Three essays on Finance and Innovation

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Abstract

Innovation is regarded as a driving force behind national and firm level competitive advantage, which leads to higher future earnings and positive long-term abnormal operating performance. The financial system also plays an essential role in increasing firm and economic growth. The literature supports the notion that better developed financial intermediaries and markets can enhance productivity growth and technological innovation. In this thesis, we consider both micro (firm-level) and macro (country-level) factors and discuss how they affect innovation performance from the perspective of financial literature.

We specifically emphasise the influence of two factors based on the empirical research on international samples. The first is stock liquidity. We provide a deep understanding of these factors by exploring how it affects innovation outputs and what impact it has on innovation performance. We find that although stock liquidity can affect firm innovation through R&D investment, the most impact on firm innovation comes from the direct impact of stock liquidity itself. Besides, while increased stock liquidity improves a firm's innovation performance, it mainly contributes to a firm's efficiency in producing high-quality patents rather than more patents. The second is the pandemic shocks. We demonstrate that following a pandemic, innovation output is disrupted for approximately seven years. In addition, the main result of the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in innovative activity in the Information and Communication technology sector.

Overall, we show that financial systems could improve innovation performance by boosting its efficiency, such as increasing stock liquidity. It could also affect innovation activities as a channel of exogenous shocks.

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Chapter 1 Thesis Introduction

Innovation is regarded as a driving force behind national and firm level competitive advantage (Porter, 1998). Although innovation can be defined differently in different contexts, put simply, it is the process of developing new ideas and putting them into practice (Neely and Hii, 1998; Tidd and Bessant, 2020). Abramovitz (1956) and Solow (1957) showed that innovation leads to new business opportunities and enhances productivity growth. Neely and Hii (1998) suggested that innovation enhances the knowledge stock of society. And more importantly, that innovation leads to higher future earnings (Ali *et al.*, 2008) and positive long-term abnormal operating performance (Eberhart *et al.*, 2008). It is clear that the innovative ability at the firm, regional and national level is the key determinant of the wealth generation capability of economies (Solow, 1956; Grossman and Helpman, 1991; Aghion and Howitt, 1992).

The financial system also plays an essential role in increasing firm and economic growth through its intermediation function, which improves investment efficiency (Goldsmith, 1969; Greenwood and Jovanovic, 1990). Schumpeter's (1911) work was one of the earliest pieces of research to emphasise the importance of finance in innovation procedures. He argued that adequate credit access encourages the widespread adoption of new technologies. An extensive literature has also explored the relationship between finance and innovation (see detail in Chapter 2 of this thesis). The literature supports the notion that better developed financial intermediaries and markets can enhance productivity growth and technological innovation (King and Levine, 1993; Levine and Zervos, 1998; Brown *et al.*, 2009).

In this thesis, we continue the research into the field of finance and innovation. More specifically, we investigate factors that may impact on innovation activities from the perspective of financial literature. By using an international sample, we consider both micro (firm-level) and macro (country-level) factors and discuss how they affect innovation performance.

In Chapter 2, we review the literature around the relationship between financial markets and firm innovation from the perspective of primary markets, equity markets and other financial markets. Regarding this, we conclude that innovation has several characteristics. First, innovation is risk-taking behaviour which involves a substantial probability of failure (Holmström, 1989). Second, innovation requires long-term, continuous investment. Manso (2011) and Ederer and Manso (2013) revealed that for innovation to perform better there needs to be a tolerance of early failures. Third, innovation is a labour-intensive, multi-stage process. Ederer (2008) suggested that innovation activities tend to succeed when innovators are encouraged to team up with others and are rewarded for long-term joint achievements. Fourth, asymmetric information is between investors and firm managers. Adverse selection problems (Stiglitz and Weiss, 1981) are more likely in R&D-intensive industries because of the inherent risk involved in the investment. Ethical problems are also an issue for high-tech firms so many find it easier to substitute high-risk projects for low-risk ventures. In addition, Allen and Gale (1999) argued that it is usually difficult to evaluate innovative projects because information about their prospects is either sparse or hard to process, which often leads to a variety of opinions. Aboody and Lev (2000) show that R&D makes a significant contribution to asymmetric information between corporate insiders and normal investors, which leads to insider trading and gains. A fifth characteristic is a high level of intangible assets. R&D investment creates intangible assets for the firm (Johnson and Pazderka, 1993) and leads to a lack of collateral (Hall, 2002). We analyse innovation performance in this thesis based on these characteristics.

In Chapter 3, we merge the patent-based data from the PATSTAT database with firm account information from Datastream. This list includes 11,371 company names from 44 countries across the period 1990 to 2010. It covers around 42.04% of patents from the PATSTAT database and 14.43% of equities from the Datastream database. Overall, we provide a basis for global research by which to investigate the innovation performance of public companies.

In Chapter 4, we study the R&D-patent relationship from the perspective of stock liquidity. R&D and patent-based data represent different steps in the innovation process. While R&D investments measure inputs in the innovation process (Ashwin *et al.*, 2015; Wen *et al.*, 2018), patent-based indicators show the ability to create inventions (Coombs *et al.*, 1996; OECD., 1997; Flor and Oltra, 2004). Previous literature has investigated the impact of stock liquidity on firm innovation (Fang *et al.*, 2014; Wen *et al.*, 2018). However, it has largely ignored the possibility that stock liquidity could affect firm innovation outputs through R&D investments. In terms of this, we propose the first hypothesis, namely that stock liquidity can indirectly affect firm innovation outputs through R&D investments. On the one hand, increased stock liquidity may improve R&D investment by reducing the cost of raising capital. On the other hand, it may impede R&D investment because of the potential threat of hostile takeovers and short-term institutional investors. Secondly, we hypothesise that stock liquidity could directly affect firm innovation outputs. An increase in stock liquidity could improve firm innovation activities by reducing asymmetric information between investors and firm managers. In addition, it could facilitate the entry of long-term and/or strategic institutional investors, thereby improving a firm’s innovation abilities.

