variable

Innovation at the firm level can be measured based on objective or subjective approach. The former uses a number of variables to capture innovation, such as R&D investment (Altomonte et al., 2016; Czarnitzki and Hottenrott, 2011; Silva and Carreira, 2012), R&D expenditure (Coad and Rao, 2010; Wakelin, 2001), number of patents and/or patent citations (Coad and Rao, 2008; Hirshleifer et al., 2012; Hottenrott et al., 2016). The objective measure of innovation appears to be input-based because investing in R&D or patents is seen as firm's input. Meanwhile, the latter relies on self-reported information of firm's representatives regarding innovation-related issues to determine whether the firm is innovative or not (Bhattacharya and Bloch, 2004; Efthyvoulou and Vahter, 2016; Gorodnichenko and Schnitzer, 2013; Mohnen et al., 2008). The subjective measures investigate the output-based aspect of firms.

Between the two approaches, the objective is less preferred due to some shortcomings (Hughes, 2001). First, for example, using patents to proxy innovation can be downward biased because some firms are unable to afford the expenditure and time spent during the patenting process. Similarly, if R&D expenditures are used to capture innovation, it may result in biased estimates because R&D or innovative investment is an input, while innovation is an output. Further, formal R&D measures are biased against small firms because they are less likely to invest in R&D activities (Archibugi and Sirilli, 2000). Second, the measures of innovation by R&D expenses or innovative investments are less likely to be observed in emerging market economies (Gorodnichenko and Schnitzer, 2013). Third, using R&D expenditures to proxy innovation may be inappropriate or irrelevant because not all innovations are generated by such expenditures. It is suggested that investing in R&D does not necessarily lead to increase firm's innovation. Hence, objective measures are inappropriate in our study for SMEs in an emerging economy.

This study follows the subjective approach to examine firm-level innovation because of its advantages over the objective measures as mentioned above. Subjective measures based on self-reported information of firm's managers or owners are not only valid for monitoring and management but also efficient for identifying barriers that hamper firms from engaging in innovation activities, particularly for SMEs (Madrid-Guijarro et al., 2009). This study relies on a number of questions in the Vietnam SME Survey to construct our dependent variable: "Has the firm introduced new products since last survey?", "Has the firm made major improvements of existing products or changed specification since last survey?", and "Has the firm introduced new production processes/new technology since last survey?". I further rely on the question "Do you plan to start up new projects/product lines in the near future?" to investigate whether a firm plans doing innovation activity in the near future.

3.2.2. Independent variable

Key independent variable

Credit constraints. As presented, this study provides understanding on how credit constraints affect innovation of SMEs in Vietnam. The key independent variable in this study is credit constraints, which reflects the inability of firms as well as obstacles that firms encounter when they have access to credit in the formal credit markets. Literature has shown two methods used to measure credit constraints, including indirect approach (e.g., Bell, 1988; Petrick, 2005) and direct approach (e.g., Byiers et al., 2010; Rand, 2007). In particular, the former relies on the assumption of the permanent income hypothesis to determine credit constraint or credit rationing of an entity. Whereas, the latter is dependent on direct information from the survey questionnaire, in which firms were asked about their financing status. Hence, credit constraint or rationing is formed based on the answers of respondents. Between the two approaches, the indirect method is shown to be limited by its inconclusiveness under uncertainty conditions (e.g., Diagne et al., 2000). The direct approach is more preferable in studies on capital constraints (Bigsten et al., 2003; Rand, 2007). This paper adopts the direct approach to construct the main independent variable—credit constraints of firms.

The main idea of the direct method is to collect data and information by direct surveys with households, individuals, or enterprises. By virtue of its straightforwardness, this method is preferred and has been widely applied in previous studies (Boucher et al., 2008; Feder et al., 1990). In this study, self-reported information of firm's managers or owners is used to determine three categories of credit constraints, including unconstrained firms, partially constrained firms, and fully constrained firms. In particular, unconstrained firms are those that applied for loans, got approved, and had no more credit demands, or those that did not apply for credit because of no demands at all. Partially constrained firms are those that applied for loans, got fully approved, and had further credit demands, or those that applied for loans and got partially approved. Fully constrained firms are those that applied for loans and got fully denied or those that did not apply for loans because of other reasons—such as interest rates, credit procedures, collateral, etc.—rather than having no credit demands.

Based on credit constraint classification, this study demonstrates the share of firms that have innovation activities in Table 2. Accordingly, in the full balanced sample, around 46% of firms made innovation, while 54% are non-innovative firms. The proportions of firms planning to start up new projects or technology account for 33.2%. By category, 25.8% of constrained firms engage in innovation activities (12.1% for partially constrained and 13.7% for fully constrained firms), compared to 20.2% of unconstrained firms. Further, 20.7% of partially and fully constrained firms plan to start up new products or processes, compared to 12.6% of unconstrained firms. Apparently, constrained firms are more towards innovation activities than their counterparts.

[Insert Table 2 here]

Control variable

Firm size. Previous studies have shown that larger firms are more likely to benefit from economies of scale, which results in better R&D (Tybout, 2000). Firm size is found to have a positive relationship with the propensity of firms to innovate (Gorodnichenko and Schnitzer, 2013). In the literature, firm size has been proxied by the logarithm of total assets (Avarmaa et al., 2013; Rand, 2007) or by the logarithm of number of employees (Rand and Torm, 2012). This study measures firm size by the logarithm of total assets.

Retained earnings. Retained earnings have been highlighted as an efficient source of internal funding for innovation, particularly for those in emerging markets (e.g., Ayyagari et al., 2013). A study by Czarnitzki and Hottenrott (2011) shows that internal funding plays a key role in firm's R&D investments. Bhattacharya and Bloch (2004) find that firms operating in the low-tech industry are likely to make innovation only when they have access to internal financing from retained profit. This finding is consistent with Efthyvoulou and Vahter (2016) who emphasise the importance of internal funding in innovation activities of firms. In this study, retained earnings are used as a proxy for firm's internal funding and measured as the logarithm of profit.

Firm age. This factor has been evidenced to significantly affect firm-level innovation (Brown et al., 2009; Gorodnichenko and Schnitzer, 2013). Huergo and Jaumandreu (2004) find that youngest firms are more likely to present the highest probability of innovation while the oldest ones are less engaged in innovation activities. This finding is confirmed by Ayyagari et al. (2011) and Gorodnichenko and Schnitzer (2013) that younger firms tend to introduce new products or new technology, improve existing products, and open a new plant, compared to older firms. In this study, firm age is measured by the difference between the surveyed year and the establishment year of firms.

Investment. Investment has been considered as one of the most crucial factors driving technological process (Chiao, 2002). Chiao finds that physical investment is positively associated with current innovation, measured by R&D, particularly in science-based industries. The investment decisions of firm's managers or owners based on market structure, technological process, etc., are to maximise their present value of cash flows. In this study, investment is measured by the amount that firms invested in physical and financial assets since last survey and expected to have a positive correlation with firm-level innovation.

Competition. This variable is used to reflect competitiveness pressures on firm-level innovation (Aghion et al., 2005; Gorodnichenko and Schnitzer, 2013). Aghion et al. (2005) show that product market competition has an inverted U-shaped relationship with innovation. Further, competition is found to positively affect innovation of firms as higher competitiveness pressures boost firms to be more innovative (Gorodnichenko et al., 2010; Gorodnichenko and Schnitzer, 2013). Ayyagari et al. (2013) find a strong and significant linkage between competition that a firm experienced and its propensity of innovation. This study considers the variable of competition by a dummy variable that reflects whether or not a firm has faced competition in its field of activity.

Share of skilled workers. Following Gorodnichenko and Schnitzer (2013), this study captures firm's human capital by adding the share of skilled workers in the specifications. It is shown that skilled workers might come up with innovative ideas based on their practical experience as well as give the firm feedback to improve products or processes. This variable is expected to positively correlate with innovation as the higher the share, the more innovation the firm. This study includes this factor as a binary variable with 1 if firms faced competition in the field of activity and 0 otherwise.

Owner characteristics, including gender, age, and education level, are included in this study. Empirical evidence has shown the effect of gender on firm's innovation (e.g., Alsos et al., 2013; Foss et al., 2013). This study focuses on the importance of gender of owner to firm-level innovation by adding a binary variable with one if owner is male, and zero otherwise. Further, age of owner is controlled because aging entrepreneurs are less likely to adopt new technologies (Hadjimanolis, 2000). In a fast-growing economy of a developing country like Vietnam, aging tends to be more responsive to firm-level innovation. In addition, the education levels of owners are associated with their learning activities to adopt new technologies and to improve products or processes, which positively contribute to the innovation outcomes of firms (Gorodnichenko and Schnitzer, 2013; Snowden, 2003). Hence, this study uses a binary variable to measure whether the owner has completed an undergraduate program or higher in order to control for the impact of human capital on firm-level innovation.

Finally, previous firm-level innovation is included as firm performance in the current period tends to be driven by performance in the past (Huynh and Petrunia, 2010; Van Vu et al., 2016). Past performance significantly raises capital flows into the internal financing source (Kaplan and Schoar, 2005), which can be an ideal funding for innovation (Gorodnichenko and Schnitzer, 2013). Further, past performance is highly associated with firm's information environment, opportunity costs, and profit potential (Harris and Raviv, 2008), which can affect the current performance of firms.

3.2.3. Instrumental variable

From the SME survey that provides information on credit, liabilities, and assets, the paper uses three variables that differ across firms and time to work as instruments. This set of instruments—including interest payment on formal loans, the Certificate of Land Use Right (CLUR), and inspection by officials—is used to address endogeneity of credit constraints.

The first instrument is the interest payment on formal loans that is correlated with credit constraints but uncorrelated with innovation to correct for the endogeneity bias. This variable is measured by the logarithm of interest paid on formal loans. Interest payment, which reflects the indebtedness of a firm, is considered to be an instrumental variable as it is correlated with the credit demands or financial constraints of firms (Bigsten et al., 2003; Schiantarelli and Sembenelli, 2000) but uncorrelated with innovation. Accordingly, interest on indebtedness reflects a cost of doing business and thus may be deducted from gross income of firms. The interest payment together with the real costs of collateral evaluation and the loan monitoring make external financing more expensive than internal financing and become the financial burden on firm (Nickell and Nicolitsas, 1999). The increase of debt relative to net worth leads to higher probability of bankruptcy that is considered as a barrier to external funds (García-Quevedo et al., 2018). As a consequence, firms have less chance to borrow from formal financing sources or to be more leveraged. In other words, firms that were heavily indebted tend to be constrained and have less access to external credit. This is consistent with Hernando and Martínez-Carrascal (2008) who show that excessive indebtedness hampers firms from having access to additional external funds. In this study, the average of interest payment on formal loans by year and banks is measured as the interest rates vary across years and lending institutions.

