Does Going Public Boost or Impede Firm Innovation?
- Evidence from firms in Sweden

Master's Thesis 30 credits
Department of Business Studies
Uppsala University
Spring Semester of 2019
Date of Submission: 2019-06-27

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Abstract

This paper investigates the effects of going public on firm innovation by comparing the innovation activities of firms that go public with firms that choose to not undergo an initial public offering (IPO) and remain privately held. Going public here is a transformation of a privately held firm into a public firm, i.e. the first time for the firm to publicly trade in stock markets. The combination of a propensity score matching (PSM) and a difference-in-difference (DiD) methods are adopted to measure the innovation trends in terms of patent applications. Using the patent-based metric, firm innovation increases following IPOs. Comparing to the innovation activities of privately held peers, going public can boost the patent growth rate of firms and delay the downward trend of patent growth in the two years following IPOs.

Keywords: Going Public, IPO, Firm Innovation, Financial Constraints, Financing Innovation, Patents, Corporate Governance, Capital Structure, Equity Finance, Sweden
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1. Introduction

Firm innovation has been one of the most vital drivers for enhancing economic growth. It helps determine competitiveness and market value of a firm, which is of interest to many stakeholders including investors, managers, owners and employees (Ertürk, 2009; Fang et al., 2014; Tohidi and Jabbari, 2012). Just as Porter and Wayland (1992, p.65) indicated, “To compete effectively in international markets, a nation’s businesses must continuously innovate and upgrade their competitive advantages. Innovation and upgrading come from sustained investment in physical as well as intangible assets”. Firms are expected to convert investments into innovations which increase their sales and earnings and, thus, increase firm value (Wies and Moorman, 2015).

However, innovation projects have special characteristics which make financing of innovation is a challenge to firms (Hall, 2010; Saunders and Steffen, 2011). Financing of innovation has a longer duration and is more sensitive to financial constraints, which needs larger capital investment than other types of projects (Brown et al., 2012; Hall, 2010; Wies and Moorman, 2015). Generally speaking, internal financing rarely meets the financial needs of innovative firms and they therefore usually utilize external financing to supplement funds (Wang et al., 2016).

An innovation project is highly uncertain. It often has a high probability of failure as well as a possibility of high returns (Müller and Zimmermann, 2009). Due to fixed interest payments, banks concern more with the high probability of failure instead of the high returns of successful outcomes (Müller and Zimmermann, 2009). In addition, the quality of innovation projects is difficult to accurately measure, thus it is difficult to measure the expected returns (Müller and Zimmermann, 2009). Due to the core innovation protection, it results asymmetric information in the form of adverse selection and moral hazard, which affects the willingness of investors to provide both debt and equity capital (Hall 2010; Müller and Zimmermann, 2009).

This paper aims to investigate the effects of going public on firm innovation, in terms of the initial public offering (IPO). The main reason for investigating the IPO effect is that a stock market provides access to a funding resource of lower cost than debt finance (Dittmar, 2008; He et al., 2017). The lower capital cost makes it easier for innovative firms to overcome their financial difficulties and enhance the survival rates of innovation projects. Firms are induced
to undergo IPOs to meet the need of capital growth in innovation activities (Bernstein, 2015). In addition, there is a large body of research examining the changes of firm performance and growth after external funding sources, especially when firms start to trade publicly (Katila and Shane, 2005; Porter and Wayland, 1992; Wang et al., 2016). However, only a few articles address how ex post firm innovation is influenced by IPOs (Bernstein, 2015). This paper aims to complement the changes of firm innovation after undergoing IPOs.

In order to get insight to innovation changes following IPOs, this paper chooses to investigate the IPO effects in the Swedish stock markets. Sweden is referenced as the European version of Silicon Valley, and Stockholm is well-known for fostering innovation and entrepreneurship (Kista, 2019). It is the second most prolific tech hub per capita in the world following Silicon Valley (Davidson, 2015). According to Global Innovation Index 2018 (Dutta et al., 2018), Sweden is in the third position of the global country innovation input rankings. As much as 3.3% of the Swedish growth domestic product (GDP) has been used to invest innovation projects with research and development (R&D) (OECD 2019; Sweden.se, 2018). Sweden is always committed to create an innovative corporate climate, which provides a good innovative environment context for this research.

Although a few similar studies have been performed in other countries such as the United States (Bernstein, 2015) and China (He et al., 2017), this paper is the first attempt -to my knowledge- to investigate the relationship between IPOs and innovation in Sweden. The research question of this paper is:

_How does going public (IPOs) affect innovation activities in Swedish firms?_

To estimate the IPO effect is challenging, since public listing can be endogenous (Bernstein, 2015). There is an inherent selection bias associated with a decision to go public. Firms choose to go public at a specific stage in their life cycles, which could correspond to innovations and produce the estimated bias of IPO effects (Chemmanur et al., 2010; Jain and Kini, 1994). It indicates that some internal factors could be correlated with both going public decisions and innovation activities. For example, if a firm goes public after a breakthrough of innovation, the post-IPO performance may reflect regression to the mean and thereby the IPO effect is mixed with the life cycle effect of innovation (Bernstein, 2015).
To mitigate the endogeneity concerns, this paper employs a difference-in-difference (DiD) model to compare the outcome changes of innovation between firms that choose to go public (IPO firms) and firms that do not go public and remain private (private firms). In the analysis, the IPO effect is identified from differences in the long-run innovation. For the DiD model to be valid, a propensity score matching (PSM) is adopted to ensure that the IPO firms are compared to the private firms which have similar characteristics with the IPO firms in the same industry.

This study finds that IPOs have a statistically significant positive effect on firm innovation activities. In term of the number of patent applications, the innovation activities of firms grow 29% after going public. Going public helps firms to maintain the annual growth rates of patent applications. Compared to a decline in the innovation trends of private peers, the IPO firms have a continuously steady growth rate of patent applications after undergoing IPOs. Going public can delay the downward trend of patent growth rates in firms.

1.1 Research Contributions

This paper contributes to two strands of literature. Firstly, studies on the IPO effects have documented a wide range of post-IPO firm performance changes, such as the decline in profitability (Jain and Kini, 1994; Pagano et al., 1998; Pereira and Sousa, 2017) and the decreases on productivity (Chemmanur et al., 2010). This paper contributes to the literature that explores firm behavior following IPOs by proposing an identification strategy to isolate the IPO effect and focus on innovation activities around IPOs.

Second, this paper is also related to the firm innovation changes following an ownership transition from private to public, specially the ex post behavior of becoming publicly traded firms (Asker et al., 2011; Jain and Shao, 2015; Magri, 2009). It contributes to a body of studies about compared behaviors between public and private firms relating to innovation activities (Bernstein, 2015), investment sensitivity (Asker et al., 2011), external financing needs (Acharya and Xu, 2017), financing of innovation (Müller and Zimmermann, 2009) and corporate governance (Rosenthal et al., 2011).
2. Theoretical Background

2.1 The Motivation of Going Public

Why do firms decide to go public? The conventional wisdom is that going public is a stage in a firm’s growth (Pagano et al., 1996, 1998). Through IPOs, firms can enhance and prolong their growth stages (Brau, 2010). For example, Mikkelson et al. (1997) proves that firms that choose to go public experience a large growth in assets following IPOs. There is some truth in it, but the answer cannot generally explain the observed phenomenon in the real world of business. For instance, some large international firms, such as Cargill, IKEA and Deloitte, are still privately-held firms. Ingvar Kamprad, the founder of IKEA, expresses that a private firm can secure true financial independence to have a long-term view on investments and business development (Alderman, 2018). Being private prevents corporate ownership dilution from purchasing stocks by outside investors. Ownership centralization reduces the managerial discretion to corporate operations and investments (Stulz, 1990; Wies and Moorman, 2015). Compared to publicly traded firms, privately-held firms have less agency conflicts between managers and shareholders (Faccio and Lang, 2002). The lower agency cost resulting from the lower managerial entrenchment makes investment decisions more consistent, and thus promotes future innovation in firms (Dittmar, 2008; Faccio and Lang, 2002; Lian and Wang, 2019).

Although entering a stock market can lead to ownership dilution and agency problems, the latest IPO statistic report by Ritter (2018) proves that publicly traded equity is still a preferable financing alternative for many firms, particularly the firms in high-tech industries. A large body of the existing literature have elaborated on the motivations of firms to go public (Acharya and Xu, 2017; Kim and Weisbach, 2008; Pagano et al., 1998). One common motivation is an improved access to capital markets (Wies and Moorman, 2015). Unlike debt markets, stock markets have financial advantages by providing flexibility in funding alternatives (Pagano et al., 1998). A more flexible capital structure allows firms to have an optimal capital structure with a great amount of external funding from diversified investors (Rajan, 2012). An immediate cash inflow following IPOs can release firms from financial constraints by sharing upside returns and transferring investment risks to the diversified institutional and individual investors (Bernstein, 2015; Wies and Moorman, 2015). Going public improves the investment capacity
of firms through reducing investment riskiness resulting from the lowering bankruptcy cost of firms (Wies and Moorman, 2015).