In terms of this, we employ a structure model to introduce high-frequency trading (hereafter, HFT) start date as an exogenous shock to stock liquidity. As High-frequency traders mainly focus on the high market value companies (Brogaard *et al.*, 2014), this chapter only includes the top 30 percentile of the largest public companies, by market capitalisation in each exchange. Our results show that while stock liquidity causes a significant negative influence on firm R&D investment, it is much lighter than the impact on firm innovation outputs. Thus, we argue that although stock liquidity can affect firm innovation through R&D investment, the most impact on firm innovation comes from the direct impact of stock liquidity itself. We also show that while R&D investment causes larger impacts on firm innovation quantity than stock liquidity, it does not significantly improve other patent-based indicators. In addition, we observe that stock liquidity significantly improves the patent generality index and originality index. It could be an explanation of the positive relationship between stock liquidity and firm innovation quality.

In Chapter 5, we focus on the relationship between stock liquidity and firm innovation performance. There is still a debate around what impact stock liquidity has on a firm's innovation outputs. Fang *et al.* (2014) and Wen *et al.* (2018) separately investigated the US and Chinese markets and obtained the opposite results. This may be due to the different macro conditions in the US and China, such as financial structures, economic regulations, and policy environment. Regarding this, we employ the hierarchical linear model to separate the within-country and cross-country impacts of firms' stock liquidity on their innovative activities (Greene, 2003; Griffin *et al.*, 2019).

Our empirical evidence shows continuously increased positive impacts of stock liquidity on firms' patent-based indicators. Our main findings in this chapter come from the perspective of innovation efficiency. We find that while increased stock liquidity improves a firm's innovation performance, it mainly contributes to a firm's efficiency in producing high-quality patents rather than more patents. In addition, from the perspective of the country's character, we assert that firms can produce more patents in larger economies with a higher level of international trading and economic freedom. Regarding levels of economic freedom across five different areas, we find that countries with better protection of people and their rightfully acquired property improves firm innovation performance over a longer period than other areas.

In Chapter 6, we investigate the economic consequences of pandemics from an idea-based theory of economic growth. We assume that pandemics pose a threat to research productivity and funding channels in the long run. Firstly, the spread of a pandemic tends to cause a rise in infection and a rise in the national death toll, thereby decreasing labour supply, whilst increasing real wages for each survivor regardless of their contribution to innovation, and impeding teamwork. Secondly, we propose that pandemics impede firm innovation activities by reducing internal funding. This leads to a drop in a firm's income and forces managers to cut long-term projects (i.e., R&D) in order to meet short-term earning targets (Bushee, 1998; Graham *et al.*, 2005). Thirdly, pandemic spreads tend to decrease firm innovation outputs by impeding external fundings. Jordà *et al.* (2020) showed that the countries tend to experience a low natural interest rate in the decades following the pandemic. This is explained through the increased precautionary savings and depressed investment opportunities. It implies that firms experience financial constraints and work poorly in producing new projects or new products. Investors are also less willing to invest in new projects during the pandemic due to adverse selection and moral hazard.

Regarding this, we analyse the long-term consequences of pandemic shocks on innovation output and demonstrate that following a pandemic, innovation output is disrupted for approximately seven years. We show that the main result of the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in innovative activity in the Information and Communication technology sector. Furthermore, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery.

Pandemic shocks lead to a short-term drop in the number of patent applications. Crucially, the duration of a pandemic has a strong effect on innovation output.

This thesis makes several contributions: In Chapter 4, we emphasise the importance of stock liquidity on firms patent outputs. Especially, we show that increased stock liquidity could benefit firms to produce high-quality innovation. In addition, we extend the empirical literature on the impact of stock liquidity on firm innovation. While Fang *et al.* (2014) argued that firm managers tend to cut R&D investments when facing the potential threat of hostile takeovers and short-term institutional investors caused by increased stock liquidity, we oppose this opinion by arguing that although increased stock liquidity may impede R&D investments, it is much lighter than the impact on firm innovation outputs. In addition, we improve the understanding of the R&D-patents relationship from the perspective of stock liquidity. We show that while stock liquidity could indirectly affect firms innovation performance through R&D investments, the most impact on firm innovation comes from the direct impact of stock liquidity itself.

In Chapter 5, we contribute to the literature around the debate of whether stock liquidity encourages or impedes firm innovation. While we support Wen *et al.* (2018)'s opinion that increased stock liquidity improves firm innovation, our study employs an international sample and includes more patent-based measurements to deeply analyse the impact of stock liquidity on firm innovation performance. In addition, we provide evidence to policymakers around how firm efficiency can be improved in order to produce better-quality patents by increasing stock liquidity. In addition, our research can encourage investors to allocate more investments in stock exchanges with higher stock liquidity, as innovation outputs could be capitalised in their market value and predict a firm's real return in the stock market (Hall *et al.*, 2005; Hsu, 2009).