Second, the Certificate of Land Use Right (CLUR) is selected as another instrument to address the endogeneity problem. This binary variable equals one if a firm possesses CLUR and zero otherwise. A CLUR or a red book has been viewed as collateral in the majority of loan applications, particularly in the formal credit markets (Barslund and Tarp, 2008; Rand, 2007). On the one hand, this variable represents the creditability of firms in repaying loans by their security of land tenure with verified collateral (CLUR or red book) in hand. In the context of Vietnam, lending officers often rely on secured property documentations to assess firm's repayment ability, then make decisions. A CLUR is somewhat even more required than a business registration certificate when firms apply for loans (Rand and Torm, 2012). Formal credit institutions, particularly commercial banks, are more favourable to offer credit to firms having a CLUR. In other words, those with a CLUR in hand obtain a higher probability to secure loans because they prove their more secure land rights for repayments. Barslund and Tarp (2008) show that in Vietnam, borrowers with a red book are granted loans with better terms in the formal financing sector than their peers. On the other hand, property rights by a CLUR or red book are found to significantly drive firm's formalisation (Malesky and Taussig, 2009). Rand and Torm (2012) confirm that property rights improve formalisation, which results in better access to credit. In this case, property rights have an indirect influence on credit access or credit constraints through the channel of formalisation. All in all, CLUR is expected to be correlated with credit constraints and uncorrelated with innovation.

Third, *inspection* is selected to be an instrument to correct for endogeneity. Inspection is binary and equals one if firms were inspected by government officials for the purposes of policy compliance, technical compliance, and others. This variable is used to capture differences of government officials in firm's activities (Rand and Torm, 2012). Basically, firms that are inspected tend to comply with regulations better than those that are not, which then increases their probability of being formalised as well as having access to formal financing. Gatti and Honorati (2008) find that more tax compliance is significantly correlated with better access to credit or less credit constrained. However, inspections are found to bring disadvantage for firms due to their negative influence on firm's formalisation (Jaramillo, 2009), which might affect credit access. Inspections impose direct administrative costs on firms, deriving from time and money that owners or managers spent dealing with visits by government officials (Rand and Tarp, 2012). Rand and Tarp find that inspections and bribes as informal payments appear to go hand in hand, showing by a gap in probability of paying bribes by 10% between inspected firms and non-inspected firms. Following Gorodnichenko and Schnitzer (2013), this study argues that from the firm's perspective, these occurrences—inspections and bribes—are exogenous and unexpected. They are likely to reduce available liquidity temporarily. Thus, not only should *inspection* work as a crucial factor influencing financial constraints but it also is expected to meet the condition of exclusion restriction.

A description of the variables used in the paper is provided in Table 3.

[Insert Table 3 here]

4. Research methods

This section provides understanding on two methods used in the study, including the two-stage econometric approach and propensity score matching. Section 4.1 discusses the two-stage approach, focusing on justifications and equations. Section 4.2 emphasises the non-parametric technique by applying the propensity score matching method.

4.1. Two-stage econometric approach (parametric approach)

It is acknowledged that the main explanatory variable—credit constraints—may suffer from endogeneity as discussed in the previous section. Estimating the effects of credit constraints on innovation or firm performance without addressing endogeneity problem may lead to biased estimated results. Thus, credit constraints need to be instrumented to correct for endogeneity. In this study, time-varying firm-level information is used as instrumental variables to deal with potential endogeneity of credit constraints. The instruments should be correlated with the likelihood of firms to be constrained but uncorrelated with innovation or firm performance. The use of instrumental variables allows me to correct for biased estimated parameter of credit constraints that is caused by endogeneity.

It is important to develop an econometric strategy that enables me to deal with endogeneity to ensure the consistency and reliability of estimated results. Following Papke and Wooldridge

(2008) and Semykina and Wooldridge (2010), this study applies the two-stage approach to address endogeneity and avoid inconsistent estimates when analysing the impact of credit constraints on firm-level innovation. In the first stage, an equation of factors affecting the probability of firms to be constrained is proposed as a reduced form. Particularly, credit constraints are regressed on the instrumental variables and a set of explanatory variables. The fitted values of credit constraints are obtained after the first stage and used in the second stage as an instrumented key variable in the structural equation of innovation. In the second stage, innovation is regressed on the instrumented credit constraints and other explanatory variables. By doing so, this study is able to address the potential endogeneity of credit constraints on innovation.

In light of the above, the paper endeavours to address the credit constraint vis-à-vis innovation endogeneity issue using instrumental variables that has a significant effect on credit constraints but no direct influence on the propensity to innovate. Tests of endogeneity are demonstrated in Table 6.

4.1.1. Stage 1: Estimating fitted values of credit constraints

In stage 1, credit constraints are regressed on the instruments and other independent variables by using a random-effects probit model. A functional form is given as:

$$CC_{it} = \begin{cases} 1 \; if \; CC_{it}^{*} > 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

where CC_{it} is the observed outcome of firm *i* in year *t*. The key independent variable in this study CC_{it} is binary that denotes credit constraint status of firms and considered in two cases: partially constrained versus unconstrained, and fully constrained versus unconstrained. CC_{it}^{*} denotes the unobserved variable or latent variable as:

$$CC_{it}^{*} = \gamma_0 Z_{it} + \gamma_1 X_{it}' + v_{it} \tag{2}$$

where Z_{it} is a set of instrumental variables which, in this study, includes the average interest payment on formal loans by year and lender, certificate of land use right, and inspection; γ_0 captures the effect of the instruments on credit constraints; X_{it}' is the observed time varying and time invariant vector of control variables, including firm characteristics (assets (log.), retained earnings, firm age, investment (log.), competition, and share of skilled workers), owner characteristics (gender, age, and education level), location effects, and year effects; γ_1 is the vector of coefficients associated with X_{it}'; v_{it} is the error term that contains the individual specific unobservable effect (a_i) and the classical random error term (u_{it}).

The average partial effect of an independent variable x_{kit} is given by:

$$\frac{\partial \Pr(CC_{it} = 1)}{\partial x_{kit}} = \emptyset(\gamma x'_{kit})\gamma_k \tag{3}$$

where $\emptyset(\gamma x'_{kit})$ is the standard normal density estimated at $\gamma x'_{kit}$.

4.1.2. Stage 2: Estimating the effect of instrumented credit constraints on innovation

In the second stage, innovation $(INNO_{it})$ is regressed on the instrumented credit constraints obtained from the first stage by using a random-effects probit model. The functional form is given as:

$$INNO_{it} = \begin{cases} 1 \; if \; INNO^*_{it} > 0 \\ 0 \; otherwise \end{cases} \tag{4}$$

where $INNO^*_{it}$ denotes the unobservable variable or latent variable as:

$$INNO^*_{it} = \beta_1 CC^{IV}_{i,t-1} + \beta_2 INNO_{i,t-1} + \beta_3 X'_{it} + a_i + u_{it} \tag{5}$$

where $CC^{IV}_{i,t-1}$ and $INNO_{i,t-1}$ denote the fitted values from the first-stage regression and innovation with one lag time period, respectively. The parameter β_1 captures the effect of credit constraints, either partially or fully, on innovation.

The average partial effect of credit constraints on innovation is given by:

$$\frac{\partial \Pr(INNO_{it} = 1)}{\partial CC_{it}} = \emptyset(\theta_0 CC^{IV}_{i,t-1})\beta_1 \tag{6}$$

where $\emptyset(\beta_1 CC^{IV}_{i,t-1})$ is the standard normal density estimated at $\beta_1 CC^{IV}_{i,t-1}$.

4.2. Propensity score matching (non-parametric approach)

Apart from the two-stage approach discussed in the previous section, the paper aims to evaluate the effect of credit constraints on firm-level innovation by applying the propensity score matching method (hereinafter PSM) to compute the average treatment effects of credit constrained firms and non-credit constrained firms.

4.2.1. Implementation of PSM

PSM was firstly introduced by Rosenbaum and Rubin (1983) and is an appropriate non-parametric approach used to estimate average treatment effects with non-experimental data (Guo and Fraser, 2014). The matching estimation refers to matching treated firms (credit constrained firms) and control ones (unconstrained firms) based on their observable characteristics X_{it}, and evaluating how the performance differs depending on treatment.

The PSM analysis has advantages over other parametric techniques in addressing a selection bias of an independent variable and demonstrating a causation while covariate control remains an association. Further, propensity score matching analysis does not impose any specific linearity assumptions on the treatment effects that are inherent in regression-based modelling (Böckerman and Ilmakunnas, 2009). This method has been widely applied in earlier, but mostly cross-sectional, studies (e.g., Oh et al., 2009; Subrahmanyam, Tang, and Wang, 2014).

PSM has been one of the most common econometric approach to address endogeneity problems because of the simplicity and efficiency (Roberts and Whited, 2013). As emphasised by Subrahmanyam et al. (2014), the PSM method is powerful over other techniques as it avoids specification of the functional form in the sense that the matching method is independent of restrictions and exogenous variation for identification. Instead, this technique relies on the one-dimensional propensity score between the treated and the control, estimated by the probability of receiving treatment of the covariates based on certain conditions. Estimates of the treatment effects from PSM are shown to be relevant and superior to those yielded from other parametric techniques (e.g., Dehejia and Wahba, 2002).

The PSM method will construct a control group with observed characteristics that are as similar as possible to the treated group, except for the credit constraints. Technically, the sample population comprises of treated firms (the constrained) and untreated firms (the unconstrained). Among the untreated firms, the PSM method will match those having the most similar propensity score, based on firm characteristics, with treated firms. In this stage, PSM trims the population of untreated firms to that of control firms, which matches the treated group.

As the paper explores a panel dataset from 2005 to 2013, I implement the PSM method for each round (year) of the dataset to construct a matched sample with treated and control observations for each year, then appending all rounds to generate a matched panel dataset (see, for example, Imai and Azam, 2012). Average treatment effect is obtained from the PSM technique by comparing the averages of outcome variable, which is innovation in this study, for constrained and unconstrained firms.

The stage of implementing PSM is illustrated in Figure 1. Technically, the idea is as follows:

Stage 1: Running PSM using `teffects psmatch` in Stata, hence obtaining the propensity score. Accordingly, each control observation can be used to match with more than one treated observation. At this stage, the baseline results from PSM are demonstrated in Stage 1.

Stage 2: Based on observed characteristics, matching treated observations (credit constrained firms) with control observations (unconstrained firms) for each year, then appending all rounds to construct a matched sample for panel data. As a result, a matched sample for panel data is generated for regression.

[Insert Figure 1 here]

4.2.2. Equations

Propensity score refers to a conditional probability of firms to be constrained, given the observed characteristics of the two groups (treated and untreated). Propensity score (PS) is given as:

$$PS = P(X) = \Pr(CC = 1|X) \tag{7}$$

where CC_{it} is a dummy variable which denotes the credit constrained status of firms as:

$$CC_{it} = \begin{cases} 1, if\ treatment, or\ if\ a\ firm\ is\ constrained \\ 0, if\ no\ treatment, or\ if\ a\ firm\ is\ unconstrained \end{cases} \tag{8}$$

Let's consider $INNO_{1it}$ to represent innovation of firm *i* at time *t* if it were to be credit constrained and $INNO_{0it}$ to denote the performance of firm *i* at time *t* if it were not. The outcome variables, $INNO_{1it}$ and $INNO_{0it}$, as well as the difference $INNO_{1it} - INNO_{0it}$, are random variables that potentially differ across firms in the population. For each firm, individually, we have the following equation of $INNO_{1it}$:

$$INNO_{it} = INNO_{0it} + CC_{it}(INNO_{1it} - INNO_{0it}) \tag{9}$$

where $INNO_{1it}$ is observed for constrained firms, and $INNO_{0it}$ for unconstrained ones.