Another motivation of firms to go public is to pursue an optimal capital structure (Brau, 2010; Chemmanur and Fulghieri, 1999; Pagano et al., 1998). According to the studies of Modigliani and Miller (1958), the irrelevance proposition theorem is that “the market value of any firm is independent of its capital structure” (Modigliani and Miller, 1958, p. 268). When corporate taxes are introduced, the tax shield of debt results in an optimal capital structure of 100% debt (Brau, 2010; Modigliani and Miller, 1963). However, too much debt can hurt the value of firms. Firms with high debt are more likely to pass up valuable investment opportunities than low-debt firms (Myers, 2001). The reason is that high-debt firms face higher threats of financial difficulty and bankruptcy (Barclay and Smith, 2005). They cannot afford the financial risks if investments fail. By considering the bankruptcy cost, the marginal cost of going public is lower than the cost of debt (Hall 2010). The current optimal capital structure is an optimal mix of debt and equity to minimize the weighted average cost of capital, in order to maximize the value of firms (Dittmar, 2008).

Different from the aim of pursuing an optimal capital structure, some firms are motivated to go public because of a poor access to debt. Due to highly variable returns, information asymmetry and a lack of collateral, debt financing is prohibitively costly or even unavailable for many small firms, especially technology firms (Carpenter and Petersen, 2002). Small high-tech firms seldom have sizable assets to pledge as collateral for debt finance, the collateral requirement discourages them from being innovative, especially considering the possibility of losing critical assets to creditors in the event of project failure (Carpenter and Petersen, 2002; Acharya and Xu, 2017). In addition, OECD indicates that small and medium sized enterprises (SMEs) specially in Europe are more vulnerable to the banking system with constrained access to lending arising in times of financial stress (Wehinger et al., 2015). This makes it hard for small high-tech firms to utilize debt to invest in a new idea or an invention. Asymmetric information causes banks hardly to evaluate the profit returns of an innovation project, so they require regular returns with a higher interest rate to cover the risks (Carpenter and Petersen, 2002; Wies and Moorman, 2015). The marginal cost of debt finance become high, which may lead a large potential funding gap to firms in the future. Debt finance in this case cannot fundamentally solve the financial stress of firms (Carpenter and Petersen, 2002). From this
perspective, going public becomes the default mode of funding to many SMEs to overcome the borrowing constraints (Pagano et al., 1996; Wies and Moorman, 2015).

Furthermore, some theories attempt to explain the motivation of going public from another standpoint. Firms choose to go public because of a “window of opportunity” (Helwege and Liang, 2004). The window is driven by information asymmetry. Firms take advantage of timing and start to issue over-priced equity when investors temporarily overestimate the future profitability of markets (Pagano et al., 1998). In the opposite case, firms wait and remain private until the positive information from previous IPOs is released, so that they do not issue equity at an undervalued price (Helwege and Liang, 2004). This signal model is characterized by the IPO popularity and divided into the “hot” and “cold” markets of IPOs (Helwege and Liang, 2004). The rationale of firms going public from this standpoint is the willingness of investors to purchase their stocks rather than the quality and characteristics of firms. In another word, the motivation of going public depends on external market conditions instead of firm internal demands.

2.2 The Determinants of Going Public

To assess the IPO effect on firm innovation, it is important to understand what drives firms to go public through their internal characteristics and external market environments. According to Pagano et al. (1998), the determinants of going public can be inferred from both the ex ante characteristics of firms and the ex post consequence of going public. In this paper, the determinants of going public are discussed from the characteristics of firms and the characteristics of industries they are in.

The internal characteristics of firms have close correlation with the decisions of going public (Pagano et al., 1998; Poulsen and Stegemoller, 2008; Rosenthal et al., 2011). For instance, high-tech and high-growth firms are more likely to go public because these types of firms are more inclined to have limited access to debt markets (Pástor et al., 2009). Due to the inherent uncertainty of innovation projects, banks concern more with the high probability of a project’s failure (Müller and Zimmermann, 2009). To reduce the risks of innovation investments, banks lend firms money with high interest rates or even decide to not lend at all (Müller and Zimmermann, 2009). Therefore, innovative firms choose to trade their equity publicly, since
IPOs can reduce the investment riskiness by sharing upside returns and releasing the financial constraints (Wies and Moorman, 2015).

According to Pagano et al. (1998), firm size is one important determinant of whether firms are likely to go public. Pagano et al. (1998) find a positive relationship between firm size and the likelihood of IPOs, due to the adverse selection. In general, investors are less informed than insiders about the true value of firms (Acs and Audretsch, 1987). The asymmetric information can adversely affect the quality of firms that are seeking new listings (Albornoz and Pope, 2004). To protect themselves, investors reduce the price they are willing to pay for IPO firms. Based on the previous studies (Albornoz and Pope, 2004; Pagano et al. 1998), younger and smaller firms are more affected by the adverse selection because they have lower visibility and shorter track record than those older and larger firms.

Some studies however indicate that firms with low fixed assets are likely to go public since the low fixed assets increase the marginal cost of debt finance (He et al., 2017; Kiyotaki and Moore, 1997). A high fixed asset ratio implies a higher collateral value and hence less stringent financial constraints (He et al., 2017). Firms with low fixed assets are more likely to have external financing needs. For example, Cassar (2004) finds that the share of fixed assets for firms in a start-up phase has a negative relationship with total leverage and outside financing. Carpenter and Petersen (2002) also find that IPOs are more likely to occur when firms face capital constraints and have fewer fixed assets.

In addition, profitability also plays a vital role in a decision to go public (Pagano et al., 1998). One opinion is that profit has a positive correlation with IPOs since less profitable firms may not afford the cost of being public (Rosenthal et al., 2011). Highly profitable firms are more willing to go public, since their earning abilities can attract more outside investors and enhance their reputations to attract more talented employees (Wies and Moorman, 2015). On the other hand, a profitable firm has less demand for external equity financing, which lead to a negative impact on IPOs (Pagano et al., 1998). Less profitable firms can be motivated to go public in order to solve their financial constraints and enhance their competitive advantages by continuously invest in core businesses (He et al., 2017). Return on asset (ROA) i.e. the ratio of net income to assets is usually used to measure the profitability of firms (Bernstein, 2015; Rosenthal et al., 2011).
Not only do the firm internal characteristics have influences on firms going public, so do the external environments. According to Maksimovic et al. (2001), the timing and choice of financing depend on three determinants: the public perception to industry's viability, the probability of a superior technology occurrence and the payment ability of new entrants to the initial R&D cost. Firms are likely to go public, where an industry 1) is perceived to be viable, 2) has a low first-stage cost, and 3) has a low probability of replacement by more technology advanced rivals (Maksimovic et al., 2001). Simply put, the industry characteristics also have an impact on whether firms undergo IPOs. For instance, firms in a high-tech industry are more likely to go public than the ones in a manufacturing industry. The reason is that the high-tech industry is recognized as a more promising industry with low entry barriers and high threats of substitutes (Carpenter and Petersen, 2002). It is easier for firms in such industry to have high variable returns, asymmetric information and a lack of collateral, which causes a poor access to debt finance (Bulk and Johansson, 2015). Therefore, publicly equity trading in form of IPOs is a vital funding source for firms in such industries, which permits a significant increase in firm size and innovation investment (Carpenter and Petersen, 2002).

2.3 The Financing of Innovation

A well-functioning financial market plays a central role in driving economic growth by spurring technological innovation (Fang et al., 2014; Kerr and Nanda, 2014). One reason is that a well-functioning financial market is believed to allocate capital to firms with the biggest potential to implement new innovative processes and to commercialize new technologies (Kerr and Nanda, 2014). Firms can choose among three types of innovation financing: internal financing, external debt and external equity (Müller and Zimmermann, 2009). In a frictionless world, firms do not need to consider the sources of innovation finance since the financing alternatives do not impact the nature of innovation (Kerr and Nanda, 2014). However, with financial friction, some characteristics of an innovation process influence how firms choose the sources of capital to invest in innovation projects.

First, an innovation process is high cost with a long duration (Hall and Lerner, 2010). Different from other ordinary investments, the investment of innovation contains a large amount of wages and salaries of highly educated scientists and engineers (Hall, 2010). Their efforts create the knowledge-based intangible assets of firms and thus may bring profits in the future years. However, the process of establishing knowledge-based assets is high cost, since
it is costly to invent a new technology and prevent talent loss (Hall and Lerner, 2010). It is often impossible to accurately measure inputs into an innovation process (Kerr and Nanda, 2014). Firms that require financing for their innovation projects usually consider internal financing first, since it has the lowest capital cost (Myers, 2001). However, innovative firms often have a high percentage of intangible assets (Kerr and Nanda, 2014), and the internal financing rarely meet their financial needs of innovative projects (Wang et al., 2016). Many innovative firms choose the external financing to supplement funds.