In Chapter 6, we provide an original view by which to investigate the economic responses to pandemic spreads. Our evidence supports the policies designed to reduce the effect of the "Great lockdown" on research productivity. We argue that governments need to be prepared to support innovators in the immediate aftermath of the pandemic, and patent offices may have to speed up the process of approving new patents. Finally, we recommend adopting policies that target the more innovative firms as this is expected to help reduce the time it will take for innovation to recover from the effects of COVID19.

In this thesis, we investigate the impacts of macro- and micro-level factors on innovation performance from the perspective of financial literature. We specifically emphasise the influence of two factors based on the empirical research on international samples. The first is stock liquidity. We provide a deep understanding of these factors by exploring how it affects innovation outputs and what impact it has on innovation performance. The second is the pandemic shocks. We provide an original view by which to analyse the response of innovation activities to pandemic spreads and discuss how financial markets affect innovation as a channel of exogenous shock. Overall, we show that financial systems could improve innovation performance by boosting its efficiency, such as increasing stock liquidity. It could also affect innovation activities as a channel of exogenous shocks.

We organise the remainder of this thesis as follows: In Chapter 2, we review the literature studying the relationship between financial markets and firm innovation from the perspective of primary markets, equity markets and other financial markets. In Chapter 3, we demonstrate the procedure that matches patent data on the PATSTAT database and firm account information on the Datastream database. In Chapter 4, we present the data, estimation method and empirical results concerning the first research topic, 'The Effect of Stock Liquidity on R&D-Innovation Relationship: A Structure Model Approach'. In Chapter 5, we discuss research methodology and empirical results on the second topic, 'Stock Liquidity and Firm Innovation: International

Evidence'. In Chapter 6, we outline the data, research methodology and the results concerning the third research topic, 'The Road to Economic Recovery: Pandemics and Innovation'.[1] In Chapter 7, we conclude our investigation results and discuss some limitations.

[1] This chapter has been published by the International Review of Financial Analysis as Wang *et al.* (2021).

Chapter 2 Literature Review

This chapter reviews the literature around the relationship between financial markets and firm innovation from the perspective of primary markets, equity markets and other financial markets. In section 2.1, the literature relating to the impacts of Initial Public Offerings (IPOs) in the primary market and firm innovation is considered. In section 2.2, we consider the literature regarding the relationship between equity markets and innovation. Section 2.3 reviews the literature around how other financial markets affect firm innovation.

2.1 The relation between the primary market and firm innovation

In Table 2.1, we review the literature around the relation between IPOs in the primary market and firm innovation. Kim and Weisbach (2008) investigated a sample of firms around the world and found that substantial funds raised in IPOs were finally invested in Research and Development (R&D). Wu (2012) concluded that the number of patents increased among medical service firms after they went public. However, a large percentage of these patents depends on the firm's previous patents. In other words, firms' innovative strategies move from an exploratory search to an exploitative search after going public. Aggarwal and Hsu (2014) showed that the number of patents and forward patent citations among biotechnology firms tended to decline in terms of short-term performance pressures after going public. This is consistent with the information confidentiality mechanisms in which firm innovation outcomes are impacted by project selection and information disclosure. The largest information disclosures are required by the public after the IPO. Bernstein (2015) suggested that going public changes a firm's strategy in their pursuing of innovation. While newly listed firms tend to attract new inventors and achieve a large number of high-quality patents through acquisitions, the average citations created by old employees decrease in the five years after an IPO filing. In addition to these points, Acharya and Xu (2017) noted that going public improves firms' innovation when they depend on external finance, and *impedes* innovation when they are less dependent on external finance. Further examination shows that going public releases the financial constraints on firms who rely on external finance, thereby improving their innovation activities. However, when firms are less dependent on external finance, going public tends to hurt them due to short-term pressure coming from peers' competition and analyst estimation.

*** Table 2.1 ***

Taken together, although the quantity of innovation is more likely to increase after going public, innovation quality measured by the number of patent citations, tends to decline (Wu, 2012; Bernstein, 2015; Wies and Moorman, 2015). In other words, compared with keeping private ownership, going public is beneficial for a firm's exploitative search but not exploratory search. Scholars explain that firms have to disclose information regularly and subject themselves to public ownership following IPO. Management is incentivised to choose projects with stable yields in order to make proper reports (Aggarwal and Hsu, 2014). Additionally, based on Holmström's (1989) career concerns theory, managers are concerned that shareholders attribute innovation failures to their poor managerial skills, even those due to purely stochastic reasons (Bernstein, 2015). Although there is a theoretical model that indicates that firms are driven to be more innovative following IPO (Schwienbacher, 2008), empirical researches find the opposite result. To my knowledge, except for Acharya and Xu (2017), few works of literature investigate which type of firms can benefit from IPO, and more research can be carried out around this in the future.

2.2 The relationship between the equity market and firm innovation

2.2.1 The effect of the equity market on innovation

Table 2.2, Panel A reviews the literature which compares the effect of two different financial systems (the equity market and the credit market) on innovation. Hsu *et al.* (2014) show that a better-developed equity market improves innovation in industries that rely more on external finance and are more high-tech intensive, while a better-developed credit market impedes innovation in these industries. Tadesse (2006) found a similar result through a different type of innovation indicator – the *size* of high-tech industries. Hsu *et al.* found that the growth of a country's high-tech sector is improved by stock market development but discouraged by credit market development. Tadesse (2006) supports the notion that technological innovation is generally improved by a market-based financial system, while innovation in industries with greater information-intensive (measured by the level of intangible assets) grows faster in a bank-based financial system. Maskus *et al.* (2012) noted that the development of the domestic equity market can prompt R&D in industries that rely on external finance, but this is not related to the level of financial constraints (calculated by the level of tangible assets, as innovative firms invest highly in R&D and usually have fewer tangible assets, thus they suffer financial constraints). Wang and Thornhill (2010) found petroleum firms with a high level of R&D investment should finance by common equity. There is a sustained positive impact of R&D spending on the use of common stock in capital raising, except the U-shaped effect of R&D investment on the utilisation of convertible securities and the inverted U-shaped influence on the utilisation of relational debt. Black and Gilson (1998) suggested that a well-developed equity market (but not a credit market) can indirectly improve innovation by providing a lucrative exit opportunity for venture capital investors.[2]