A constant-effects model is postulated to estimate the causal effects as:

$$INNO_{1it} - INNO_{0it} = \delta \tag{10}$$

where δ is constant.

Let *E[.]* represent the mathematical expectation operator and X_{it} be a vector of observed covariates. X_{it} and CC_{it} may be correlated. The key assumption of causal inference—or the identifying assumption, is as follows:

$$E[INNO_{0it}|X_{it}, CC_{it}] = X'_{it}\beta \tag{11}$$

where β is a vector of regression coefficients. Two parts are included in this assumption. Firstly, $INNO_{0it}$ and $INNO_{1it}$ (under the constant-effects assumption) is mean-independent of CC_{it} conditional on X_{it}. Secondly, the conditional mean function for $INNO_{0it}$ on X_{it} is linear. Equation (4.10) leads to:

$$\frac{E\{INNO_{it}(CC_{it} - E[CC_{it}|X_{it}])\}}{E\{CC_{it}(CC_{it} - E[CC_{it}|X_{it}])\}} = \delta \tag{12}$$

This is the coefficient on CC_{it} from the population regression of $INNO_{it}$ on CC_{it} and X_{it}, also called the regression coefficient in an infinite sample. The law of large numbers ensures that the sample regression coefficients estimate this population regression coefficient consistently.

In a similar way with regression estimators, matching is motivated by the assumption that omitted variables or selection bias is a set of observational covariates X_{it}. However, matching differs from regression at the point that treatment effects are constructed by matching firms which have the same covariates rather than by a linear model for the effect of covariates. Hence, it is assumed that the effect of covariates $INNO_{0it}$ is not linear. The conditional independence assumption is as follows:

$$E[INNO_{0it}|X_{it}, CC_{it}] = E[INNO_{0it}|X_{it}] \tag{13}$$

$$E[INNO_{1it}|X_{it}, CC_{it}] = E[INNO_{1it}|X_{it}]$$

Hence, average treatment effect (ATET) is given as:

$$ATET = E(\alpha) = E(INNO_1 - INNO_0) \tag{14}$$

where *E(.)* represents the average or expected value.

Similarly, average treatment effect on the treated (ATT) is estimated as follows:

$$ATT = E(INNO_1 - INNO_0|CC = 1) \tag{15}$$

4.2.3. Evaluating the validity of matching assumptions

Following Caliendo and Kopeinig (2008) and Lee (2013), the paper highlights three major assumptions of PSM, including conditional independence, common support, and balancing tests.

Conditional Independence Assumption (CIA). The conditional independence assumption cannot be directly tested. In this paper, the covariates X_{it} on which the treatment and the control groups differ are observable and deterministic, such as firm size, firm age, owner's age, gender, location of firms, etc. Therefore, after controlling for X, the treatment assignment is "as good as random", which allows the control group to be used to construct a counterfactual for the treatment group and reduce the selection bias (Heinrich et al., 2010). Basically, the possibility of being credit constrained should be independent of the outcome measures as:

$$(INNO_0, INNO_1) \perp Constraint|X \tag{16}$$

where ⊥ denotes independence.

The common support or overlap condition. This is another required assumption that needs to be fulfilled. Accordingly, the probability to be constrained for the treated group and the control group is supposed to lie in the same domain, also known as the common support area, given as:

$$0 < P(Constraint = 1|X) < 1 \tag{17}$$

This condition implies that for each value of X, there is a positive probability of being both treated and untreated. It also ensures a sufficient overlap in the characteristics of the treated and untreated units to find adequate matches.

Balancing tests. The balancing score is primarily served by the propensity score as shown in Equation 7. The balancing tests consider the balance of characteristics between the treatment and the control groups after obtaining the estimated propensity score. The balancing test is used to check whether the propensity score is an adequate balancing score, implying that *X* remains the same distribution for both treated and control groups at each value of the propensity score. It is given as:

$$Constraint \perp X|p(X) \tag{18}$$

It suggests that there should be no other variables that could be added to the set of covariates and no statistically significant differences between covariate means of the treatment and the control groups.

In summary, PSM is applied in the paper to estimate average treatment effects of two groups (the treated and the control). A key idea of this approach is to match treated firms—those under credit constrained situation—and untreated firms—those without credit constraints, based on their propensity scores in the population of unsupported firm groups. This technique enables me to deal with the selection bias issue arisen from a sample selection in which the randomisation is not achieved. Further, PSM is advantageous in making a comparison between the factual and the counterfactual in order to yield the sole outcome under the credit constraint situation. To the best of my knowledge, this is the first study that applies the PSM technique to estimate the credit constraints vis-à-vis innovation association.

5. Empirical results and discussion

This section provides results regarding the impact of credit constraints on innovation and innovation plans. Section 5.1 demonstrates descriptive statistics of variables used in the study, while Sections 5.2 and 5.3 show the empirical results according to approaches: the two-stage techniques and the PSM approach, respectively. Section 5.4 discusses the empirical results.

5.1. Descriptive statistics

Table 4 presents the descriptive statistics of variables used in the study for the full sample as well as the mean comparisons for subsamples categorised by firm's credit constraints. The statistics—averages for the period 2005–2013–show that 28.8% of firms are partially constrained and 38.1% are fully constrained. In the full sample, 46% of firms implemented innovation activities. As shown, 33.2% of firms plan to start up new products and/or new processes. As shown, the means of total assets of firms and investments in the sample are 13.6 (standard deviation is 1.82) and 6.11 (standard deviation is 5.85) in logs, respectively, which is equivalent to 4.09 billion VND and 0.46 billion VND. The mean of retained earnings as logarithm of net profit reaches 11.61 (standard deviation is 1.84) in logs, equivalent to 0.59 billion VND.

Regarding firm age, SMEs in the sample are around 15 years of age, on average, since the establishment, with the standard deviation of 10.12. On average, 86.6% of firms have faced competition in the same field (standard deviation is 0.34). In addition, the share of skilled workers to the labour force is 2.6%. Regarding owner characteristics, 66.9% of firms are run by male owners with the average age of 46.5. Meanwhile, 25% of firm's owners completed the bachelor program or higher. The average of interest payment to formal loans is approximate 9.2 in logs, which is equivalent to 43.8 million VND. Further, 53.3% of firms hold a Certificate of Land Use Right (CLUR) and 33% were inspected by government officials.

Table 4 also shows simple *t*-test of firm and owner characteristics between constrained and unconstrained firms. The test shows a significant higher share of constrained firms—either partially or fully—engaging in innovation activities than unconstrained firms. This is an early indication that constrained firms might have been more innovative than unconstrained firms—contrary to our expectations. Constrained firms are more likely to plan starting up new projects, products, or processes. This group of firms is larger sized and obtains a greater investment level than its counterparts. Constrained firms also significantly encounter higher levels of competition in their markets and perceive a higher share of skilled workers. The businesses of constrained firms are generally owned more by men, which is significant in the case of fully constrained firms. Owners of partially constrained firms are better educated than those of the unconstrained, with the significance at 1%. Regarding interest paid on borrowed funds, partially constrained firms tend to pay more interests than unconstrained firms do. Further, both partially and fully constrained firms are inspected more frequently than their peers. Compared to fully constrained firms, the partially constrained are more engaged in innovative activity. This group of firms is also larger in size, have higher investment levels, and face more competition in the field. They perceive a slightly higher share of skilled workers and are run by educated owners. Overall, the descriptive statistics reported in Table 4 confirm the importance of constraint levels in the empirical analysis.

[Insert Table 4 here]

5.2. Results from the two-stage econometric approach

5.2.1. The linkage between credit constraints and innovation

Stage 1: Estimations from credit constraints equation

This Section first reports the results of factors affecting the probability that firms are constrained as described in the first stage in previous section. Table 5 shows results from the first stage when the factors affecting credit constraints are identified before obtaining the fitted values. As seen, the likelihood of being constrained significantly increases with the size of firms in the case of fully constrained firms, consistent with Tran and Santarelli (2013) and Rand (2007) in the case of Vietnamese firms. However, the coefficient is insignificant. The variable of retained earnings is found to have a positive relationship with credit constraints—either partially or fully—regardless of its insignificance. Also, firm age negatively affects the likelihood of credit constraints and is insignificant in both cases. Mature firms have less access to external financing sources than young firms, thus they are less likely to experience financial constraints (Coluzzi et al., 2015).

Investment has a positive and significant relationship with the probability to be either partially or fully constrained. The average partial effects show that firms increasing 1% of the investment amount are more likely to be partially constrained by 0.7% and to be fully constrained by 1.0% than those without investment. Berger and Udell (2002) point out two problems occuring in firms making investment, including adverse selection and moral hazard. Accordingly, lending institutions are unable to verify the quality of investment opportunities (adverse selection problem) or to certify that firms do not spend the funding on other projects (moral hazard problem). Hence, the higher the level of investment is, the more likely that firms are constrained.

In terms of competition, the results show that firms facing competition in the same field are more likely to be partially constrained (significance at 10% level) and fully constrained as well (significance at 1% level). As shown by the average patial effects, firms being competed by others in the same field experience a higher likelihood of being partially constrained by 3.4% and of being fully constrained by 5.5%. Intuitively, competition in the market might increase the difficulty of firms having access to credit (Fisman and Love, 2003). Berger and Udell (2006) show that market competition worsens credit access through lending technology. As a consequence, firms facing competition are more prone to be constrained than their counterparts.

Similar to other variables discussed above (firms size, retained earnings, and firm age), this study finds no significant evidence of the association between share of skilled workers and credit constraints. Regarding owner characteristics, the results suggest that male-owned firms are more likely to be constrained than female-owned firms—significant in the case of fully constrained firms only. The average partial effects show that male-owned firms hold a higher probability of being fully constrained by 2.9%. This finding is consistent with Barslund and Tarp (2008) and Tran and Santarelli (2013) show find a significant and positive relationship between male entrepreneurs and credit constraints of SMEs in Vietnam.

Conversely, the variable of owner's age perceives a negative linkage with credit constraints and is significant for fully constrained firms. Accordingly, firms run by older owners are less likely to be fully constrained by 0.8%. That older owners are less likely to encounter credit constraints is consistent with Tran and Santarelli (2013) and others, such as Barslund and Tarp (2008) and Hoque et al. (2016). Because of their experience and relationship with the lenders, older entrepreneurs appear to have their loan applications well-prepared and approved, making them less credit constrained. In the same vein, firms run by educated owners tend to face less full constraint than their peers by 3.0%. The result remains significant to the fully constrained only.