Second, an innovation process is inherently uncertain (Kerr and Nanda, 2014). An innovation project usually contains a high probability of failure combined with a possibility of high expected returns (Müller and Zimmermann, 2009). However, no one knows the probability associated with the outcomes. This makes it harder to evaluate potential innovation projects specially the ones may require funds. Due to the fixed interest payment system, banks are not particularly interested in the high returns of successful outcomes. They concern more with the probability of project failure, and thus require high interest rates to reduce the investment risks, or even decide to not lend money (Müller and Zimmermann, 2009). Going public can overcome the problems since it shares the upside returns and has no regular fixed dividends requirement (Myers, 2001).

Third, the quality of innovative projects is difficult to measure (Müller and Zimmermann, 2009). Many innovative firms keep both their technological knowledge and the details of innovation projects’ secrets (Müller and Zimmermann, 2009). This behavior is to protect their core technologies and enhance their market competitiveness. However, it results in asymmetric information between insiders and outsiders, and further causes adverse selection and moral hazard (Müller and Zimmermann, 2009). Without detailed information, outsider investors have more difficulty to distinguish the good projects from bad ones (Hall and Lerner, 2010), and thus they prefer to underestimate the equity value of firms to protect their self-interests (Myers, 2001). Trading equity publicly can be one financing alternative for firms to reduce the information asymmetry (Hall and Lerner, 2010). The full disclosure requirement of going public can provide good information to investors, but it may also reduce the quality of innovation projects by revealing information to their competitors (Hall and Lerner, 2010).
2.4 Going Public and Innovation

Going public can be one alternative for innovative firms to finance innovation. It overcomes internal financial constraints, a lack of collateral and information asymmetry. Many previous studies indicate that going public has significant effects on firm innovation (Fang et al., 2014; He et al., 2017; Wang et al., 2016; Wu, 2007). The relationship between IPOs and firm innovation is a dilemma. With all trade-offs, whether going public boosts or impedes firm innovation is an empirical question (Bernstein, 2015). Theoretically, in a frictionless financial market, IPOs should have no bearing on subsequent innovation activities (Bernstein, 2015). Under the financial friction, however, the financing consequence of IPOs on firm innovation uncovers both positive and negative effects (Bernstein, 2015; He et al., 2017; Wies and Moorman, 2015).

On the one hand, going public has a positive impact on firm innovation activities (He et al., 2017; Wies and Moorman, 2015). IPOs provide financial advantages for innovation activities. It improves firms access to capital, which can lead to an increase in firm innovation activities (He et al., 2017). An immediate cash inflow following IPOs encourages firm innovation by releasing the financial stress which is widely regarded as a major bottleneck for firm innovation (Wies and Moorman, 2015). The research of financial constraints and SMEs innovation in Finland also proves that financial constraints hold back firm innovation (Hyytinen and Toivanen, 2005). In addition, going public allows outside investors with diversified opinions to participate, which enhances the capitalization and diversification of innovation investments. (Acharya and Xu, 2017). Beside these, IPOs can boost firm innovation by enhancing the competitiveness of firms in a product market (Wies and Moorman, 2015). Going public enhances firm recognition and reputation (Brau and Fawcett, 2006), which can strengthen bargaining power to suppliers and spread reliable quality signals to customers. Furthermore, it improves the human capital by attracting more high-skilled employees (Wies and Moorman, 2015). All these factors contribute to firm innovation activities.

On the other hand, going public impedes firm innovation activities (Bernstein, 2015; Fang et al., 2014). IPOs may lead to ownership dilution. The decentralized ownership may interfere with the consistency of future strategy and the investment of innovation (Lian and Wang, 2019; Wies and Moorman, 2015). The disclosure requirement of IPOs leads to the spillover of innovative core information to competitors, which damage firms’ economic benefits from their
innovation (Celikyurt et al., 2010; Wies and Moorman, 2015). Short-term stock expectation can also have a detrimental effect on firm innovation (Fang et al., 2014). A group of investors presumably chase short-term performance as they invest heavily in firms with greater expected near-term earnings. The outside short-term return pressures, the career concerns and the takeover threats incentivize the management to pursue current earnings and market price by cutting the innovation investments (Bernstein, 2015; Giannetti, 2003; Hall and Lerner, 2010; Wies and Moorman, 2015). Furthermore, innovation with novel projects is a time-consuming task that often seldom leads to returns (Fang et al., 2014). Firms therefore are also willing to sacrifice their future innovation, growth and long-term market cap for current profits. It is for preventing the firm equity from being undervalued and being a victim of a hostile takeover (Fang et al., 2014).
3. Data Collection and Construction

3.1 IPO Data

To examine firm going public and its subsequent effects on innovation activities, this paper collects a set of firms that have completed IPO filings in Sweden from 1999 to 2014. IPO filings are collected from both Nasdaq OMX and Nyemissioner.se. The data from Nasdaq OMX includes all listed firms that took place in Sweden on both Nasdaq Stockholm and Nasdaq First North from 1999 to 2014. The data from Nyemissioner contains all Swedish listed firms that occurred in the Spotlight Stock Market (Aktietorget) and Nordic Growth Market (NGM) from 2005 to 2014.

Nasdaq Stockholm is the main stock market of Nasdaq in Sweden (Nasdaq Nordic, 2019) and First North is the Nasdaq growth market that provides an alternative stock exchange for smaller Swedish firms (Nasdaq First North, 2019). Spotlight Stock Market, also named Aktietorget before 2018, is a less regulated Swedish stock market for growth firms to be listed (Spotlight Stock Market, 2019). Nordic Growth Market (NGM) is a regulated exchange that delivers trading, exchanges technology and public firm service in Sweden (Nordic Growth Market, 2018). NGM contains two capital markets, NGM Equity and Nordic MTF. They provide listing and trading services in equities for small and medium sized firms in Nordic countries.

The reason for including these four stock markets in Sweden is that many growth and technology firms prefer to list on the First North, Spotlights and NGM exchanges since these stock markets are not fully regulated (Vismara et al., 2011). With less stringent listing requirements, the growth markets have satisfied the appetite for the new issues of stock exchange. The growth markets allow firms to focus more on their business and development as well as avoid high administration cost within cumbersome procedures and lengthy time.

In total, this paper collects 686 Swedish firms, including 429 firms from Nasdaq, and 257 firms from both Spotlight and NGM. The firms contain new issues, re-listings, secondary listings and spin-offs. To analyze the true causal effect of IPOs on firm innovation, I solely include the firms that are new issues. The relisted and secondary listed firms are excluded, because they have already absorbed the IPO effects in their initial listings. The firms that are
spin-offs have the similar reason to be excluded since they, as a part of large publicly traded firms, have already achieved certain listing effects. In addition, the foreign firms that have no organizational numbers in the Swedish Tax Office are excluded, because they cannot be traced in the Swedish market. Lastly, some firms have been regarded as new issues twice in different stock markets and this paper only counts the firm once in the earliest listing year. For example, one firm was listed on Nordic MTF in 2006 and issued new stocks on Nasdaq Stockholm in 2011. Nordic MTF and Nasdaq both regarded the firm as a new issue in their markets in 2006 and 2011 respectively.

These criteria combined reduce to 476 new issues of 686 Swedish firms, approximately 69.4% of IPO firms or an average of 29.75 IPOs per year. Figure 1 displays the number of new issuing firms from 1999 to 2014. One can observe that the IPO events peak in 2007 and 2014, and downturn in 2001-2004 and 2009-2012. The trend is in line with the “window of opportunity” studies in terms of the “hot” and “cold” IPO markets (Helwege and Liang, 2004). When the time frame is divided into two time periods, one can observe that the IPO events are averagely higher in the second eight years than the first eight years. The upwards trend result could be increased IPO events on First North, the newly founded Swedish growth market in 2006. The reason could also be the available IPO data of Spotlight and NGM starts from 2005.

Figure 1. The Number of IPO Firms from 1999 to 2014
3.2 The Measure of Firm Innovation

According to the studies of Edwards et al. (1984, p. 1), technical innovation can be defined as “a process that begins with an invention, proceeds with the development of the innovation, and results in the introduction of a new product, process or service to the marketplace”. Innovation begins with an invention that firms choose for development and introduce to market (Katila and Shane, 2005). Practically it is impossible to track firm innovation activities by evaluating a new idea or an invention, since the cost of an invention does not separately display in the firm annual reports (Katila and Shane, 2005).

Patents can provide a signal to outside investors and users, which makes it easier to evaluate the innovation activities of firms (Hottenrott et al., 2016). Economic theory regards patents as an important instrument to foster innovation, especially regarding its implications to economic growth (Jalles, 2010). Additionally, it can create property rights to the knowledge and it is an effective instrument to reduce information asymmetries between firms and outside investors (Hall, 2018; Hottenrott et al., 2016). Patenting activities can reflect the quality and extent of firm innovation, and thus patents are used as a universally accepted proxy variable to measure innovation or technical progress (Bernstein, 2015; He et al., 2017). Unlike R&D expenditure, patent information is easier to access in both publicly traded and privately held firms (Bernstein, 2015).