*** Table 2.2 ***

In conclusion, when compared with the credit market, a better-developed equity market is generally more beneficial for innovation, especially in industries that depend on external finance, because it has no collateral requirements and provides more efficient information. The equity market is more useful in diversifying the risk associated with innovative projects (King and Levine, 1993), and offers a higher stock price compared to non-R&D-intensive firms (Kapadia, 2006; Pástor and Veronesi, 2009), thereby improving innovation. From the perspective of information feedback function, the equity market can provide valuable information based on the real trading of stocks. In particular, Tadesse (2006) showed that the market-based system was advantageous in identifying and funding new projects, especially when a diversity of opinion persists in the market. Banks are more efficient in the handling of proprietary information because information-intensive firms have more to lose from information leakage when they invest in innovation.

In Table 2.2, Panel B, the literature focuses on the association between stock markets and firm innovation. Brown *et al.* (2009) show that fluctuations in the supply of both internal (measured by cash flow) and external equity finance (computed by stock issue) can explain a large portion

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[2] It is clear that venture capital funds are beneficial for innovation (Kortum and Lerner, 2001). According to Black and Gilson (1998), however, the efficiency advantages offered by venture capital to a company is mainly in the embryonic stage through financial capital, nonfinancial services and reputational capital. It will gradually reduce as company enters maturity. Additionally, venture capital managers' skill can be valued by exit prices. In particular, a successful entrepreneur can achieve control of companies from venture capital investors by IPO, which cannot be done in a credit market. Therefore, compared with the credit market, the well-developed equity market is more efficient for venture capital investors to exit and then reinvestment in new ideas, thereby indirectly improving innovation.

of the 1990s boom and subsequent drop in aggregate R&D in the US. In particular, changes in both finance supplies are strongly related to the R&D cycle for young high-tech companies rather than mature high-tech companies. Following on from Brown *et al.* (2009), Martinsson (2010) found a similar result in the UK, while only the cash flow effect was significant for new high-tech firms on continental Europe. This means that although new high-tech firms in the UK and continental Europe both experienced a dramatic increase in stock issue in the late 1990s, it only mattered for the firms in the UK. Therefore, the market-based financial system outperforms bank-based financial system in providing external equity finance for R&D investment.[3] Brown *et al.* (2013) support the view that access to stock market funding at country level can improve long-term R&D investment, and it is stronger for younger and smaller firms. In addition, R&D created by small firms in industries that are highly dependant on external finance is greater than firms in industries which are less dependent on external finance. Martinsson and Lööf (2013) show that a stable equity supply plays a vital role for firms in maintaining a smooth patenting profile over the duration of the business cycle. The patenting of firms that efficiently access external equity is impacted little by economic downturn, while the decline of patenting can be seen mostly in firms with a middle average external equity supply. Brown *et al.* (2013) found laws are exogenous variations that influence stock issues, thereby affecting long-term R&D investment. The impact of the law on stock issues and R&D is mainly driven by small firms. Brown *et al.* (2012) showed that stock markets have a significant impact on firms' innovative activities when their R&D finance faces financial constraints. They found that younger firms in market-based systems, such as can be found in the UK and Sweden, have higher R&D-intensities.

[3] There are market-based financial systems in the UK and US, whilst continental Europe operates bank-based financial systems.

As a conclusion to Table 2.2, Panel B, we see that access to the stock market is beneficial for firm innovation, and that it mainly contributes to younger and smaller high-tech firms rather than to mature firms. These young and small R&D-intensive firms are less likely to obtain debt finance in terms of their uncertain and volatile returns (Stiglitz, 1985). Additionally, moral hazard and adverse selection are likely to be more severe for high-tech firms because they are in a high-risk industry and can more easily substitute high-risk for low-risk projects (Brown *et al.*, 2009). Finally, high-risk R&D-intensive firms are restricted to using debt finance based on the limited collateral value of their intangible assets (Berger and Udell, 1990). Therefore, they benefit from the supply of external equity finance and achieve better innovation.

In addition to this, Table 2.2, Panel C, shows that equity market liberalisation is beneficial for innovation. Moshirian *et al.* (2015) revealed that equity market liberalisation enhances innovation output in more equity-dependent industries by releasing financial constraints, utilising human capital and transmitting foreign technology. Luong *et al.* (2017) supported the positive effect of equity market liberalisation (on a firm's innovation) through a positive, causal impact of foreign institutional investors. These investors promote innovation by working as active monitors, providing insurance against innovation failures and transmitting foreign technology. In a survey of small Italian high-tech firms, Giudici and Paleari (2000) suggested that relatively larger but younger firms plan to issue equity on foreign stock markets in the future. In some cases, this is viewed as a method by which to establish a corporate image and acquire a reputation.

Taken together, the literature which considers the relationship between equity market development and innovation supports the notion that a better developed and open equity market can promote innovation and is generally more efficient than the credit market. This effect will be stronger for small and young companies in industries that depend on external finance, and in a market-based financial system.