[Insert Table 5 here]

It is noted that the set of variables that work as instruments in the next stage, including interest payment, certificate of land use right (CLUR), and inspection, are strongly correlated with firm's credit constraints. First, as expected, interest payment is significantly correlated with credit constraints, which is consistent with Bigsten et al. (2003) and Schiantarelli and Sembenelli (2000). The average partial effects show that 1% increase in interest payment on formal loans leads to 11.2% and 16.5% increase in the probability of being partially constrained and fully constrained, respectively. Second, firms holding the Certificate of Land Use Right (CLUR) are less likely to be constrained—either partially or fully—by around 3%. This finding stems from the study context that in Vietnam, CLUR is considered as powerful collateral when lending institutions screen credit applications of firms (Rand, 2007). As a result, those possessing CLUR are more likely to have their applications approved than those that do not, resulting in a decrease of the probability to be constrained. Third, this study includes the variable *Inspection* to the specification of full constraint. Results show that fully constrained firms are more likely to be inspected by 7.2%. The relevance, validity, and power of the three instruments are reported in Table 6.

Endogeneity

This study performs tests of endogeneity to prove the relevance and validity of the instruments in addressing endogeneity of credit constraints (see Table 6). First, in Panel A that shows the analysis of credit constraints and innovation, the Hausman test of endogeneity shows significant χ^2 statistics (P-values < 0.05), rejecting the null hypothesis that the specified independent variable *(credit constraints)* is exogenous. Thus, credit constraints—either partially or fully—are indeed endogenous and need to be instrumented. The Sargan test of overidentification shows insignificant χ^2 statistics in both columns [1] and [2], indicating that the null hypothesis cannot be rejected and the model is not over-identified. This statistics imply the validity of the instruments in the sense that the three instruments are uncorrelated with the error term and valid to address the endogeneity problem (Hayashi, 2000). Further, the significant statistics from the LM test of underidentification in both columns [1] and [2] (P-values = 0.000) show a rejection of the null hypothesis that the equation is not identified (Kleibergen and Paap, 2006). This implies an exact identification of the equation, suggesting that the instruments are relevant and correlated with the endogenous variable—credit constraints. The significant Cragg-Donald Wald F-statistics of weak identification test show a rejection of the null hypothesis of weak instruments (Sanderson and Windmeijer, 2016). The test confirms an adequate power of the instruments.

Second, in Panel B that analyses the linkage between credit constraints and innovation plans, the Hausman test of endogeneity shows the insignificant χ^2 statistics (P-values > 0.10). This suggests that the null hypothesis of an exogenous independent variable *(credit constraints)* cannot be rejected, or, the variable of credit constraints is exogenous in the analysis of innovation plans. As the Sargan test of overidentification reports insignificant χ^2 statistics in both columns [1] and [2], the model is exactly identified and the instruments are valid. Similarly as shown in Panel A, the LM test of underidentification yields the significant statistics in both columns, implying an exact identification of the model as well as the relevance of the instruments. Last, the significant Cragg-Donald Wald F-statistics of weak identification test demonstrates an adequate power of the instruments in the analysis.

[Insert Table 6 here]

Stage 2: The linkage between credit constraints and innovation

The main results regarding the impacts of credit constraints on innovation are demonstrated in Table 7. Overall, the empirical results suggest that credit constraints do affect firm-level innovation. This study shows interesting findings that partial constraint positively affects the propensity of innovation, while full constraint has an inverse impact. The linkage is found significant in Panel A (partial constraint and innovation) and insignificant in Panel B (full constraint and innovation). The average partial effects show that partially constrained firms have 1.7% higher likelihood of doing innovation than unconstrained firms (Panel A). As indicated in the descriptive statistics section, the partially constrained appear to be more engaged in innovation activities than their peers. This finding is partly consistent with Hewitt-Dundas (2006) and Savignac (2008) in their first estimates regarding the negative impact of credit constraints on the likelihood to have innovation activities. Regarding fully constrained firms, this study finds that they are less likely to innovate but the coefficient remains insignificant (Panel B). Among others, the findings are consistent with previous studies that financing constraints hold back innovation (Ayyagari et al., 2011; Efthyvoulou and Vahter, 2016; Gorodnichenko and Schnitzer, 2013). Further justifications with regard to the linkage between two categories of constraints and innovation is presented in the discussion section.

[Insert Table 7 here]

With regard to other control variables, the results demonstrate a significant and positive association between lag innovation and the probability of firms doing innovation in both Panels, implying that firms engaging in innovation activities in the past are more likely to continue innovating. Further, the results show a positive relationship between firm size, measured by logarithm of total assets, and innovation. This suggests that larger firms are more likely to engage in innovative activity, which is consistent with a study by Gorodnichenko and Schnitzer (2013). The size effect is positive in both Panels but significant in the case of full constraint. The average partial effects show that to fully constrained firms, a 1% increase in firm size results in 1.5% increase in the propensity of innovation, holding other factors constant.

While retained earnings remain insignificant in both Panels, the positive coefficients imply that firms with a higher level of retained earnings tend to engage in innovation. Further, firm age and owner's age significantly and negatively affect the probability of firms to be innovative, though the magnitudes are relatively small (less than 1% in both Panels—holding other factors unchanged). It is suggested that mature firms are less likely to report innovations than newly established firms, which is in line with Gorodnichenko and Schnitzer (2013). Firms run by older owners are less likely to innovate, consistent with Hadjimanolis (2000) who shows that aging decreases the likelihood of firms to adopt new technologies.

As expected, investment and competition of either partially constrained or fully constrained firms are positively and significantly correlated with innovation in both Panels. As reported from average partial effects, a 1% increase in investment helps to increase the probability of doing innovation by around 1.3% in both Panels. The findings confirm the importance of investment in innovative activity, implying that the higher level of investment, the more likely that firms are innovative. A notable feature when analysing innovation at the firm level is of competition in the business field. The average partial effects show that competition increases the probability of innovation by 11.1% for partially constrained firms and 7.6% for fully constrained firms, holding other factors unchanged. The impact of competition on innovation appears to be larger in the case of partially constrained firms. Apparently, competition encourages innovation, which is consistent with Gorodnichenko et al. (2010) and Gorodnichenko and Schnitzer (2013).

Similarly, human capital plays a key role in firm-level innovation. As presented, the share of skilled workers is positively and significantly correlated with innovation of firms. In particular, a 1% increase of skilled workers leads to around 24% increase of probability that both groups of constrained firms innovate with the significance of 1%. Regarding gender of owner, male-owned firms are more likely to innovate than women-owned firms by 5.0% and 5.4% in the cases of partial constraint and full constraint, respectively. This is because men tend to simultaneously involve in more than one business projects (Kalleberg and Leicht, 1991). Kirton (1976) shows that men are innovators and women are adaptors. Compared to women, men are likely to utilise a learn-acquired system because of their motivations to achieve financial access and develop a revenue stream quickly (DeTienne and Chandler, 2007). Thus, men-owned firms tend to perform better innovation than female-owned firms. Last, this study finds no significant evidence of the effects of owner’s education level on firm-level innovation.

5.2.2. The linkage between credit constraints and innovation plans

All in all, regardless of credit constraint levels—either partially or fully, firms demonstrate their plans to innovate, as stated by Freeman and Soete (1997) “not to innovate is to die”. Table 8 reports the linkage between credit constraints and innovation plans of firms in the near future. In columns [1] and [3], future innovation plans are regressed on partial and full constraints along with the binary innovation and its one lag period. At first glance, credit constraints positively and significantly affect the plans of firms engaging in innovative activity. It means that no matter how severely constrained that firms are, they still plan starting up new projects. The average partial effects (APE) show that partially constrained firms are more likely than unconstrained firms to consider doing new projects by around 4.8% (column [2]), holding other factors unchanged. Fully constrained firms also express their higher probability of starting up new projects or products in the near future by around 5.2% (column [4]). Because innovation is a signal of firm quality (Bontems and Meunier, 2005), constrained firms need to develop new projects or consider introducing new products in order to gain competitive advantages, resulting in better opportunities of long-term survival (Banbury and Mitchell, 1995). The findings regarding the positive linkage between credit constraints and innovation plans imply the motivation that constrained firms engage in innovation in order to enhance their competitiveness and quality in the markets.

This study finds that plans to start up new projects in near future are positively and significantly affected by innovation—either current or lagged, suggesting that innovative firms appear to desire doing further innovations. The average partial effects report innovative firms hold a higher likelihood of doing further innovation in the future by around 15% than non-innovative firms—either in the case of partially or fully constrained firms (columns [2] and [4]), holding other factors unchanged. Likewise, firms engaging in innovation activities in the past are more likely to make innovation plans by around 4.3% than their counterparts (columns [2] and [4]). The findings are consistent with McAdam et al. (2004) who show evidence that firms embracing innovation dominate those that did not.

It appears that SMEs, particularly those being credit constrained, are aware of incorporating innovation into their business strategy as an efficient way to guarantee their success and survival in the markets. As documented, small firms that perform innovation achieve higher chances of growth and survival (Cefis and Marsili, 2006). Therefore, the findings in this study of the positive relationship between credit constraints and the propensity of engaging in future innovative activity affirm the importance of innovation to the growth and development of SMEs, particularly those under credit constraint conditions, to better achieve their competitive advantages. It implies that firms might consider familiarising themselves to the innovative process and strategy in order to generate their innovative capability that, in turn, becomes an important driver for gaining success in the market (Hult et al., 2004).

[Insert Table 8 here]

5.3. Results from the propensity score matching approach

This section provides results from a non-parametric approach—propensity score matching. In this section, the linkages between credit constraints and innovation as well as innovation plans are discussed through baseline estimates and regressions on matched samples.

5.3.1. The linkage between credit constraints and innovation

As discussed in previous section, the potential endogeneity of credit constraints and innovation might lead to biased estimates if endogeneity is not addressed. Therefore, the paper uses a non-parametric approach of propensity score matching to control for observed time-variant factors that might have simultaneous impacts on both credit constraints and innovation. The results of credit constraints vis-à-vis innovation association using PSM are reported in Table 9. The method corrects biased estimates by using the nearest neighbour procedure with four nearest matches per treated observation with replacement.

Panel A shows the comparison of probability to innovate between partially constrained firms or treated firms and their untreated counterparts that remain unconstrained. Other control variables in terms of firm and owner characteristics are included in the PSM technique. As a result, the average treatment effect (ATE) reports a 5.6% higher probability of partially constrained firms to engage in innovation than their peers. Yielding the similar result, the average treatment effect on the treated (ATET) shows that partially constrained firms are more likely to innovate than unconstrained firms by 4.5%. The results once affirm the estimates in previous section based on the two-stage approach regarding the positive association between partial constraint and innovation.

Panel B reports the difference of innovation probability of fully constrained firms as compared to the unconstrained (or untreated firms). Overall, fully constrained firms witness a lower likelihood of engaging in innovation than their peers, suggesting that full constraint holds back innovation despite the insignificant coefficient of the average treatment effect (ATE). Although the coefficient of such the difference is not well-determined, the result once affirms the earlier findings that full constraint hampers firm's innovation. The average treatment effect on the treated (ATET) yields a negative result as well. The economic size of both ATE and ATET in this case (Panel B) is not relatively small (smaller than 1%).