The outcomes of technological innovation can be measured by the number of patents that firms have granted, but it does not mean patents can comprehensively represent the degrees of firm innovation. Firms may not attempt to patent all their innovations because of time delays, high administration fees, disclosure requirements and the availability of alternative way to protect innovation (Wies and Moorman, 2015). The value of patents as a proxy for innovation success is limited by the big variance between significance and value. It renders patents a noisy indicator of R&D success (Bernstein, 2015; Hall et al., 2005). Patents cannot fully measure the value of innovation, since some cover useless technologies or products that are economically irrelevant (Comino and Graziano, 2015). Although patents cannot be an effective measure of firm innovation, it is still a useful proxy of firm innovation to this paper. Instead of utilizing patents to measure the innovation value, this paper attempts to evaluate the changes of firm post-IPO innovation by using patent counts in the long time series. The trouble issues of patents above can be ignored.
3.2.1 Patent Data

An extensive literature in economics demonstrates that patenting activities are widely accepted as a measure of reflecting the firm innovation (Bernstein, 2015; Hottenrott et al., 2016; Jalles, 2010). Importantly for this paper, patent information, unlike R&D expenditures, is available for both public and private firms from the European Patent Office’s statistical database PATSTAT and the Swedish House of Finance’s PatLink dataset project. This paper attempts to investigate firm innovation by measuring the number of patent applications, thus the research sample is restricted with at least one successful patent application in an eight-year time window i.e. three years before and four years after the IPO filing year (He et al., 2017). The goal of collecting patent counts in an eight-year time window is to prevent the effects from short-lived firms.

Therefore, the patent applications of firms per year is treated as a proxy for the firm innovation activities. PatLink contains global patent applications of Swedish firms with their organizational numbers from 1996 to 2016. Through the organizational numbers, the IPO firms is manually matched with their patent applications in the eight-year time window from 1996 to 2016. For the patent counts in 2017 and 2018, this paper uses the latest names of IPO firms to collect in PATSTAT.

In the end, 134 IPO firms have at least one patent in the eight-year time window, i.e. three years before and four years after IPO filing year, from 1996 to 2018. The number of patent applications in each year is calculated from PatLink and PASTAT. In this paper, a natural logarithm of annual patent counts plus one is adopted. This is a common method to treat raw number of patents, which is applied in many prior literature (Bernstein, 2015; He et al., 2017; Lütkepohl and Xu, 2012). Since the IPO firms do not have patent applications every year, the natural logarithm of annual patent counts plus one can make each observation valid. The natural logarithmic transformation is used because it can obtain a more homogenous variance of a series and make the distribution more normal (Lütkepohl and Xu, 2012). It is a convenient method of transforming a highly skewed variable into one that is more approximately normal (Lütkepohl and Xu, 2012). To compare the variance of raw patents and natural logarithm of patents, a descriptive statistic table is established in Appendix (see Table 7 in Appendix). One can observe that the standard deviation of natural logarithm form is smaller than the one of the
raw patent counts. It means the natural logarithm form make patent counts have a smaller variance of observations.

### 3.3 Firm-level Data

To investigate the IPO effect on firm innovation, two groups need to be compared to estimate the IPO effect. One group is a treatment group that contains the 134 IPO firms. Another group is a control group that contains the private firms that have a similar financial and innovative situation as the IPO firms before IPOs occur. In this paper, the annual reports of IPO firms are collected from Business Retriever. Business Retriever is a company database with information about all Swedish companies, individual companies and groups. The database includes board information, annual reports, group structure, income statement and balance sheets. The financial information of 134 IPO firms are manually collected in their IPO filing year on Business Retriever by using the organizational numbers. There are 134 observations of annual reports in the 134 IPO firms.

The financial information of private firms come from the Swedish House of Finance’s Serrano database. The Serrano database provides a comprehensive financial history of Swedish firms in various industries. This database consists of financial statement data and bankruptcy information recorded from the Swedish Companies Registration Office (Bolagsverket), general firm information data from the Statistics Sweden (SCB) and the group information data from Bisnode’s Group Register. For instance, firm name, organizational number, industry, legal forms as well as annual income statements and balance sheets.

The Serrano database contains about 11 million annual reports of Swedish legal entities from 1998 to 2016. To obtain the observed population scope of private firms, the data of annual reports of all Swedish legal entities is filtered. This paper selects all annual reports of privately-held firms that have patent assets from 1999 to 2014. The reason is to collect all observations of private firms may contain patents in the observed period and exclude the firms with no patent assets. In the end, there are 89,895 annual reports of privately-held firms that contain patent assets from 1999 to 2014. Since the Serrano database does not contains the information of patent applications, the organizational numbers are used to connect the firm financial data in the Serrano database from 1999 to 2014 and firm patent data in PatLink from 1996 to 2016. The information of patent applications in 2017 and 2018 are collected from PATSTAT through
matching the latest name of the observed private firms. These 89,895 firm-year observations of private firms are used to match the 134 IPO firm-year observations.
4. Empirical Strategy

4.1 Research Methods

The goal of research is to properly assess the IPO effect on firm innovation in the years following IPOs, i.e. to compare the trends of innovation activities between the IPO firms and the private firms that have similar financial situations with the IPO firms. Theoretically, if an IPO event is truly random it is good enough to just compare the ex-post innovation outcomes of the firms that undergo IPOs to the ones that remain private. However, the data used in this paper is observational data instead of completely randomized data. To reduce the bias caused by a non-random treatment, this paper decides to use the combination of a difference-in-difference (DiD) and a propensity score matching (PSM) methods.

A difference-in-difference (DiD) model is a common statistical method used for evaluating the effects of an event in a quantitative research in the social sciences (Stuart et al., 2014). It is numerously employed to mimic an experimental research design by using observable secondary data (Clair and Cook, 2015), and can calculate the effect of a treatment on an outcome by comparing the average change over time in the outcome variable for a treatment group to a control group (Angrist and Pischko, 2008). In addition, the DiD model can rely on a less strict exchangeability assumption, for instance, without treatment the unobserved differences between the treatment group and the control group are the same over time (Yan and Hongbing, 2018).

Due to the above reasons, the DiD model is employed to eliminate the unobservable variables in this paper. He et al. (2017) indicated that a legitimate concern of panel data regression results is an endogenous problem. There is a possibility that both IPO decisions and firm innovation are influenced by some unobservable characteristics of firms, a confounder. For instance, a rapid growing firm is more likely to go public, as well as it reaches a growth stage whereby it increases the innovation activities no matter how IPOs affect. The DiD model can overcome the endogenous problem. It provides unbiased effect estimates whether the trend over time is the same between the treatment group and the control group, in the absence of the intervention (Stuart et al., 2014). The DiD model rules out some determinants that are correlated with IPO events and innovation in both treatment group and control group (He et al., 2017). For example, an industry can simultaneously has the same likelihood of IPO stimulation
to both treatment group and control group. The DiD model can rule out the possibility of industry effects.

However, a concern of the DiD model is that the treatment group and the control group may differ in ways that affect the trends over time (Stuart et al., 2014). In order to isolate the IPO effect without intervention, the control group need to be as similar as possible to the treatment group in all dimensions before IPO events occur. To make the DiD model valid, a propensity score matching (PSM) method need to be adopted in this paper. In practice, the combination of PSM and DiD is commonly used to investigate the effect of a treatment in the observational studies, such as the IPO effect on firm innovation or training education effect on labor salary (He et al., 2017; Stuart et al., 2014; Yan and Hongbing, 2018). PSM allows the DiD model to overcome the dimensionality problem and reduce the selection bias (Yan and Hongbing, 2018). In this paper, PSM is used to build the control group, since a good control group can reduce the bias in estimating the IPO effect and allows to reduce the likelihood of confounding when analyzing the non-randomized, observational data (Haukoos and Lewis, 2015).

4.2 Building the Control Group

PSM, first introduced by Rosenbaum and Rubin (1983), is an advanced matching technique that is commonly used to minimize selection bias in the non-randomized experimental studies (Nian et al., 2018). It is a balancing score to ensure the distribution of baseline covariates is similar between the observations of treatment group and the observations of control group (Austin, 2011; Stuart et al., 2014; Yan and Hongbing, 2018). This technique is defined as the probability of receiving the similarity of those covariates between the treatment group and the control group (Rosenbaum and Rubin, 1983). The key of PSM is to estimate the counterfactual outcome under no treatment for a treated observation by using individuals from the control group that share the same observed characteristics (Heckman et al., 1998; Imai, 2005; Nian et al., 2019). It is sufficient to remove the bias due to all observed covariates (Rosenbaum and Rubin, 1983). PSM allows for reduction or elimination of the confounding effects when using observational data to estimate the treatment effects (Austin, 2011).