2.2.2 Equity market's function of evaluating innovation

This section reviews the literature on the equity market's function in terms of evaluating innovation in Table 2.3, where market reactions to innovation data are usually represented by the presence of abnormal returns. In Table 2.3, Panel A, we show that an equity market can evaluate innovation based on R&D investment as an input of an innovative process. Lev and Sougiannis (1996) proved the positive influence of R&D expenditure on the market value of the firm in the US. This kind of relationship is also supported by Toivanen *et al.* (2002) in the UK. Regarding this, Hall and Oriani (2006) show a significant positive correlation between R&D investment and the stock price of firms in France, Germany, the UK and the US, but not in Italy. They found that for firms in a country with weaker protections for minority shareholders, such as France and Italy, controlling shareholders could embezzle the profits of minority shareholders through asymmetric information generated by R&D activities. Under such circumstances, firms with large shareholders are penalised by the stock market via an undervaluing of their R&D investment. Booth *et al.* (2006) supported the notion that the stock market evaluation function of R&D investment can be improved by a higher degree of a market-based financial system rather than a higher overall level of financial development. In other words, a country's financial structure, rather than its overall level of financial development, determines the channel by which the equity market utilises the value of R&D spending. The equity market will provide a stronger response to changes in R&D expenditures when a country leans toward equity finance. Kallunki *et al.* (2009) suggested that technology-oriented Mergers and Acquisitions (M&As) prompts the influence of the acquirer firm's R&D expenditures on its current stock price and future profitability, but not acquired firms.

*** Table 2.3 ***

In Table 2.3, Panel B, we present the argument that firm innovation can be evaluated by the equity market via event studies of innovation announcements. Woolridge and Snow (1990) suggested that the announcement of R&D investment has a positive impact on a stock market return. Their argument supports the opinion that stock markets tend to reward well-conceived, long-term strategic investment decisions. In addition to supporting this opinion, Sood and Tellis (2009) showed that the market reaction to the announcement of initial innovation activities is lower than with development activities but higher than in the case of commercialisation activities. The negative market returns generated by negative announcements across all events are higher in absolute value than positive announcements. Smaller firms enjoy more profits attendant to R&D announcements than larger firms. Moreover, a firm's return is *not* subject to the number of prior announcements, the period between announcement within a project or research productivity. Finally, Sood and Tellis (2009) showed the importance of the first announcement of an innovation event and the negative reaction from the market to competitors announcing firms on event days. This is in addition to the stock market's function in evaluating an innovation announcement. Adcock *et al.* (2014) found that more innovation-intensive countries experienced better market reactions to negative news during the global financial crisis. These conditions were unique during the crisis, meaning that investors value innovation to a greater degree during a challenging economic period.

In Table 2.3, Panel C, we demonstrate that patent-based indicators can be employed in the equity market in order to evaluate a firm's market value.[4] Hall *et al.* (2005) found that a firm's stock price not only depends on R&D but also on the number of patents and patent citations. In particular, companies with a high degree of citations per patent produce a disproportionately large market value. Past citations are helpful in forecasting future returns. In addition, self-citations lead to higher valuations than citations from external patents. However, this influence *decreases* with the size of patent portfolios held by the firm. Hsu (2009) proved that fluctuations in innovation progress improve expected market returns and premiums at the aggregate level, globally. Hirshleifer *et al.* (2018) demonstrated that innovative originality can be a strong predictor of abnormal stock returns.[5] Although this information can predict more persistent and less volatile profitability in the future, investors tend to neglect it and the reasons why are relatively complicated and hard to evaluate. This effect is stronger when the firm has a greater level of valuation uncertainty, lower investor attention and a stronger sensitivity to the future profitability of innovative originality. Hirshleifer *et al.* (2013) showed that firms with higher efficiency in innovation on average have higher current and future market valuations. The new innovative efficiency variable which is represented as the ratio of patents divided by R&D expenditure can capture incremental value-related information about future stock returns relative to other innovation-related variables, such as R&D growth, R&D intensity, the number of patents and the number of patent citations.

In addition to stock returns, Table 2.3, Panel D shows that stock return volatilities are also enhanced by innovation activities. Chan *et al.* (2001) suggested that companies that are more

[4] According to Gu (2005), patent-based indicators, such as the number of patents and patent citations, contain the information about firms' technological advantages. Therefore, they can predict a firm's stock value even they are not dollar-denominated and not subject to the well-defined standards of measurement and disclosures.

[5] According to Hirshleifer *et al.* (2018), innovative originality is defined as the number of unique technological classes of patents which are cited by a firm's patents.

R&D-intensive (the ratio of R&D to sales) generate a larger average monthly return volatility than firms without R&D. Gharbi *et al.* (2014) focused on high-tech firms in France and found that both a firm's total stock volatility and idiosyncratic volatility are positively correlated with the intensity of their R&D investment. Shiller (2000) and Perez (2003) suggested that investors' irrationality leads to the high volatility and bubble-like stock prices of firms during technological revolutions. Pástor and Veronesi (2009) expounded the argument by underlining the uncertainty around the average productivity of new technologies in the rational world. This relationship can also be explained as the notion that R&D investment tends to produce a higher degree of asymmetric information than tangible investment (Aboody and Lev, 2000), and stock volatilities are enhanced with the increased degree of asymmetric information about a firm's prospects and performance (Gennotte and Leland, 1990; Eden and Jovanovic, 1994).