[Insert Table 9 here]

Table 10 demonstrates the linkage between credit constraints and innovation on a matched sample. As panel data is used in this study, I generate a panel matched dataset from each individual matched round. Technically, I implement PSM for each single year of the data in order to match the continuous participants (those being constrained) with non-participants (those being unconstrained). After that, all unmatched firms are dropped to generate a sample of constrained firms (treated) versus unconstrained firms (controls). This PSM approach allows the study to control for initial conditions of both treated and control observations by taking into account their observed characteristics, then match the treated group with the control group based on their propensity scores. In this study, partial constraint and full constraint are considered separately. Last, random-effects probit models are run on the ultimate matched dataset to discover the difference of innovation probability between constrained firms (treated) and unconstrained firms (controls). Once, results show the positive and significant impact of partial constraint on firm-level innovation. This suggests that partially constrained firms (treated) are more likely to innovate than their unconstrained peers (controls). The average partial effects (APE) report a 4.1%

higher probability of partially constrained firms doing innovation than unconstrained firms, holding other factors unchanged. The differences regarding the impacts of partial and full constraints on innovation are discussed in the next section.

Adversely, full constraint holds a negative coefficient, implying an inverse relationship between full constraint and innovation. This estimate is consistent with that yielded from the two-stage approach. In general, fully constrained firms are less likely to engage in innovation as this group of firms is unable to have access to formal credit. As demonstrated in the descriptive statistics section, fully constrained firms appear not to maintain adequate retained earnings for their investment activities, while innovation has been shown to mostly rely on internal financing (e.g., Efthyvoulou and Vahter, 2016). This characteristic of fully constrained firms helps to explain the inverse association with innovation.

Regarding other control variables, Table 10 shows a significant and positive coefficient of innovation in the last period in both Panels. This implies that firms implementing innovative projects in the past are more likely to innovate than their peers. The average partial effects of lag innovation range from 10.2% for fully constrained firms to 20.1% for partially constrained firms, holding other factors constant. Similarly, retained earnings hold a positive relationship with innovation. Accordingly, a 1% increase in retained earnings leads to the increase in the probability that partially and fully constrained firms innovate by 3.8% and 0.2%, respectively. However, the coefficient is significant in the case of partial constraint only. In sum, the results once confirm the findings in previous section that has discussed the estimates yielding from the first-stage approach, in which innovative is positively affected by partial constraint but negatively affected by full constraint. The linkage is well-determined in the case of partial constraint only.

[Insert Table 10 here]

5.3.2. The linkage between credit constraints and innovation plans

Table 11 reports the results of how credit constraints affect firm's innovation plans using PSM. Similar to previous section in terms of credit constraints vis-à-vis innovation linkage, this PSM approach in this section applies the nearest neighbour procedure with replacement for four matches per treated observation. Control variables regarding firm and owner characteristics are included. Panels A and B demonstrate the association between partial constraint and full constraint, respectively, and innovation plans from the baseline estimates. In both Panels, credit constraints—either partially or fully—are positively and significantly associated with innovation plans. The findings are consistent with those in earlier section given the two-stage approach. As shown in Table 11, the average treatment effects yield positive coefficients and significance at 1% in both Panels. This implies that as compared to unconstrained firms, partially constrained firms perceive 7.1% higher likelihood of starting up new innovative projects or products, while fully constrained firms are more likely to plan innovation activities by 4.6%. Meanwhile, the average treatment effects on the treated yield the difference of probability that partially and fully constrained firms plan to implement new projects by 8.3% and 5.9%, correspondingly. All in all, constrained firms demonstrate their plans to start up new innovative projects or products in the near future as they might be aware of the significance of innovation to their survival and growth as highlighted by Banbury and Mitchell (1995) that launching or improving new products results in better opportunities of survival in the long run.

[Insert Table 11 here]

Table 12 shows the impact of credit constraints on innovation plans based on a matched sample. Overall, credit constraints are positively associated with innovation plans, which confirms the earlier estimates that credit constraints have a positive effect on innovation plans. The positive coefficients in both Panels imply that constrained firms tend to make innovation plans than unconstrained firms. The average partial effects show that holding other factors constant, partially constrained firms have 7.1% higher probability to plan starting up new innovative projects than their unconstrained peers (Panel A), while fully constrained firms perceive 5.9% higher likelihood of planning innovation (Panel B). Likewise, lag innovation significantly and positively affects innovation plans, consistent with earlier estimates. In particular, firms having innovation in the past are more likely to make innovation plans by 9.7% for partially constrained firms and 8.0% for fully constrained firms, holding other factors unchanged. Retained earnings also yield positive coefficients, implying that firms with a higher level of retained earnings tend to obtain a higher probability of innovation plans by 5.2% in both cases of partial and full constraints. This financing source is considered a major driver for firms to not only engage in innovation activities but also innovation plans. In summary, the finding of a positive linkage between partial and full constraints with innovation plans once affirms the importance of innovative strategy and orientation in boosting firm's competitiveness.

[Insert Table 12 here]

5.3.3. Testing the validity of matching assumptions

Major assumptions of PSM are tested in this section in order to check the validity of matching.

<u>Balancing tests</u>

Balancing tests of PSM based on the propensity score are demonstrated in Tables 13 and 14. Basically, this test relies on observed characteristics of firms to check the balance of covariates for becoming partially constrained (Table 13) or fully constrained (Table 14) after obtaining the estimated propensity score. In other words, this test compares the balance if characteristics between the treated (constrained firms) and the controls (unconstrained firms) based on propensity score. In both Tables, the matching approach succeeds in making the means of the treated covariates close to those of the control covariates for all the variables. Further, in almost all variables, the means of the treated covariates appear to be larger than those of the control group after match. Table 13 shows that the treated group (partially constrained firms) perceives higher means of covariates—including firm size, retained earnings, competition, share of skilled workers, gender of owner, age of owner, and location—than those of the control group (unconstrained firms). Meanwhile, as reported in Table 14, the means of covariates of the treated group (fully constrained firms) remain higher than those of the control group (unconstrained firms), holding for lag innovation, firms size, retained earnings, competition, gender of owner, age of owner, and location. All in all, the matching approach are efficient in making the covariates of both groups similar. Further, the reduction of bias as a widely-used balancing check is shown to demonstrate the appropriateness of the PSM in making the means of the treated covariates as close as possible to those of the control covariates after match. Apparently, the matching method succeeds in reducing bias in almost all variables effectively.

Figures 2 and 3 illustrate the propensity scores of partial constraint and full constraint (the treated group), respectively, versus non-constraint (the control group). This again confirms the success of matching in making the two groups balance or similar for comparison.

[Insert Table 13 here]

[Insert Table 14 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

Overlap

Figure 4 plots the distributions of the propensity scores to check the overlap between constrained firms (treated) and unconstrained firms (controls). As illustrated, in both cases (partial constraint versus non-constraint and full constraint versus non-constraint), the overlaps between each single set appear to have an inverse association with propensity scores, implying that they become large when the two groups perceive small propensity scores and vice versa. In the case of partial constraint, the overlap remains relatively big when propensity scores range from 0.1 to around 0.5. Meanwhile, the overlap in the case of full constraint is considered large when propensity scores fall between 0.3 and 0.45. Apparently, the two cases affirm that the matching method with replacement succeeds in providing the best matches.

[Insert Figure 4 here]

5.4. Discussion

This Section discusses the difference of the relationship between two types of constraints and innovation—positive in the case of partially constrained firms and negative in the case of fully constrained firms, which derives from the features of these firms. In Table 15, several unique features are performed, including growth and internal funding, of constrained firms, which enables me to further explain the relationship between two categories of constraints and innovation. Among others, partially constrained firms maintain their internal funding better as well as perceive higher growth potential.

5.4.1. Partial constraint and innovation: A positive linkage

The paper explains the positive association between partial constraint and innovation based on three major points. First, these constrained firms do mostly rely on internal financing for their businesses and operations, including innovative activity, consistent with earlier studies (Hall, 2002; Hottenrott and Peters, 2012; Efthyvoulou and Vahter, 2016). Debt or new equity securities is an uncertain financing source for new projects because innovation may contain risks and take long time prior to success (Branch, 1974). The transaction cost theory and the agency theory suggest that debt is a major impediment to innovations due to high transaction costs (Jensen and Meckling, 1976). In turn, the high risk of innovation activities and the presence of information asymmetries lead to problems with debt financing. Hence, retained earnings and other internally generated funds from profits are more favourable to generate innovative activity. Table 15 shows that holding other factors unchanged, partially constrained firms obtain a higher level of internal funding from their net profits than unconstrained firms by 14.8%[4]. Possibly this is the main source that constrained firms rely on to fund their businesses, including innovation, as highlighted by Efthyvoulou and Vahter (2016) and Gorodnichenko and Schnitzer (2013) that innovation is always financed internally by retained profits. The better availability of internal financing sources can relax external financial constraints for firms to innovate. It is noted that partially constrained firms are still able to obtain credit in the formal markets although the amount is insufficient to meet their financing demands. Thus, along with formal credit, partially constrained firms perceive an alternative of internal funding for their innovative projects.

[4] Due to data unavailability of new equity, internal funding is estimated from firm's net profits only.

The second underlying reason of the positive association between constraints and innovation is of growth potential. The partially constrained are more dynamic firms with higher potential for revenue growth, implying that this group might be in the growth and expansion stage of the firm's life cycle. As stated, "The faster a firm's sales are increasing, the more confidence it will have about its ability to secure the benefits from uncertain R&D projects, and the more patience it can afford to show in waiting for these benefits" (Mueller, 1967, p.73). Hirshleifer et al. (2012) find that the growth of firms helps to foster firm's innovative activity, shown by the positive relationship between sales and the number of patents. It can be explained that firms with high growth opportunities accumulate cash for their future investments and that cash-rich firms are more likely to innovate. In sum, the growth of firms enables them to obtain greater economic reward as well as the incentive from innovative activity. As a result, growing firms are more likely to innovate than their peers.

[Insert Table 15 here]

Third, in the presence of credit constraints, the decision of making innovation enables firms to increase their quality and competitiveness to survive in the markets. Compared to unconstrained and fully constrained firms, the partially constrained appear to encounter more competition as analysed in the descriptive statistics section. Under the competition pressure, partially constrained firms are motivated to engage in innovative activity to remain their survival in the markets. The empirical results in previous section show that competition significantly and positively affects the probability of engaging in innovation, consistent with Gorodnichenko et al. (2010) who show a positive effect of competition on innovation incidence. Further, constrained firms making innovation as an efficient way to lower their exit risk. Pérez et al. (2004) find that firms investing in innovation through R&D activities perceive 57% lower exit risk than their peers. This is consistent with previous studies that firm's survival is positively impacted by R&D innovation or architectural innovation, or introduction of new products in the market (Banbury and Mitchell, 1995; Christensen et al., 1997). Cefis and Marsili (2006) confirm the positive relationship between innovation and the probability of firms' survival. The authors show that innovation is a critical factor affecting the survival of both established and mature firms as it enables them to improve their extant capabilities.

Apparently, that partially constrained firms tend to perform a higher propensity of innovation is explained by their typical characteristics of higher levels of internal funding and growth potential, as compared to unconstrained and fully constrained groups. Further, as partially constrained firms also face more competition, they are seemingly forced to innovate to survive in the market.

5.4.2. Full constraint and innovation: A negative linkage

As shown in previous section, fully constrained firms are less likely to innovate than unconstrained firms and partially constrained firms as well, though the evidence is insignificant. The findings are consistent with earlier studies (Ayyagari et al., 2011; Canepa and Stoneman, 2007; Gorodnichenko and Schnitzer, 2013; Mohnen et al., 2008).