Unlike randomized experiments, a true propensity score is not known in the observational studies, therefore it is estimated by running a logistic regression model in practice (Angrist and Pischko, 2008; Austin, 2011). The estimated propensity score is the predicted probability of
treatment derived from the fitted regression model. According to Rosenbaum and Rubin (1983), PSM can be defined as the conditional probability of treatment given covariates:

\[ e(x) \equiv Pr(T = 1|x) \quad (1) \]

In the Equation (1), the function \( e(x) \) is the propensity score, which is the conditional probability of treatment given observed covariates. \( T \) is the dummy variable, which equals to 1 when IPO events occur and equals to 0 when IPO events do not occur. \( x \) is the observed covariates. The Equation (1) is used to obtain \( e(x) \), the propensity score, of each private firm in the observed population and then select the highest score private firms to match the IPO firms. The set of selected private firms is the control group.

PSM entails the forming matched sets of treated observations in the treatment group and the non-treated observations in the control group who shares the similar value of propensity score \( e(x) \) (Austin, 2011; Rosenbaum and Rubin, 1983). The most common implementation of PSM is one-to-one matching, in which the pairs of treated observations and non-treated observations are formed, and matched observations have the similar values of propensity score (Austin, 2011). Once a matched sample is formed, the treatment effect can be estimated by comparing outcomes between treated observations and non-treated observations in the matched sample. In this paper the outcome trends of firm innovation are continuous, therefore the IPO effect can be estimated as the difference between the mean outcomes of observations in the treatment group and the ones in the control group (Austin, 2011).

Although PSM is suitable to assemble comparable study groups, the quality of matching depends on the quality and size of available matching data (Haukoos and Lewis, 2015). Before the PSM technique runs to get the paired IPO firms and control firms, there are three criteria that observations in the control group need to meet (Bernstein, 2015; He et al., 2017). It is to make sure the control firms selected from the ‘right’ scope of private firms.

First, it has the same two-digital industry code of Swedish Industrial Classification (SNI) as the IPO firms, so that the matching firms stay in the same industry as the IPO firms. Second, it should be a private firm in an eight-year time window i.e. three years before and four years after the IPO filing year. This makes sure the selected matching firms have no influence of IPOs. Third, it has at least one patent in the eight-year time window. Since the firm innovation
is measured by the number of patent applications, the matching firms also need to have at least one patent during the sample period, otherwise the estimate bias is increased by including no patent firms.

In addition, four covariates are selected to obtain the propensity score and match the IPO firms with selected control firms during three year before and the IPO filing year. The four covariates adopted in this paper are the same as the previous IPO studies (Bernstein, 2015; He et al., 2017). The covariates are (1) firm size, measured by the natural logarithm of total asset, Ln (TA); (2) liquidity, a reflection of controlling for financing-restrictions, measured by cash divided by total asset, C/TA; (3) profitability, measured by net income divided by total asset, ROA; (4) firm innovation, measured by the mean of natural logarithm of patent counts plus one in four years, i.e. three year before and the IPO filing year, Ln (Pre3-0). The choice of Ln (AT), C/AT, ROA and Ln (Pre3-0) are motivated by the fact that they are suitable proxies for firm size, liquidity, profitability and innovation (Bernstein, 2015; He et al., 2017). The matching result is shown in the Table 1.

Table 1. Propensity Score Matching Results

This table provides the matching results of PSM. The PSM regression result is in Appendix Table 6. The matching tolerance is 0.05. The IPO firms are one-to-one matched with the control firms. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th>IPO Firms</th>
<th>Private Firm Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>134</td>
</tr>
<tr>
<td>Number of Exact Matches</td>
<td>0</td>
</tr>
<tr>
<td>Number of Fuzzy Matches</td>
<td>96</td>
</tr>
<tr>
<td>Number of Unmatched Cases</td>
<td>38</td>
</tr>
</tbody>
</table>

The Table 1 displays that there are no private firms have exact same financial and innovative situations with the IPO firms. In order to reduce the risk of bad matches, i.e. the closest neighbor is far away, a 5% tolerance level is imposed on the maximum propensity score distance (Caliendo and Kopeinig, 2005). Within the 5% matching tolerance, 96 IPO are fuzzy matched with one control firms, resulting in an average match rate of 72%. There are 38 IPO firms cannot be matched within the 5% matching tolerance.
4.2.1 The Baseline Year

In this paper, the baseline year of firm financial information is the IPO filing year, which is the same as Bernstein’s study (Bernstein, 2015). In the IPO filing year, the innovative and financial situations stimulate firms to be most likely to go public. This can reduce the likelihood of selection bias. Among the IPO firms, 78% firms have negative net incomes in their annual reports in the IPO filing year. The paired control firms should have the same financial constraints as the IPO firms. The financial constraints of IPO firms at the IPO filing year could be one reason for Swedish firms to undergo IPOs. The negative net incomes might be caused by firms spending a lot of money on innovation activities before they attempt to undergo IPOs. It could also be that firms decide to go public because they attempt to solve the financial constraints. To ensure the estimated IPO effect valid, the control firms should have similar financial situations and innovation activities as the IPO firms at the IPO filing year.

Another reason for applying the IPO filing year as the baseline year is to consider IPOs may not affect firms’ patent applications in the IPO filing year. The IPO process typically starts six months before the intended first day (GLI, 2018). It could take longer time to complete IPOs than firms expect. Besides that, the patenting activity is a long-term investment, it is hard to have rapid outcome increase within a year. Many firms attempt to boost the number of granted patents before they issue IPOs, in order to make their firms more attractive to investors. Using the IPO filing year can reduce the estimate bias, since the patent counts could abnormally increase in the year before the IPO filing year. By considering the time consumption of IPO process and the firm intention of granting patents, it is reasonable to use the IPO filing year as the baseline year.

4.3 Similarity Test of Control Group

To test whether the control group share the similar distributions of covariates with the IPO firms, an independent-sample T-test is adopted on a 5% significant level. This is used to compare the mean values of two independent groups in order to determine whether there is statistical evidence that the associated population means are significantly different (Yeager, 2019). In this paper, it is used to compare the mean values of four covariates between the treatment group (IPO firms) and the control group (Control firms) in the previous four years i.e. three year before and the IPO filing year (See Table 2).
Table 2. Statistic Summary Between IPO Firms and PSM Control Group

This table provides key summary statistics, comparing IPO firms and Control firms on a 5% significant level. Average innovation measures are calculated over the previous three years up to (and through) IPO filing year. Financial characteristics are at the time of the IPO filing. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th>Innovation measures in the four years until IPO filing year</th>
<th>IPO firms</th>
<th>Control firms</th>
<th>Mean Difference</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ln (Pre3-0)</strong></td>
<td>0.85</td>
<td>0.83</td>
<td>0.02</td>
<td>0.492</td>
</tr>
<tr>
<td><strong>Ln Pre_3</strong></td>
<td>0.72</td>
<td>0.76</td>
<td>-0.04</td>
<td>0.873</td>
</tr>
<tr>
<td><strong>Ln Pre_2</strong></td>
<td>0.83</td>
<td>0.83</td>
<td>0.00</td>
<td>0.454</td>
</tr>
<tr>
<td><strong>Ln Pre_1</strong></td>
<td>0.92</td>
<td>0.88</td>
<td>0.04</td>
<td>0.084</td>
</tr>
<tr>
<td><strong>Ln Pre_0</strong></td>
<td>0.92</td>
<td>0.85</td>
<td>0.07</td>
<td>0.099</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Financial characteristics in the IPO filing year</th>
<th>IPO firms</th>
<th>Control firms</th>
<th>Mean Difference</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ln TA</strong></td>
<td>11.27</td>
<td>11.38</td>
<td>-0.11</td>
<td>0.358</td>
</tr>
<tr>
<td><strong>C/TA</strong></td>
<td>0.26</td>
<td>0.23</td>
<td>0.03</td>
<td>0.545</td>
</tr>
<tr>
<td><strong>ROA</strong></td>
<td>-0.18</td>
<td>-0.16</td>
<td>-0.02</td>
<td>0.330</td>
</tr>
</tbody>
</table>

In Table 2, none of the covariates have significant differences between the IPO firms and the control firms on a 5% significant level. For example, Ln (Pre3-0) is the mean value of natural logarithm of patents over the previous three years up to (and through) the IPO filing year. One can observe the mean difference of Ln (Pre3-0) between IPO firms and control firms is 0.02, and it is not statistically significant (0.492). This means the observed difference in the means of patent counts between the IPO firms and the control firms has no significant difference. To observe the rest three covariates Ln (TA), C/TA and ROA, they also have no significant differences. It shows that the control group has the same or similar innovative and financial situations as the IPO firms in the three year before and the IPO filing year.