In Table 2.3, Panel E, there is a debate around whether or not the equity market thoroughly evaluates firm innovation. While some scholars show that information embedded in innovation is entirely incorporated by the stock market, most of the others find contrary evidence of that. From one perspective, Chan *et al.* (2001) suggested that the full benefits of R&D spending are incorporated by stock price on average in several R&D-intensive industries during the period between1975 and 1995. The most evident signs of the association are created by stocks with a high ratio of R&D to market equity. We can surmise therefore that inventors are very pessimistic about the prospects of R&D-intensive firms with a history of poor performance, thereby generating mispricing of R&D stocks.

Conversely, Cohen *et al.* (2013) found that the stock market tends to ignore information about R&D success embedded in past track records even if this information is expected, stable and simple to compute. A firm tends to persist with its innovation ability across several years.In addition, the R&D expenditure by firms with high degree of innovation will produce the real outcome in patents, patent citations and new product innovation. Gu (2005) showed changes in patent citation have a substantial impact on a firm's future earnings, but is not fully incorporated by the stock market. In particular, the positive association is clearer in industries with a shorter innovation cycle because firms in these industries can quickly transform their research breakthroughs into real profits. Furthermore, a firm's long-term performances can be predicted by the competitiveness of intangible assets. Eberhart *et al.* (2004) suggested that although it is beneficial for firms to spend on R&D projects, the extent of this benefit is only slowly being recognised by the market and investors tend to 'under-react'. Dong *et al.* (2017) showed that stock market overvaluation is positively related to both the quality and quantity of a firm's innovation activities. Finally, they found R&D investment and innovative outputs in firms with good growth prospects, a high stock turnover rate and overvaluation are more sensitive to market misevaluation.

The reason why the stock market misvalues firm innovation is explored by the literature in Table 2.3, Panel F. Chambers *et al.* (2002) show that the measured excess stock returns in R&D-intensive firms is due to compensation for risk-bearing rather than mispricing. Hirshleifer *et al.* (2013) support the notion that the positive relationship between innovation efficiency (IE) and current/future market valuations cannot be entirely explained by risk and mispricing, even though IE is incremental to other innovation-related variables. Further examination shows that the ability of IE as a measure for predicting stock returns is made stronger by adding the proxies of investor inattention and valuation uncertainty. Thus, this relationship cannot be fully explained by rational pricing but can be partly explained by psychological bias or constraints. Overall, mispricing is not the main reason for misvaluing firm innovation. Further researches could be carried out in order to investigate the cause of this.

Taken together, scholars in this area find that innovation is relevant in predicting stock market returns and volatilities. However, research also shows that the information about innovation activities and outcomes are not entirely embedded in stock prices and the main reason is not mispricing.

2.2.3 The relation between trading in the equity market on innovation

In Table 2.4, we review the literature around the relationship between trading in the equity market and innovation from the perspective of market manipulation, takeover and trading by institutional investors. In Table 2.4, Panel A reviews the relationship between market manipulation (i.e., insider trading, end-of-day dislocation) and innovation. Levine *et al.* (2017) found that the enforcement of insider trading laws improves innovation. They found increased innovation in industries which are naturally innovative following the country restricting insider trading. Additionally, industries with a more naturally innovative experience have a much bigger increase in IPOs and SEOs after a country begins to enforce its insider trading laws (when compared to other, less innovative industries). This supports the hypothesis that the enforcement of insider trading laws attracts outside investors who value the firm's innovation activities and decreases the degree of asymmetric information between outside investors and insiders. By applying a different proxy (insider trading) and studying a different period, we can see that there is no significant relationship between insider trading and innovation, as demonstrated by Cumming *et al.* (2020).[6] However, Cumming *et al.* (2020) demonstrated a significantly negative influence in end-of-day manipulation on patenting. Furthermore,

[6] In Cumming *et al.* (2020), insider trading is measured by considering the surveillance data of suspected insider trading (computer algorithms that send messages to surveillance authorities), while insider trading in Levine *et al.* (2017) is presented as the dummy variable of enforcement indicators which equal one after the country first enforces its insider trading laws, and zero otherwise.

intellectual property rights and a firm's age are positively related to subsequent innovation. Aboody and Lev (2000) proved that innovation exerts a positive influence on insider gains. They demonstrated that R&D makes a big contribution to asymmetric information between both corporate insiders and normal investors, leading in turn to insider trading and gains.

*** Table 2.4 ***

In Table 2.4, Panel B, we present a debate about the influence of anti-takeover on innovation. Atanassov (2013) found that firms experience a reduction in patent citations after passing anti-takeover laws, especially after two or more years. This effect is mitigated but not eliminated by large shareholders, activist pension funds, financial leverage and product market competition. By contrast, Chemmanur and Tian (2018) showed that anti-takeover provisions (ATPs) can have a positive effect on innovation. This influence is more pronounced when firms are subject to a more significant degree of asymmetric information and engage in more competitive product markets. They also found that by adopting ATPs, the market value of firms participating in innovation will increase, while the market value of firms which do not significantly participate in innovation will decrease. Overall, the relationship can be explained from two perspectives: On the one hand, regarding moral hazard (Seru, 2014), the threat of hostile takeover forces managers to focus on the most innovative and valuable projects. On the other hand, there are few incentives for managers to invest in innovation when they have less power than shareholders in terms of takeover threats (Shleifer and Summers, 1988). In addition, shareholders tend to undervalue the stocks of a firm that is investing in innovative projects because of asymmetric information. Under such circumstances, hostile takeovers are required earlier in order to achieve control of the firms by buying cheap shares (Stein, 1988). Comparing these two papers, the anti-takeover variables are represented separately from the perspective of the country and of the firm. While Atanassov employs the enforcement of anti-takeover laws as the proxy of the dependent variable, Chemmanur and Tian (2018) use a regression discontinuity design surrounding a firm's close-call votes about passing or failing to pass an ATP in an annual meeting, which eliminates the endogenous effects.