Investment in innovative projects can be funded from external sources (e.g., bank loans, informal credit, etc.) and internal sources (including retained earnings and new equity). Different from the partially constrained, fully constrained firms are completely unable to obtain credit in the formal markets, which limits their opportunities to innovate. In this case, informal credit might be an alternative; however, the informal markets provide credit in the short term with small amount. Thus, informal credit appears not suitable for long-term investment like innovation. Ideally, it is better to finance innovation from internal source to avoid the costs of external funding—particularly formal credit—caused by information asymmetries (Efthyvoulou and Vahter, 2016). However, fully constrained firms fail to reach these two cases (external and internal financing): (i) these firms are unable to access bank loans as defined; (ii) they remain a lower level of retained earnings from profits than unconstrained firms (Table 15). Thus, this group of firms is less likely to innovate than their peers. This finding is consistent with and Gorodnichenko and Schnitzer (2013) and Efthyvoulou and Vahter (2016) who emphasise that firms with limited internal funds tend to experience more difficulty in their innovation activities. Hall et al. (2016) demonstrate that financing constraints prevent firms from investing in profitable R&D projects when firms are lack of internal funds. Due to their limited financing, fully constrained firms might have to decide to leave innovation projects on the shelf (Hottenrott and Peters, 2012). By hindering R&D investments, financial barriers are likely to affect firm’s innovative activity and economic performance as well.

All in all, partially constrained firms tend to obtain a higher level of growth potential and internal funding, which might be favourable conditions for them to innovate. Meanwhile, fully constrained firms appear not to maintain adequate internal funding for their innovation-related activities, which limits them in implementing new projects.

6. Conclusion

This study explores data from five biennial rounds of the Vietnam SME survey to investigate the linkage between credit constraints and innovation at the firm level. This research contributes to the literature by showing the importance of classifying firms into unconstrained, partially constrained, and fully constrained, which enables me to avoid the misleading results imposed on the middle class of constraints. This is the first to analyse the impact of two levels of constraints on the propensity of innovation and further analyse how credit constraints affect innovation and innovation plans in the future of SMEs. By applying the two-stage econometric strategy to correct for the endogeneity problems and the propensity score matching method to control for initial conditions of both constrained firms (treated) and unconstrained firms (controls), this study avoids biased estimates arisen from unobserved heterogeneity factors that affect both credit constraints and the propensity of innovation.

The empirical results are intriguing in both parametric approach (the two-stage method) and non-parametric approach (the PSM technique). The paper finds significant evidence that credit constraints affect firm-level innovation. Specifically, compared to unconstrained firms, partially constrained firms are more likely to innovate. The paper might report that fully constrained firms are less likely to be innovative than unconstrained firms though the relationship between full constraint and innovation remains insignificant. The impact differences between two groups of constrained firms on innovation derive from their different characteristics. First, partially constrained firms maintain internal funding from profits better than fully constrained, which is a key financing channel for them to implement innovative activity. Further, they perceive higher growth potential than the fully constrained, showing that they tend to obtain more opportunities to innovate. It appears that partially constrained firms are more dynamic and active than their peers as well as might be in the growth stage of the business life cycle. This study also finds that lagged innovation significantly and positively affects innovation in the current period. All in all, no matter how severely constrained firms are, they demonstrate their plans to start up new projects in the future. The linkages between both levels of constraints and future innovation are significant in the specifications.

The results highlight the importance of credit constraints as one of the key factors motivating firm’s innovation. Constrained firms do need to innovate to increase their quality and competitiveness to survive in the markets, especially in the globalisation context. Although credit constraint—in the case of partially constrained firms—is found to foster firm’s innovation, this impact is unanticipated to last for the long term. If partially constrained firms rely on internal funding from profits to finance their innovative projects, they face high risk when the markets are unfavourable for their business that might decrease their earnings. Further, any external shocks from the markets may have either direct or indirect impacts on firm performances. Therefore, in the long term, formal credit markets should be considered as one of the main financing channels to support SMEs’ innovation, particularly for those having limited internal funding (e.g., Efthyvoulou and Vahter, 2016; Gorodnichenko and Schnitzer, 2013). Reforms in the banking and finance sector might be considered to facilitate SMEs to have better access to credit, such as relaxing conditions in collateral, interest rates, or lending procedure.

In addition, as innovation in the future is affected by current innovation, technological supports in information, technology, and guidance from the government and associations (e.g., the Vietnam Association of Small and Medium Enterprises) are important for SMEs to enhance their capacity. As highlighted by Akman and Yilmaz (2008) regarding the importance of innovation and strategy, firms might consider developing their innovation strategy so that they can implement their innovation plans better as well as manage innovation more effectively.

To some extent, the study remains several limitations that offer rooms for further research. As it only focuses on the linkage between constraints in the formal credit markets and innovation, future studies might consider investigating the influences of different funding sources, such as formal credit, informal credit, internal funding, etc., on innovation. Further, the relationship among financing, innovation, and firm growth might be of interest of future studies. Due to data limitations, this paper does not investigate the association between credit constraints and innovation at different stages of firm life cycle, which opens a room for further research to look at this aspect. Future research might take into account other measures of innovation, such as sales increase from innovation or innovative practices, the quantity of innovation-related products and/or processes, etc.

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Tables and Figures

Table 1. Number of surveyed firms in the sample

	2005	2007	2009	2011	2013	Full sample
Total	2,820 (100)	2,632 (100)	2,659 (100)	2,552 (100)	2,569 (100)	13,232 (100)
Surveyed firms by ownership structure						
Household business	1,925 (68.3)	1,789 (68.0)	1,734 (65.2)	1,640 (64.3)	1,608 (62.5)	8,696 (65.7)
Private firm	285 (10.1)	209 (7.9)	214 (8.0)	203 (8.0)	209 (8.2)	1,120 (8.5)
Partnership/collective	105 (3.7)	109 (4.2)	83 (3.1)	71 (2.8)	59 (2.3)	427 (3.2)
Limited liability company	444 (15.7)	459 (17.4)	531 (20.0)	532 (20.9)	573 (22.4)	2,539 (19.2)
State-owned/joint stock enterprise	61 (2.2)	66 (2.5)	97 (3.7)	106 (4.2)	120 (4.7)	450 (3.4)
Surveyed firms by formality						
Registered firm	1,005 (35.6)	1,559 (59.2)	1,775 (66.7)	1,795 (70.3)	1,681 (65.4)	7,815 (59.1)
Non-registered firm	1,815 (64.4)	1,073 (40.8)	884 (33.3)	757 (29.7)	888 (34.6)	5,417 (40.9)
Surveyed firms by size						
Micro	1,873 (66.4)	1,728 (65.6)	1,735 (65.2)	1,776 (65.6)	1,869 (72.8)	8,981 (67.9)
Small	909 (32.2)	873 (33.2)	906 (34.1)	756 (29.6)	687 (26.7)	4,131 (31.2)
Medium	38 (1.4)	31 (1.2)	18 (0.7)	20 (0.8)	13 (0.5)	120 (0.9)

Note: Percentages are in parentheses.

Source: Calculation based on the SME Survey (2005, 2007, 2009, 2011, 2013)

Table 2. Share of firms doing innovation by credit constraint

	Full balanced sample		Un-constrained firms		Partially constrained firms		Fully constrained firms	
	Obs.	*Pct.*	Obs.	*Pct.*	Obs.	*Pct.*	Obs.	*Pct.*
Innovation	2,795	46.01	1,227	20.20	735	12.10	833	13.70
Non-innovation	3,280	53.99	1,779	29.30	481	7.90	1,020	16.80
Innovation plans	1,615	33.23	612	12.60	475	9.80	528	10.90
No innovation plans	3,245	66.77	1,843	37.90	418	8.60	984	20.20

Note: Calculation from the SME Survey in Vietnam

Table 3. Variable description

Variable	Description
	Dependent variable
Innovation	Dummy variable; = 1 if firms introduced new products or new production processes, or made major improvements to existing products; = 0 otherwise
Innovation plans	Dummy variable; = 1 if firms plan to start up new projects or products in the near future; = 0 otherwise
	Independent variable
Partial constraint	Dummy variable; = 1 if firms applied for loans, got fully approved, and had further credit demands; or if they applied for loans and got partially approved; = 0 if firms are unconstrained
Full constraint	Dummy variable; = 1 if firms applied for loans and got fully denied; or if they did not apply for loans because of other reasons rather than no credit demands; = 0 if firms are unconstrained
Assets (log.)	Firm size, measured by the logarithm of total assets in the end of year
Retained earnings (log.)	The logarithm of profit in the end of year
Firm age	The age of firm expressed in years as the difference between the surveyed year and the establishment year of firms
Investment (log.)	Firm’s investment, measured by the logarithm of the amount that was invested since last survey
Competition	Dummy variable; = 1 if firms faced competition in the field of activity; = 0 otherwise
Share of skilled workers	The ratio of professional employees to total employees
Gender of owner	Dummy variable; = 1 if owner/manager is male; = 0 if female
Age of owner	The age of owner/manager expressed in years as the difference between the year of survey and the year of birth
Education	Dummy variable; = 1 if owner/manager completed an undergraduate or a postgraduate program; = 0 otherwise
Location	Dummy variable; = 1 if firms are located in urban provinces (Ha Noi, Hai Phong, Ho Chi Minh City); = 0 otherwise (Ha Tay, Long An, Phu Tho, Quang Nam, Nghe An, Khanh Hoa, Lam Dong)
	Instrumental variable
Interest payment (log.)	Logarithm of mean of interests by year and banks that was paid on formal loans
CLUR	Certificate of Land Use Right. Dummy variable; = 1 if firms hold the certificate of land use right; = 0 otherwise
Inspection	Dummy variable; = 1 if firms were inspected by government officials for the purposes of policy compliance (labour, tax, etc.), technical compliance (environment, fire, etc.), and others (accidents, etc.); = 0 otherwise

Table 4. Descriptive statistics

	Mean	S.D.	Min.	Max.	Obs.
Partial constraint (Yes = 1)	0.288	(0.453)	0.000	1.000	6,075
Full constraint (Yes = 1)	0.381	(0.486)	0.000	1.000	6,075
Innovation (Yes = 1)	0.460	(0.498)	0.000	1.000	6,075
Innovation plans (Yes = 1)	0.332	(0.471)	0.000	1.000	4,860
Assets (log.)	13.650	(1.824)	4.595	19.567	6,075
Retained earnings (log.)	11.608	(1.836)	0.000	19.523	6,075
Firm age	15.236	(10.123)	1.000	75.000	6,075
Investment (log.)	6.110	(5.847)	0.000	18.258	6,075
Competition (Yes = 1)	0.866	(0.340)	0.000	1.000	6,075
Share of skilled workers	0.026	(0.059)	0.000	0.771	6,075
Gender (Male = 1)	0.669	(0.471)	0.000	1.000	6,075
Age of owner	46.509	(10.420)	17.000	94.000	6,075
Education	0.250	(0.433)	0.000	1.000	6,075
Avg. of interest payment (log.)	9.176	(1.986)	5.864	12.200	6,075
CLUR (Yes = 1)	0.533	(0.499)	0.000	1.000	6,075
Inspection (Yes = 1)	0.330	(0.470)	0.000	1.000	6,075