4.4 Empirical Design of the DiD Model

In this section, a specific regression model is elaborated to measure the IPO effect on firm innovation. It compares mean values of patent counts in the natural logarithm form between IPO firms and control firms in an eight-year time window around IPOs. The DiD model here
is formally employed to test the observed effects. The DiD regression model can be formalized as followed (Wing et al., 2018):

\[ Y_{i,t} = \alpha + \beta (Post_{i,t} \times IPO_i) + \gamma Post_{i,t} + \delta IPO_i + firm_i + year_t + \epsilon_{i,t} \]  

(2)

where \( Y \) is the dependent variable, i.e. Ln (patents), \( i \) represent the firm \( i \) in the sample, \( t \) is a time-factor expressed in years. In the Equation (2), the term \( IPO \) is a dummy variable which equals to 1 for firms that undergo IPOs and 0 for firms that remain private. \( Post \) is another dummy variable for the pre- and post-period, equals to 1 when the year is after the IPO filing year and 0 for the year before the IPO events occur. The term \( firm_i \) is the firm fixed effect and the term \( year_t \) is the year fixed effect. The term \( \beta \) is the estimated average change given IPOs have occurred. The \( \beta \) therefore can be formulated as followed (Wing et al., 2018):

\[
\hat{\beta} = (\bar{y}_{T,2} - \bar{y}_{T,1}) - (\bar{y}_{C,2} - \bar{y}_{C,1})
\]  

(3)

where \( T \) is the treatment group of IPO firms and \( C \) represents the control group of control firms. 2 is the post-IPO years, i.e. four years after the IPO filing year, and 1 is the pre-IPO years i.e. three years before and the IPO filing year. The result of the Equation (3) is the estimated result of this paper, i.e. the estimated IPO effect on Swedish firm innovation. Figure 2 illustrates the theoretical presentation of IPO effect that this paper aims to isolate by estimating the differences of mean values between the IPO firms and the control firms.
Equation (2) includes both firm fixed effect $firm_i$ and year fixed effects $year_t$, which is referenced from the prior IPO studies (Boucly et al., 2011; He et al., 2017). Firm and year fixed effects are employed here to control for time-invariant confounders (Bertrand et al., 2004; Boucly et al., 2011; Strumpf et al., 2017). The reason is that fixed effects possess the ability to control for both observed and stable unobserved confounders (Strumpf et al., 2017). They can lead greater credibility to the assumption to estimate unbiased causal effect (Strumpf et al., 2017). The term $IPO_i$ is subsumed when the firm and year fixed effects are included in the Equation (2), since the term $IPO_i$ is a time-invariant dummy variable (He et al., 2017; Strumpf et al., 2017). The $IPO$ dummy therefore is not reported in the result tables in the Chapter 5.

According to Bertrand et al. (2004), many published papers ignore the issue of serial correlation in the DiD regressions. To illustrate the serial correlation problem, Bertrand et al. (2004) have generated the placebo tests on the estimate results of existing papers. They find the ‘effect’ at 5% significance works on the 45% of the placebo interventions. This trouble is caused by the serially correlated independent variable of interest in the DiD model. This creates the bias and underestimation of standard errors (Bertrand et al., 2004). As recommended by
Bertrand et al. (2004) and Boucly et al. (2011), this paper decides to cluster error terms at the firm level. The same method is also employed by the prior IPO studies (He et al., 2017).

4.5 Limitations of Research Methods

Although it is proven to be feasible by many previous studies (He et al., 2017; Stuart et al., 2014; Yan and Hongbing, 2018), the combination of DiD and PSM methods contain inherent limitations (Garrido et al., 2014; Nian et al., 2018; Stuart, 2010; Zhou et al., 2016).

One limitation of PSM is that it can only control for the observed covariates (Nian et al., 2018). It cannot account for the unobserved factors that may influence the outcome and the treatment assignment in the matching procedure (Garrido et al., 2014). Due to the latent factors, any hidden bias may remain after matching (Garrido et al., 2014). This is always a limitation of non-randomized studies, which makes assessment of unconfoundedness assumption difficult (Nian et al., 2018). In addition, it is a challenge to deal with multiple covariates (Stuart, 2010). Due to the computational and data problems, when there are more than just a few covariates, it can be very difficult to find matches with close or exact values of all covariates (Stuart, 2010). For example, Chapin (1947) finds only 23 matched pairs on six categorical covariates within 671 treated observations and 523 control observations. Applying PSM could result in a small sample size, since unmatched observations are dropped from the final sample (Zhou et al., 2016). In this paper, four covariates are applied to find the 96 matched pairs on a 5% matching tolerance level.

The limitation of DiD is finding a control group for which the two main assumptions are met (Dimick and Ryan 2014; Zhou et al., 2016). The two assumptions are parallel trends and common shocks (Dimick and Ryan, 2014). The parallel trend assumption states that in the absence of treatment, the average outcomes of the treatment group and the control group should follow parallel paths over time (Zhou et al., 2016). The common shock assumption states that any event that occurs during or following the intervention, should equally affect both the treatment group and the control group (Zhao et al., 2016). If any of the assumptions do not hold, then there is no guarantee that the estimated results of the DiD model is unbiased (Zhao et al. 2016). For instance, to ensure that the DiD model accounts for unobserved variables, the parallel trends of both groups should be same before the treatment is intervened (Dimick and Ryan, 2014). If the trends are significantly different prior to the intervention, the estimated
result of the DiD method would be biased. Therefore, the limitation of this method is in finding the treatment and control groups that can meet these two assumptions.
5. Results

5.1 Empirical Evidence

Figure 3 illustrates the IPO effect on innovation activities by measuring the mean values of patent counts in the natural logarithm form. To obtain this figure evidence, 96 IPO firms and 96 control firms are used to observe the patent trends in an eight-year time window i.e. three years prior and four year post the IPO filing year. In the Figure 3, the black line with spots represents the patent trend of IPO firms and the grey line with squares denotes the patent trend of control firms. The spots and squares are the mean values of patents in the natural logarithm form in each adjusted year.

As one can observe, the patent trends of IPO firms and control firms are highly similar from Year -3 leading up to Year 0. It provides another piece of evidence for the valid PSM method as well as the parallel trend assumption of the DiD model. Moreover, it also provides an evidence for the baseline year choice. The patent trends of IPO firms and control firms start to differ after the IPO filing year. The patent trend of IPO firms is steady from Year -1 to Year 2. It indicates that the IPO firms have a similar growth rate of patent applications in these three years. From Year 2, a decline occurs in the IPO firms until Year 3, and a stable growth rate occurs again between Year 3 and Year 4. In contrast, the patent trend of control firms reduces directly from the IPO filing year but maintains a steady trend from Year 1 to Year 3. A decline occurs again in the fourth year after the IPO filing year.
Importantly, the patent trend of IPO firms from Year 2 to Year 4 is parallel with the patent trend of control firms from Year 0 to Year 2. The changes of these two-period trends are almost the same. This can be explained by the IPO effect starting to disappear from the innovation activities in the second-year post IPO events. The IPO effect on the patent growth rate of IPO firms could last just two years. After Year 2, the patent trend of IPO firms comes back to the ordinary tendency, i.e., the trend without the IPO effect. Through comparing the patent trends from Year 0 to Year 4, one can see that the IPO firms have slower declined tendency than the control firms. It demonstrates IPOs have positive effects on firm patenting activities. IPOs can maintain the growth rate of patent applications and delay the downward trend of patenting activities in firms.

5.2 Regression Result

To formalize the results discussed above, the empirical evidence is supplemented by a regression analysis. The Equation (2) in the section 4.3 is employed to test the IPO effect on firm patenting activities. The DiD regression model is built in two different time-window samples. First one is an eight-year time window sample, i.e. three years before and four years after the IPO filling year. Second is a five-year time window sample, i.e. two years before and
two years after the IPO filing year. There are two reasons to adopt a five-year time window sample. First, it is referenced by Bernstein (2015). In Bernstein’s study (2015), the IPO effect is identified from differences in innovation over a five-year period. It implies that IPO effect can be identified in a five-year time window. Second, it considers the empirical evidence in the Section 5.1. As mentioned in the previous section, the IPO effect could dissipate after two years post IPO events. The IPO effect could be underestimated by adding more years after the IPO filing year. The Table 3 displays the key regression estimates of both eight-year and five-year samples.

Table 3. Panel Results of the DiD Regression Model

This table provides the key estimates of IPO effects, for example the estimate for IPO effect on the treatment group (Post*IPO) and the estimate on the control group (Post). IPO firms and control firms are collected from 1999 to 2014 and patent counts are collected from 1996 to 2018. The DiD regression model includes both Firm Fixed Effect and Year Fixed Effect. The standard error is clustered on the firm level. The number of observations is collected from both 96 IPO firms and 96 control firms in the respective eight-year time window and five-year time window. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th>Ln(patents)</th>
<th>Eight-year time window</th>
<th>Ln(patents)</th>
<th>Five-year time window</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post</td>
<td>-0.268***</td>
<td>0.082</td>
<td>-0.195**</td>
</tr>
<tr>
<td>Post*IPO</td>
<td>0.216***</td>
<td>0.074</td>
<td>0.251***</td>
</tr>
<tr>
<td>Firm fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1536</td>
<td>1536</td>
<td>960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.560</td>
<td>0.560</td>
<td>0.648</td>
</tr>
</tbody>
</table>

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level

In the Table 3, the coefficient of Post*IPO is the degree of IPO effect on firm patenting activities. The coefficients in the five-year time window (0.251) is bigger than the one in the eight-year time window (0.216). It indicates the IPO effect is more significant in the five-year time window. The R-squared are 0.648 and 0.560 in the respective five-year time window and eight-year time window, which means the five-year time window can explain observations better. By considering both coefficients and R-squared, the DiD regression model of five-year
time window fit observed data better. In this case, the estimated results in the five-year time window can be regarded as a better explanation to this research paper.