In Table 2.4, Panel C, we show that trading by institutional investors in an equity market influences a firm's innovative activity. Bushee (1998) suggests that when institutional investors, such as major shareholders, trade based on current earning news, the firm's managers tend to reduce long-term R&D projects and concentrate on myopic investment. However, when these investors do not frequently consider a firm's current information, they tend to reduce the managers' short-term pressures as monitors. Abdioglu *et al.* (2015) found that the Sarbanes-Oxley Act improves institutional investment in a firm's R&D expenditures. The Sarbanes-Oxley Act, aims to improve the accuracy of a public firm's disclosures, enables firms with high R&D expenditures to attract more institutional investments, and in so doing strengthens the relationship between institutional ownership and a firm's R&D spending. They found a higher level of passive and dedicated institutional investment in high innovation firms after the enactment of this legislation. In other words, this result is mainly driven by a reduction of asymmetric information.

In summary, trading in the equity market can affect firm innovation. There is an association between market manipulation, takeover and trading by institutional investors in the stock market and a firm's innovative activities and results. Excepting the aforementioned research, few studies cover this field.

2.2.4 The impact of equity market microstructure on innovation

To the best of my knowledge, current literature largely revolves around the relationship between exchange market structures and innovation, and focuses on the impact of stock liquidity on innovation. While Fang *et al.* (2014) found a negative impact of stock liquidity on firm innovation, Wen *et al.* (2018), Tadesse (2006), and Cumming *et al.* (2020) all support that there is a positive relationship between them and Dass *et al.* (2017) finds the impact to be insignificant. Comparing these papers, Fang *et al.* (2014) ran their tests during the period surrounding the large shocks in minimum tick size in order to overcome the interplay between stock liquidity and innovation.[7] Their results show that firms which experience a larger increase in stock liquidity following decimalisation and movements of minimum tick size produce significantly fewer patents and patent citations. Additionally, during the phase-in feature of decimalisation that occurred on the NYSE in 2000, they found the number of patents generated by pilot firms that converted to decimal pricing in 2000 experienced a large decrease in the first year when compared with non-pilot firms that moved in 2001. Following Fang *et al.* (2014)'s approach, however, Wen *et al.* (2018) applied two different exogenous variations to avoid interrelationship, namely, split-share structure policy and the adjustment of stamp duty rate. They posit that liquidity improves the valuation of privatised State-Owned Enterprises (SOEs) and participants of dedicated institutional investors, thereby decreasing agency problems and rising innovation amongst SOEs. In addition, Cumming *et al.* (2020) found that a positive impact of stock liquidity on innovation can be mitigated by the presence of end-of-day manipulation.

[7] According to Furfine (2003), changes in minimum tick size can straight affect stock liquidity but less likely influence innovation directly.

*** Table 2.5 ***

Overall, research in this area mainly focuses either on one single country, or on several. And, there is still a debate around what impact stock liquidity has on a firm's innovation outputs.

2.3 The relationship between other financial markets and firm innovation

Recent papers also analyse how trading in derivative markets, which consists of exchanges and over the counter (OTC) markets, influences firm innovation. In Table 2.6. Blanco and Wehrheim (2017) found active options trading encourages firm innovation in R&D-intensive industries. In particular, firms with active options trading tend to increase the diversity and originality of their innovative activities and participate in risk-taking behaviours. Blanco and Wehrheim further suggest that the higher the product market competition, the less managerial entrenchment there is, the younger CEO, the lower the profitability pressure and the better the control of managerial compensation. Chang *et al.* (2015) supported the argument that non-executive employee stock options improve corporate innovation, mainly through encouraging employees to take the risk rather than just exert effort in order to raise stock value. Employees are driven to push innovation based on the nature of R&D investment. In other words, they are encouraged to work together, take more risks in the innovation process and stay in the firms until innovation brings successes. Chang *et al.* (2019) suggested the trading of credit default swaps (CDS) to lenders is positively associated with a firm's innovative success. In particular, innovation in firms who are more dependent on debt finance and have more continuous lender monitoring are more sensitive to the CDS trade initiation. In addition, borrowing firms improve innovation by increasing innovation efficiency instead of R&D investment after the introduction of CDS trading on them.

*** Table 2.6 ***

In summary, derivatives trading (i.e., options, non-executive employee stock options and CDS trading) is positively related to both quantity and quality of firm innovation. A common finding amongst the aforementioned three papers is that firms which encouraged derivative trading are more likely to take risks during the R&D process and generate more patents and patent citations.

This shows that derivative markets are beneficial to firms seeking to improve their innovation activities because the value of derivative products, such as options and CDSs, usually depends on the firm’s long-term earnings. For example, an active options market can improve information transmission about long-term investment, thereby achieving a more efficient stock price and reducing asymmetric information (Blanco and Wehrheim, 2017). In terms of this, firms will be more incentivised to participate in value-enhancing innovative activities.