	PC. vs. UC.		FC. vs. UC.		PC. vs. FC.	
	Diff.	Obs.	Diff.	Obs.	Diff.	Obs.
Innovation (Yes = 1)	0.196***	4,222	0.041***	4,859	0.155***	3,069
Innovation plans (Yes = 1)	0.283***	3,348	0.100***	3,967	0.183***	2,405
Assets (log.)	0.706***	4,222	0.165***	4,859	0.540***	3,069
Retained earnings (log.)	0.744***	4,222	0.112**	4,859	0.632***	3,069
Firm age	-2.830	4,222	-1.024	4,859	-1.806	3,069
Investment (log.)	5.219***	4,222	0.267*	4,859	4.952***	3,069
Competition (Yes = 1)	0.076***	4,222	0.046***	4,859	0.030***	3,069
Share of skilled workers	0.019***	4,222	0.007***	4,859	0.012***	3,069
Gender (Male = 1)	0.019	4,222	0.025**	4,859	-0.006	3,069
Age of owner	-2.783	4,222	-1.112	4,859	-1.671	3,069
Education	0.089***	4,222	0.003	4,859	0.087***	3,069
Avg. of interest (log.)	2.376***	4,222	-0.794	4,859	3.171***	3,069
CLUR (Yes = 1)	-0.101	4,222	-0.065	4,859	-0.037	3,069
Inspection (Yes = 1)	0.114***	4,222	0.038***	4,859	0.076***	3,069

Note: *t*-test is used to test the null hypotheses H_0: difference of mean is greater than 0. Standard deviations are in parentheses. UC., PC., and FC. stand for unconstrained, partially constrained, and fully constrained firms, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively.

Table 5. Estimations from credit constraints equation

Variable	Partial constraint (Panel A)				Full constraint (Panel B)			
	Prob.	S.E.	APE.	S.E.	Prob.	S.E.	APE.	S.E.
Assets (log.)	-0.019	(0.023)	-0.004	(0.005)	0.020	(0.017)	0.007	(0.006)
Retained earnings (log.)	0.028	(0.019)	0.005	(0.004)	0.009	(0.015)	0.003	(0.005)
Firm age	-0.003	(0.003)	-0.001	(0.001)	-0.003	(0.002)	-0.001	(0.001)
Investment (log.)	0.037***	(0.006)	0.007***	(0.001)	0.030***	(0.004)	0.010***	(0.001)
Competition (Yes = 1)	0.173*	(0.090)	0.034*	(0.017)	0.165***	(0.061)	0.055***	(0.020)
Share of skilled workers	0.700	(0.509)	0.136	(0.099)	0.778	(0.417)	0.260	(0.139)
Gender (Male = 1)	0.042	(0.062)	0.008	(0.012)	0.085*	(0.047)	0.029*	(0.016)
Age of owner	-0.004	(0.003)	-0.001	(0.001)	-0.008***	(0.002)	-0.003***	(0.001)
Education	0.012	(0.070)	0.002	(0.014)	-0.090*	(0.054)	-0.030*	(0.018)
Avg. of interest pmt. (log.)	0.578***	(0.024)	0.112***	(0.003)	-0.493***	(0.025)	-0.165***	(0.008)
CLUR (Yes = 1)	-0.178***	(0.058)	-0.035***	(0.011)	-0.098**	(0.044)	-0.033**	(0.015)
Inspection (Yes = 1)					0.216***	(0.057)	0.072***	(0.019)
Location effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes	
Observations	4,222		4,222		4,859		4,859	

Note: Dependent variable is credit constraints, including partial constraint (Panel A) and full constraint (Panel B). Probability and average partial effects (APE) are reported in both Panels. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 6. Tests of endogeneity

	Partial constraint		Full constraint	
	[1]		[2]	
Panel A: Credit constraints and innovation				
Hausman test of endogeneity	11.255	[0.001]	4.604	[0.032]
Sargan test of overidentification	0.008	[0.931]	2.276	[0.321]
LM test of underidentification	439.950	[0.000]	208.641	[0.000]
Cragg-Donald test of weak identification	270.722	[0.000]	75.094	[0.000]
Panel B: Credit constraints and innovation plans				
Hausman test of endogeneity	1.559	[0.212]	0.077	[0.782]
Sargan test of overidentification	2.133	[0.144]	2.539	[0.281]
LM test of underidentification	439.950	[0.000]	208.641	[0.000]
Cragg-Donald test of weak identification	270.722	[0.000]	75.094	[0.000]

Note: P-values are in brackets. PC. and FC. stand for partial constraint and full constraint, respectively.

Table 7. Credit constraints and firm-level innovation: A two-stage approach

Variable	PC. and innovation (Panel A)				FC. and innovation (Panel B)			
	Prob.	S.E.	APE.	S.E.	Prob.	S.E.	APE.	S.E.
Lag PC. (instrumented)	0.053**	(0.021)	0.017**	(0.007)				
Lag FC. (instrumented)					-0.014	(0.032)	-0.004	(0.010)
Lag innovation	0.407***	(0.049)	0.133***	(0.016)	0.349***	(0.046)	0.113***	(0.015)
Assets (log.)	0.031	(0.019)	0.010	(0.006)	0.046**	(0.018)	0.015**	(0.006)
Lag retained earnings (log.)	0.030	(0.021)	0.010	(0.007)	0.032	(0.020)	0.010	(0.006)
Firm age	-0.008***	(0.003)	-0.003***	(0.001)	-0.009***	(0.002)	-0.003***	(0.001)
Investment (log.)	0.041***	(0.004)	0.013***	(0.001)	0.043***	(0.004)	0.014***	(0.001)
Competition (Yes = 1)	0.342***	(0.072)	0.111***	(0.023)	0.235***	(0.068)	0.076***	(0.022)
Share of skilled workers	0.733*	(0.430)	0.239*	(0.140)	0.730*	(0.417)	0.237*	(0.135)
Gender (Male = 1)	0.155***	(0.050)	0.050***	(0.016)	0.165***	(0.048)	0.054***	(0.015)
Age of owner	-0.008***	(0.002)	-0.003***	(0.001)	-0.007***	(0.002)	-0.002***	(0.001)
Education	-0.004	(0.056)	-0.001	(0.018)	0.022	(0.054)	0.007	(0.018)
Location effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes	
Observations	3,461		3,461		3,806		3,806	

Note: Dependent variable is innovation plans. Probability and average partial effects (APE) are reported. PC. and FC. stand for partially constrained, and fully constrained firms, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 8. Credit constraints and innovation plans

Variable	PC. and innovation plans (Panel A)				FC. and innovation plans (Panel B)			
	[1]		[2]		[3]		[4]	
	Prob.	S.E.	APE.	S.E.	Prob.	S.E.	APE.	S.E.
Partial constraint	0.156***	(0.054)	0.048***	(0.017)				
Full constraint					0.172***	(0.048)	0.052***	(0.015)
Innovation	0.483***	(0.053)	0.150***	(0.016)	0.521***	(0.051)	0.158***	(0.015)
Lag innovation	0.139***	(0.053)	0.043***	(0.016)	0.144***	(0.050)	0.044***	(0.015)
Firm characteristics	Yes		Yes		Yes		Yes	
Owner characteristics	Yes		Yes		Yes		Yes	
Location effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes	
Observations	3,461		3,461		3,806		3,806	

Note: Dependent variable is innovation plans. Probability and average partial effects (APE) are reported. Firm characteristics include assets (log.), lag retained earnings (log.), firm age, investment (log.), competition, and share of skilled workers. Owner characteristics include gender, age, and education level. PC. and FC. stand for partial constraint and full constraint, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 9. Credit constraints and innovation: Baseline from PSM estimates

	PC. and innovation (Panel A)		FC. and innovation (Panel B)	
Average treatment effect (ATE)	0.056***	(0.020)	-0.006	(0.016)
Average treatment effect on the treated (ATET)	0.045**	(0.020)	-0.008	(0.017)
Total observations	3,461		3,806	
Treated observations (lag constraint)	1,054		1,399	

Note: Dependent variable is innovation. Four matches per treated. Abadie-Imbens (AI) robust standard errors are in parentheses. Control variables are specified in Table 3. PC. and FC. stand for partial constraint and full constraint, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 10. Credit constraints and innovation: A matched sample

Variable	PC. and innovation (Panel A)				FC. and innovation (Panel B)			
	Prob.	S.E.	APE.	S.E.	Prob.	S.E.	APE.	S.E.
Lag PC.	0.114**	(0.053)	0.041**	(0.019)				
Lag FC.					-0.001	(0.049)	-0.000	(0.016)
Lag innovation	0.563***	(0.054)	0.201***	(0.018)	0.313***	(0.051)	0.102***	(0.016)
Lag retained earnings (log.)	0.106***	(0.017)	0.038***	(0.006)	0.007	(0.022)	0.002	(0.007)
Year effects	Yes		Yes		Yes		Yes	
Location effects	Yes		Yes		Yes		Yes	
Treated obs.	1,054		1,054		1,399		1,399	
Control obs.	1,607		1,607		1,763		1,763	

Note: Dependent variable is innovation. PC. and FC. stand for partial constraint and full constraint, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 11. Credit constraints and innovation plans: Baseline from PSM estimates

	PC. and innovation plans (Panel A)		FC. and innovation plans (Panel B)	
Average treatment effect (ATE)	0.071***	(0.018)	0.046***	(0.016)
Average treatment effect on the treated (ATET)	0.083***	(0.021)	0.059***	(0.017)
Total observations	3,461		3,806	
Treated observations (lag constraint)	1,054		1,399	

Note: Dependent variable is innovation. Four matches per treated. Abadie-Imbens (AI) robust standard errors are in parentheses. Control variables are specified in Table 3. PC. and FC. stand for partial constraint and full constraint, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 12. Credit constraints and innovation plans: A matched sample

Variable	PC. and innovation plans (Panel A)				FC. and innovation plans (Panel B)			
	Prob.	S.E.	APE.	S.E.	Prob.	S.E.	APE.	S.E.
Lag PC.	0.204***	(0.056)	0.071***	(0.019)				
Lag FC.					0.018***	(0.049)	0.059***	(0.016)
Lag innovation	0.277***	(0.058)	0.097***	(0.020)	0.244***	(0.052)	0.080***	(0.017)
Lag retained earnings (log.)	0.149***	(0.019)	0.052***	(0.007)	0.160***	(0.020)	0.052***	(0.006)
Year effects	Yes		Yes		Yes		Yes	
Location effects	Yes		Yes		Yes		Yes	
Treated obs.	1,054		1,054		1,399		1,399	
Control obs.	1,607		1,607		1,763		1,763	

Note: Dependent variable is innovation plans. PC. and FC. stand for partial constraint and full constraint, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 13. Test of covariate balancing and absolute bias reduction before and after matching: Partially constrained firms and unconstrained firms—nearest neighbour matching

Variable	Sample	Mean		% bias	% reduct of bias	t-test
		Treated	Control			
Lag innovation	Unmatched	0.650	0.465	37.8		10.15***
	Matched	0.650	0.665	-3.0	92.0	-0.71
Assets (log.)	Unmatched	14.295	13.650	35.0		9.60***
	Matched	14.295	14.252	2.3	93.3	0.53
Lag retained earnings (log.)	Unmatched	12.102	11.415	41.0		11.56***
	Matched	12.102	12.067	2.1	94.9	0.45
Firm age	Unmatched	14.124	16.919	-28.7		-7.48***
	Matched	14.124	14.151	-0.3	99.0	-0.07
Investment (log.)	Unmatched	8.425	5.088	57.2		15.61***
	Matched	8.425	8.436	-0.2	99.7	-0.04
Competition (Yes = 1)	Unmatched	0.892	0.848	13.2		3.47***
	Matched	0.892	0.890	0.5	96.3	0.12
Share of skilled workers	Unmatched	0.036	0.021	26.0		7.23***
	Matched	0.036	0.033	5.2	80.1	1.11
Gender (Male = 1)	Unmatched	0.676	0.649	5.6		1.52
	Matched	0.676	0.663	2.7	51.8	0.62
Age of owner	Unmatched	45.364	47.787	-23.1		-6.23***
	Matched	45.364	45.308	0.5	97.7	0.12
Education	Unmatched	0.343	0.258	18.4		5.07***
	Matched	0.343	0.343	-0.1	99.4	-0.02
Location (Urban = 1)	Unmatched	0.303	0.346	-9.3		-2.50**
	Matched	0.303	0.296	1.5	83.6	0.36

Note: Average treatment effect on the treated (ATET) is reported.
*, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively.