In the Table 3, one can observe that the natural logarithm of patents is treated as the dependent variable. To forecast the estimated results, one can reverse the log transformation by applying the exponential function, and thereby to obtain a forecast of original variable (Lütkepohl and Xu, 2012). The procedure is to exponentiate the coefficient, subtract one and multiply by 100. For example, the coefficient is 0.251. \[ \text{Exp}(0.251) \times 100 \approx 28.5 \]. For every one-unit increase in the independent variable \( Post* IPO \), the number of patents increases by about 29%. This means once a firm undergoes an IPO, the patent growth rate of the firm is increased by 29%.

**Table 4. The DiD Estimate in Four Mean Values**

This table provides the calculated mean values in the four groups by separating treatment and non-treatment as well as prior IPOs and post IPOs. Mean treatment difference is the mean differences of \( \text{Ln}(\text{patent}) \) in the IPO firms between the years after and the years before and up to the IPO filing year. Mean control difference is mean differences of \( \text{Ln}(\text{patent}) \) in the control firms between the years after and the years before and up to the IPO filing year. The Mean DiD estimate should be the same as the estimated coefficient in the regression model. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th></th>
<th>IPO</th>
<th>Post</th>
<th>( \text{Ln}(\text{patent}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>No</td>
<td>Before</td>
<td>0.852</td>
</tr>
<tr>
<td>Group 2</td>
<td>Yes</td>
<td>Before</td>
<td>0.888</td>
</tr>
<tr>
<td>Group 3</td>
<td>No</td>
<td>After</td>
<td>0.623</td>
</tr>
<tr>
<td>Group 4</td>
<td>Yes</td>
<td>After</td>
<td>0.909</td>
</tr>
<tr>
<td>Mean Treatment Difference (IPO Firms After-Before)</td>
<td></td>
<td></td>
<td>0.021</td>
</tr>
<tr>
<td>Mean Control Difference (Control Firms After-Before)</td>
<td></td>
<td></td>
<td>-0.229</td>
</tr>
<tr>
<td><strong>Mean DiD Estimate (Treatment-Control After-Before)</strong></td>
<td></td>
<td></td>
<td><strong>0.25</strong></td>
</tr>
</tbody>
</table>

To double check the estimated coefficient in the five-year DiD model, the Equation (3) is employed by dividing the 960 observations into four groups: Group 1) observations in the control firms before the IPO filing year; Group 2) observations in the IPO firms before the IPO filing year; Group 3) observations in the control firms after the IPO filing year; and Group 4) observations in the IPO firms after the IPO filing year. In the Table 4, the mean values of \( \text{Ln} \) (patent) are calculated in each group. One can see in the Table 4, the mean DiD estimate is...
0.25, which is the same as the estimated coefficient in the five-year regression model in Table 3. It means the result of Equation (3) is the same as the estimated result of Equation (2). The estimated coefficient is correct in the regression model.

### 5.3 Robustness Check on DiD Estimation

This section is to test whether the estimated result in the DiD regression model is reliable and robust. A robustness check is adopted since it is used to examine how estimated coefficients behave when the regression model is modified in some specific way (Leamer, 1983; Lu and White, 2014). A sensitivity analysis is conducted to test the reliability of estimated coefficients through modifying the specifications. If the estimated coefficients are plausible and robust, it can be regarded as an evidence of structural validity (Lu and White, 2014).

According to Wing et al. (2018), there are several ways to do the robustness check of the DiD regression model. One is a graphical evidence check. Although estimated coefficients are not testable in a simple two-group two-period DiD model, they can be partially validated in settings with multiple pretreatment time periods (Wing et al., 2018). According to the Figure 3, going public can be proved to have positive effects on innovation through observing the patent trend of IPO firms in the four years after IPO events. IPOs help firms to maintain a steady growth rate of patents and delay the downward trend of patents in the two years after the IPO filing year.

Another strategy for evaluating the estimated coefficients is to test the group-specific linear trends (Wing et al., 2018). This method is to nest the original post-IPO innovation trend into the group-specific post-IPO innovation trend. If the coefficients in the group-specific DiD models are same or highly similar as the coefficient in the original DiD model, it demonstrates that the treatment effect is not sensitive to the alternative specifications and thus the estimated coefficient in the original DiD model is credible (Wing et al., 2018).

Following this method, the paired IPO firms and control firms are randomly divided into two subgroups. The subgroups are separated by the median value of the observed IPO years, i.e. 2007. Subgroup 1 includes all observations that occur IPOs from 1999 to 2007, which is 41 IPO firms and their paired control firms. Subgroup 2 contains the rest observations that undergo IPOs from 2008 to 2014, which is 55 IPO firms and their paired control firms. The
procedures of original DiD estimates are repeated in the group-specific DiD regression models. The estimated coefficients of subgroups are displayed in the Table 5.

### Table 5. Robustness Check on IPO Effects of Two Subgroups

This table provides the key estimates of robustness check by repeating the procedures of DiD model in Subgroup 1 and Subgroup 2. The observations are 410 in Subgroup 1 and 550 in Subgroup 2. The group-specific DiD regression models include both Firm Fixed Effect and Year Fixed Effect. The standard error is clustered on the firm level. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ln(patents)</td>
<td>Ln(patents)</td>
</tr>
<tr>
<td>Post</td>
<td>-0.377***</td>
<td>0.138</td>
</tr>
<tr>
<td>Post*IPO</td>
<td>0.283*</td>
<td>0.149</td>
</tr>
<tr>
<td>Firm fixed effect</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effect</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of observations</td>
<td>410</td>
<td>410</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.71</td>
<td>0.71</td>
</tr>
</tbody>
</table>

*** indicates statistical significance at the 1% level.  
** indicates statistical significance at the 5% level.  
* indicates statistical significance at the 10% level

Table 5 shows that the coefficient of Post*IPO is 0.283 in the Subgroup 1 and 0.228 in the Subgroup 2. The coefficients in two subgroups are the similar as the coefficient (0.251) in the original DiD regression in the Table 3. It can prove that the IPO effect on firm innovation is not sensitive to the group specifications. The estimated coefficient in the original DiD model is credible and valid. By applying the exponential function, the group-specific estimated results are about 32.7 in the Subgroup 1 and 25.6 in the Subgroup 2. It indicates that the number of patent applications will increase 33% if a firm undergoes an IPO from 1999 to 2007, and the patent growth rate will rise 26% if a firm undergoes an IPO from 2008 to 2014. This points out that IPOs have stronger effects on patenting activities to firms that go public from 1999 to 2007 than firms that undergo IPOs from 2007 and 2014.
6. Analysis and Discussions

6.1 Results Analysis

The key finding of this paper is that going public has a positive effect on firm innovation. Compared to their private peers, the number of patent applications will increase 29% in the firms that undergo IPOs. This positive effect may start to dissipate from the second year following IPOs. When the IPO effect is dissipated, the innovation trend of IPO firms falls back to the ordinary tendency, i.e., the trend has no IPO intervention. Going public can maintain the growth rate of patent applications and slow down the downward trend of patenting activities in firms.

The findings are contrary to the results of Bernstein’s studies (2015) in the US. Bernstein demonstrated that the internal innovation of listed firms declines following IPOs. The agency problem between management and shareholders, such as career concerns, impedes publicly traded firms to have internal innovations (Bernstein, 2015). Compared to Bernstein’s result (2015), a positive effect of going public on firm innovation is estimated in this paper. It may indicate that the agency conflict between management and shareholders is not a leading hinder for Swedish firms to pursue innovation activities following IPOs. The inference is also proved by the studies of Henrekson and Jakobsson (2012). They also indicated that the dispersed ownership with management control, which is commonly employed in the US, has not proven to be a viable model of corporate governance for Swedish publicly traded firms (Henrekson and Jakobsson, 2012). The Anglo-American model, in term of management entrenchment, cannot take place in Sweden unless the institutions are reformed (Henrekson and Jakobsson, 2012).

The estimated result of this paper is in line with the previous IPO studies by He et al. (2017) in China. They have proven IPOs can lead to an increase in both quantity and quality of firm innovation activities. Except patent applications, He et al. (2017) also test the impact of going public on financial constraint, governance, ownership structure and human capital perspectives. They found that the key reason of IPO boosting innovation activities is that going public can release the financial constraints of firms in China (He et al., 2017). This reason has also been echoed in this paper. As mentioned in the Chapter 4, nearly 80% of Swedish firms that undergo IPOs from 1999 to 2014 have negative net incomes in the IPO filing year. Many of them even
have negative net incomes in the previous year. Going public enhances firm innovation activities through releasing their financial constraints.