Table 14. Test of covariate balancing and absolute bias reduction before and after matching: Fully constrained firms and unconstrained firms—nearest neighbour matching

Variable	Sample	Mean		% bias	% reduct of bias	t-test
		Treated	Control			
Lag innovation	Unmatched	0.520	0.465	10.9		3.24***
	Matched	0.520	0.516	0.8	92.4	0.22
Assets (log.)	Unmatched	13.768	13.650	6.8		2.02**
	Matched	13.768	13.741	1.5	77.5	0.42
Lag retained earnings (log.)	Unmatched	11.462	11.415	3.1		0.93
	Matched	11.462	11.461	0.1	96.9	0.03
Firm age	Unmatched	15.779	16.919	-11		-3.24***
	Matched	15.779	15.843	-0.6	94.4	-0.17
Investment (log.)	Unmatched	5.514	5.088	7.4		2.21**
	Matched	5.514	5.524	-0.2	97.8	-0.04
Competition (Yes = 1)	Unmatched	0.882	0.848	10.1		2.96***
	Matched	0.882	0.880	0.6	94.3	0.16
Share of skilled workers	Unmatched	0.026	0.021	10.1		3.01***
	Matched	0.026	0.027	-0.9	91.2	-0.22
Gender (Male = 1)	Unmatched	0.668	0.649	3.9		1.17
	Matched	0.668	0.665	0.6	84.7	0.16
Age of owner	Unmatched	46.805	47.787	-9.5		-2.80***
	Matched	46.805	46.663	1.4	85.5	0.36
Education	Unmatched	0.254	0.258	-0.9		-0.27
	Matched	0.254	0.258	-0.8	13.9	-0.21
Location (Urban = 1)	Unmatched	0.423	0.346	15.9		4.75***
	Matched	0.423	0.422	0.2	98.6	0.06

Note: Average treatment effect on the treated (ATET) is reported.
*, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively.

Table 15. Credit constraints, internal funding and growth

Variable	Internal funding				Growth			
	[1]		[2]		[3]		[4]	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Lag partial constraint	0.148**	(0.059)			0.071***	(0.024)		
Lag full constraint			-0.025	(0.050)			0.014	(0.018)
Lag profit (log.)	0.613***	(0.019)	0.557***	(0.018)				
Lag growth (log.)					-0.000	(0.020)	-0.012	(0.013)
Location effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes	
Observations	3,461		3,806		3,461		3,806	
	Diff.	S.E.	*t*-stat.		Diff.	S.E.	*t*-stat.	
PC. vs. UC.	0.744***	(0.063)	11.869		0.084***	(0.021)	4.050	
FC. vs. UC.	0.112**	(0.052)	2.165		0.042**	(0.020)	2.142	
PC. vs. FC.	0.632***	(0.068)	9.231		0.042*	(0.030)	1.417	

Note: Internal funding is represented by firm's net profits. Growth is calculated as $Growth_{i,t} = \Delta Revenue_{i,t} = Revenue_{i,t} - Revenue_{i,t-1}$. UC., PC., and FC. stand for unconstrained, partially constrained, and fully constrained firms, respectively. *, **, and *** denote the levels of significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Figure 1. Framework of PSM method

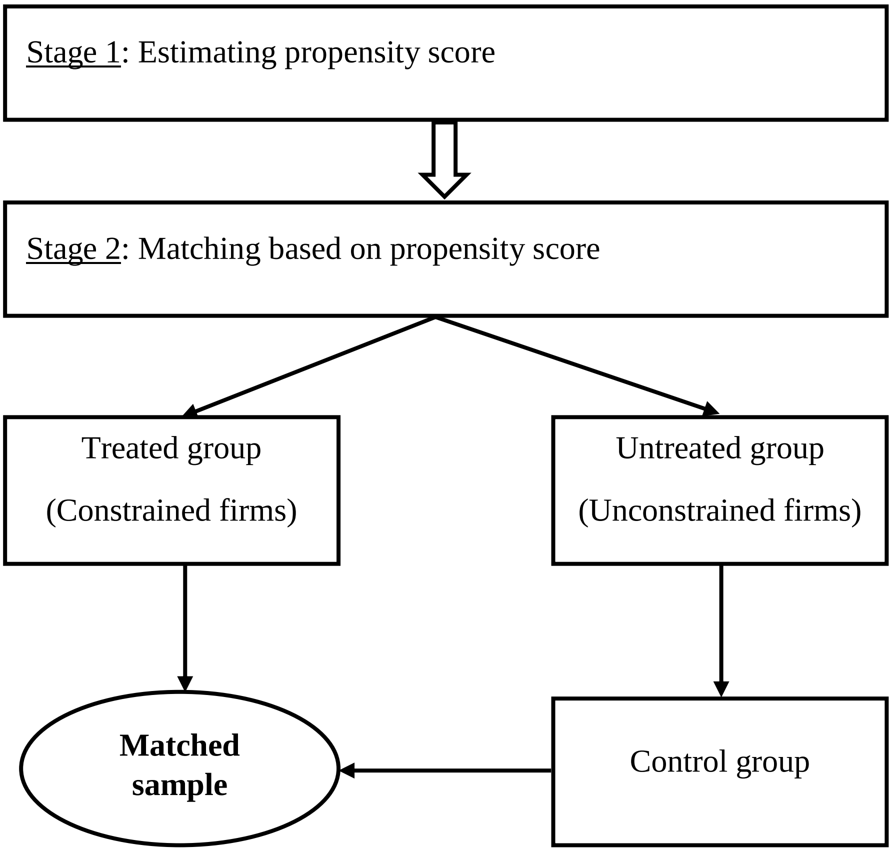

Figure 2. Propensity scores of partial constraint (treated) and non-constraint (controls) before and after match

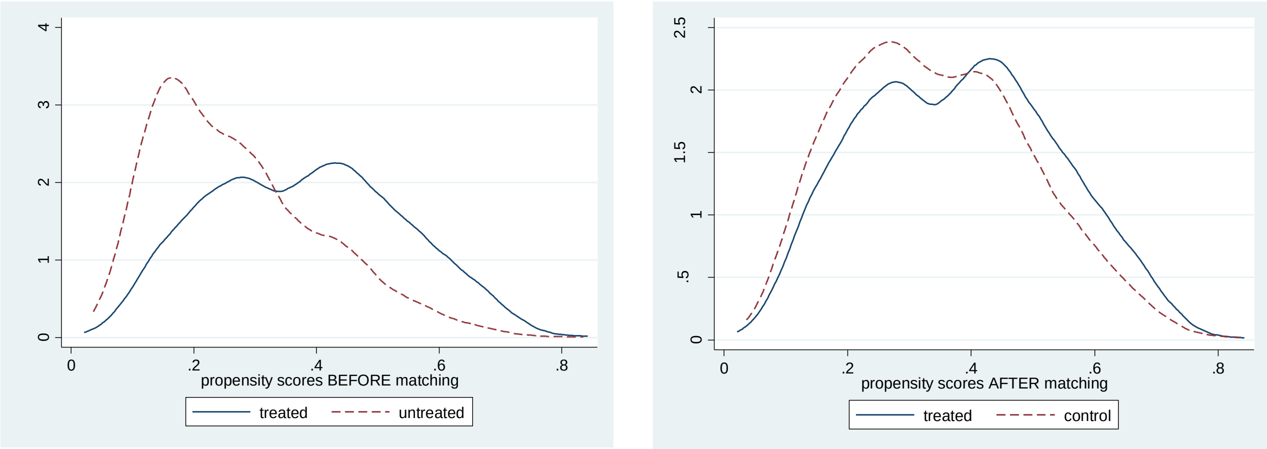

Figure 3. Propensity scores of full constraint (treated) and non-constraint (controls) before and after match

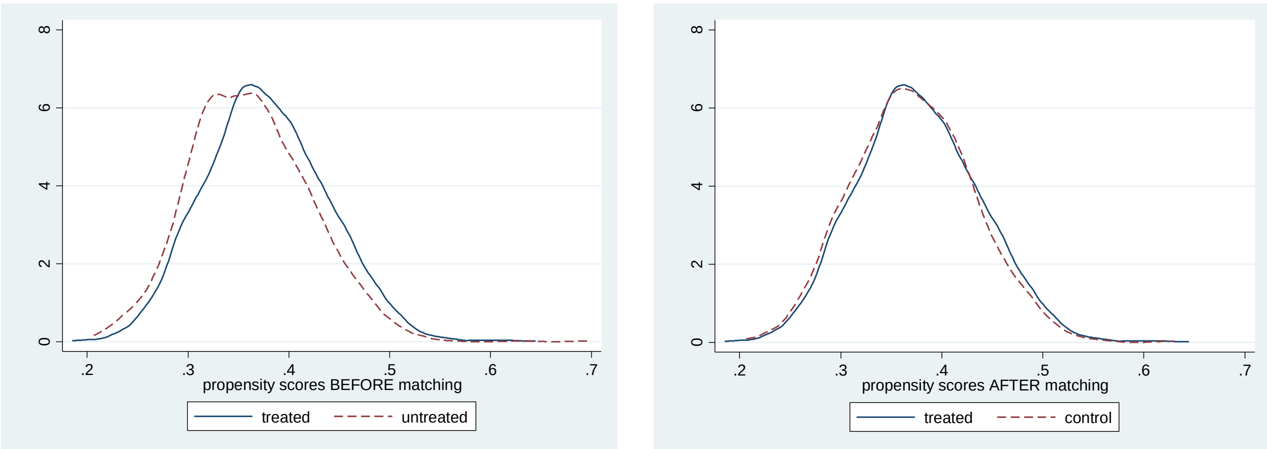

Figure 4. Overlap in propensity scores of treated and control groups