In addition, the firms that undergo IPOs from 1999 to 2007 have stronger level of innovation than the firms that have IPOs from 2008 and 2014 (see Table 5). Do note there was an IT-crisis in 2000 as well as the world financial crisis in 2007 (Carlgren, 2019). Going public may have more effective acceleration on firm innovation since the investment of innovation become even more sensitive to financial constraints under the financial crisis.

6.2 Limitations

No matter how ‘perfect’ empirical design is, there are always limitations in studies (Angrist and Pischko, 2008). One limitation of this paper is to contain certain inherent endogeneity bias. Due to the relationship between IPOs and firm growth stage, IPO events cannot be purely regarded as an exogenous event in the study. The estimated result derived from the observational data is relatively subject to a certain endogeneity bias (Angrist and Pischko, 2008). For example, IPO firms may have a stock of innovations and such a stock could be released following IPOs to boost the appearance of innovation. This paper employs the combination of PSM and DiD methods to mitigate the extent of endogeneity bias by comparing post-IPO innovation trends between publicly traded firms and their privately held peers. This research methodology is proved by a series of papers (Boucly et al., 2011; Bulk and Johansson, 2015; He et al., 2017). Due to a 5% matching tolerance level, the result of PSM contains certain differences of innovative and financial situations between the IPO firms and the control firms. It causes a not entirely appropriate parallel trend assumption of the DiD model.

Another limitation is that a certain number of observations are excluded in the PSM technique since they do not have matched control firms. It is difficult to estimate the IPO effect on innovation over time without a comparable parameter. This may lead to a small difference of estimated result by omitting several observations. Compared to the previous IPO studies (Bernstein, 2015; He et al., 2017), the sample of observations in this paper is small. It may affect the predictive value and generalization of the estimated result. This is because, compare to the US and China, Sweden is a small country with small number of IPO events in new issuing firms. The key finding of this paper is in line with previous IPO studies (He et al. 2017), which can be a good evidence to prove the value of estimated result. To consider the inherent
endogeneity of IPO events and the sample size, one advisable interpretation of the estimated result is that it is descriptive and supplement to the predictive value.
7. Conclusions

This paper investigates an important yet understudied aspect of IPOs, which is the effect on firm innovation. Similar studies have already been performed in other countries. This paper is the first attempt - to my knowledge - to investigate the impact of IPOs on firm innovation in the Swedish market.

The paper finds that going public has a significant positive influence on firm innovation, in terms of the patent growth. The number of patent applications will increase 29% following IPOs. Going public can maintain the growth rate of patent applications and slow down the downward trend of patents following IPOs. The findings are in line with the results of similar previous studies (He et al., 2017; Wies and Moorman, 2015), which can be strong evidences to prove the research value of this paper in the Swedish market. Based on the estimated results in the robustness check, this paper finds that going public have stronger impacts on firms that undergo IPOs from 1999 to 2007 than firms that have IPO events from 2008 to 2014. Do note there were an IT-crisis in 2000 and the world financial crisis in 2007 (Carlgren, 2019). These two world crises may cause more innovative firms to go public in order to solve the internal financial constraints which are affected by the world financial crisis.

The research method employed in this paper is a combination of PSM and DiD methods, which is commonly used in other papers on event-driven firm performance in various dimensions (He et al., 2017; Hyytinen and Toivanen, 2005; Wu, 2012). These methods are used to correct for industry specific trends and developments across the overall economy over time (Bulk and Johansson, 2015). It yields a more accurate representation of true effect of IPOs on firm innovation by disregarding the time and industry. However, the observed research sample in this paper is small and it may cause limitations in generalization made from the estimated results. The causal effect of this paper is supplemented by two group-specific estimated results in the robustness check. The significant differences are not observed between the original estimated results and the robust group-specific results. The estimated results of this paper are valid and reliable.

The findings of this paper can provide insight into the innovation activities of firms in various sizes and characteristics in the Swedish market, especially ex post innovation performance following IPOs. This paper provides a good reference for Swedish firms that face
various options of financing innovation. Firm could choose to go public to solve the financial constrictions and boost the appearance of innovation. For the further studies, this paper attempts to include citations and trademarks which are regarded as other proxies to have a full scope of measuring firm innovation. In addition, this paper will further research on the changes following going public, such as how going public affects the number of inventors or whether going public enhances agency problems and further leads to managerial entrenchment.
References:


Appendix

Table 6. Regression Results of PSM
The table provides the regression result of PSM in the SPSS statistic software. Ln (TA) is not significant with 0 score in the Step 0. The reason could be the variable is blocked in the Step 0. One can observe in the Step 1. All variables are significant. This could be that the large amount of control firm population leads normal regression distribution. The one-to-one matching result displays in the Table 1.

<table>
<thead>
<tr>
<th>Step 0 Variables not in the Equation</th>
<th>Score</th>
<th>df</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln (TA)</td>
<td>0.000</td>
<td>1</td>
<td>0.992</td>
</tr>
<tr>
<td>C/A</td>
<td>161.418</td>
<td>1</td>
<td>0.000</td>
</tr>
<tr>
<td>ROA</td>
<td>92.447</td>
<td>1</td>
<td>0.000</td>
</tr>
<tr>
<td>Ln (Pre3-0)</td>
<td>3.096</td>
<td>1</td>
<td>0.078</td>
</tr>
<tr>
<td>Year</td>
<td>14.323</td>
<td>1</td>
<td>0.000</td>
</tr>
<tr>
<td>Industry</td>
<td>41.444</td>
<td>1</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step 1 Variables in the Equation</th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>P-value</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln (TA)</td>
<td>0.245</td>
<td>0.044</td>
<td>31.622</td>
<td>1</td>
<td>0.000</td>
<td>1.278</td>
</tr>
<tr>
<td>C/A</td>
<td>3.792</td>
<td>0.391</td>
<td>94.046</td>
<td>1</td>
<td>0.000</td>
<td>44.360</td>
</tr>
<tr>
<td>ROA</td>
<td>-0.957</td>
<td>0.150</td>
<td>40.412</td>
<td>1</td>
<td>0.000</td>
<td>0.384</td>
</tr>
<tr>
<td>Ln (Pre3-0)</td>
<td>-0.301</td>
<td>0.106</td>
<td>8.021</td>
<td>1</td>
<td>0.005</td>
<td>0.740</td>
</tr>
<tr>
<td>Year</td>
<td>0.072</td>
<td>0.021</td>
<td>11.292</td>
<td>1</td>
<td>0.001</td>
<td>1.075</td>
</tr>
<tr>
<td>Industry</td>
<td>0.018</td>
<td>0.004</td>
<td>18.310</td>
<td>1</td>
<td>0.000</td>
<td>1.018</td>
</tr>
</tbody>
</table>

Table 7. Statistic Summary of Patent Data
The table provides the descriptive statistic summary between the raw patent counts and natural logarithm patent count plus one. The patents of IPO firms are observed in eight-year time window from 1996 to 2018. All variables are defined in the Appendix.

<table>
<thead>
<tr>
<th>IPO Firms</th>
<th>Total observations</th>
<th>Mean</th>
<th>Median</th>
<th>Min.</th>
<th>Max.</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent</td>
<td>1071</td>
<td>3.69</td>
<td>0</td>
<td>0</td>
<td>130</td>
<td>9.721</td>
</tr>
<tr>
<td>Ln (patent)</td>
<td>1071</td>
<td>0.78</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>1.034</td>
</tr>
</tbody>
</table>
Table 8. Definitions of Variables

The table contains the descriptions of variables used in this paper. It includes the descriptions of both innovation measure and financial characteristics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Innovation Measure</strong></td>
<td></td>
</tr>
<tr>
<td>Patent</td>
<td>Number of patents a firm applied for in a given year from 1996 to 2018.</td>
</tr>
<tr>
<td>Ln (patent)</td>
<td>Natural logarithm of the patent counts plus one in a given year.</td>
</tr>
<tr>
<td>Ln (Pre3-0)</td>
<td>The mean value of natural logarithm of the patent counts plus one in the three years before and up to the IPO filing year.</td>
</tr>
<tr>
<td>IPO Firm</td>
<td>The firm that goes public in a given year from 1999 to 2014.</td>
</tr>
<tr>
<td>Control Firm</td>
<td>The firm that does not go public and has similar characteristics with the matched IPO firm at the IPO filing year</td>
</tr>
<tr>
<td><strong>Financial Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Ln (TA)</td>
<td>Natural logarithm of total book value of assets in an observed firm.</td>
</tr>
<tr>
<td>C/TA</td>
<td>The ratio of cash holdings to book value of assets in an observed firm.</td>
</tr>
<tr>
<td>ROA</td>
<td>The ratio of net income before taxes to book value of assets in an observed firm.</td>
</tr>
</tbody>
</table>