2.4 Chapter Conclusion

In terms of the literature review, we can conclude that there are several characteristics in innovation. 1) Corporate innovation is risk-taking behaviour that involves a substantial probability of failure (Holmström, 1989). 2) Innovation requires long-term, continuous investment. Manso (2011) and Ederer and Manso (2013) reveal that for innovation to perform better there needs to be a tolerance of early failures. 3) Innovation is a labour-intensive, multi-stage process. Ederer (2008) suggests that innovation activities tend to succeed when innovators are encouraged to team up with others and are rewarded for long-term joint achievements. 4) The asymmetric information is between investors and firm managers. Adverse selection problems (Stiglitz and Weiss, 1981) are more likely in R&D-intensive industries because of the inherent riskiness of the investment. Moral hazard problems are also severe for high-tech firms because it is easy for them to substitute high-risk projects for low-risk ventures. In addition, Allen and Gale (1999) argue that it is usually difficult to evaluate innovative projects because information about their prospects is either sparse or hard to process, which often leads to a variety of opinions. Aboody and Lev (2000) show that R&D makes a significant contribution to asymmetric information between corporate insiders and normal investors, which leads to insider trading and gains. 5) A high level of intangible assets. R&D investment creates intangible assets for the firm (Johnson and Pazderka, 1993) and leads to a lack of collateral (Hall, 2002).

A financial market can enhance firm innovation when it gives the greatest possible consideration to the innovation(s) in question. We investigate the impact on innovation activities in the following chapters based on these characteristics.

Table 2.1 Literature studied on firm innovation in the primary market

Reference	Period of study	Country(s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Kim and Weisbach (2008)	1990-2003	38 countries	Substantial funds which companies raise in IPO are finally invested in R&D.	WorldScope, Standard and Poor’s Compustat Global, Compustat North America
Wies and Moorman (2015)	1980-2011	US	Going public increases the number and variety of firm innovation but decreases the risk of it.	ProductLaunch Analytics
Wu (2012)	1980-2008	US	The number of patents tends to increase among medical service firms after going public. However, a large percentage of these patents dependents on the firm’s previous patents.	USPTO, Granted database
Aggarwal and Hsu (2013)	1980-2000	US	The number of patents and forward patent citations among biotechnology firms tends to be declined after going public in terms of short-term performance pressures.	IQSS Patent Network database (Lai et al. 2011)
Bernstein (2015)	1985-2003	US	Going public changes firm's strategy in pursuing innovation that decreases the quality of innovation,	NBER (Hall, Jaffe, and Trajtenberg, 2001), Harvard

			namely, relying more on hiring new inventors and acquiring external technologies.	Business School (HBS) patent database
Acharya and Xu (2017)	1976-2006	US	Going public improves firms' innovation when they depend on external finance and impede innovation when they are less dependent on external finance.	NBER

Table 2.2 Literature studied on firm innovation in the equity market

Reference	period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel A literature that investigates the effect of equity financing on innovation by comparing with other financing methods.				
Hsu et al. (2014)	1976–2006	32 economies	A better-developed equity market improves innovation in industries that more rely on external finance and that are more high-tech intensive, while a better-developed credit market impedes innovation in these industries.	NBER
Brown et al. (2017)	1980–2005	38 countries	Equity market development improve the overall growth of an economy's high-tech sector	UNIDO and World Bank Development indicators, Compustat North America, Hsu, Tian, and Xu (2014).
Tadesse (2006)	1980-1995	34 countries	Technology innovation is generally improved by market-based financial systems, while innovation in industries with greater intangible assets grows faster in bank-based financial systems.	UNIDO database

Reference	period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Maskus et al. (2012)	1990–2003	18 OECD countries	The development of the domestic equity market can positively impact R&D in industries that rely more on external finance but not changes in terms of the level of tangible assets.	OECD data
Wang and Thornhill (2010)	1976-2005	US	It is appropriate for a firm to finance through common equity if it has high level of R&D investment.	Compustat North America dataset
Black and Gilson (1998)	1984-1996	US, Germany, Japan, UK and Other 14 European Countries	A well-developed equity market but not a credit market can indirectly improve innovation by providing a lucrative exit opportunity for venture capital investors.	No

Panel B literature that studies the relationship between the equity market and innovation.

Reference	period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Brown et al. (2009)	1990-2004	US	Fluctuations in the supply of both internal and external equity finance can explain a significant part of the 1990s boom and subsequent decline in aggregate R&D in the US.	Compustat

Martinsson (2010)	1995–2004	UK and Other 9 European Countries	Supply shifts in both internal and external equity finance during the late 1990s and early 2000s explains the R&D cycle for new high-tech firms in UK, while only the cash flow effect is significant for new high-tech firms in continental Europe.	Compustat Global database
Brown et al. (2013)	1990-2007	32 countries	Law rules are exogenous variations that influence stock issues, thereby affecting long-term R&D investment.	Compustat Global and Compustat North America
Martinsson, and Lööf (2013)	1997–2005	Sweden	A stable equity supply plays an important role for firms in maintaining a smooth patenting profile over the business cycle.	PATSTAT
Brown et al. (2012)	1995–2007	16 countries	Firms that have better access to stock market finance invest more in R&D and achieve more patents.	Compustat Global database
Reference	period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel C literature that studies the impact of equity market liberalisation on innovation.				
Moshirian et al. (2015)	1980-2008	51 developed and emerging economies	Equity market liberalisation tends to improve innovation output in more equity finance dependence industries through releasing financial	Orbis patent database (PATSTAT)

			constraints, utilising human capital and transmitting foreign technology.	
Luong et al. (2017)	2000-2010	26 non-US economics	The entry of foreign institutional investors improves the firm's innovation through active as active monitors, providing insurance against innovation failures and transmitting foreign technology.	DWPI database
Giudici and Paleari (2000)	1997	Italy	The equity market is more attractive for innovative firms which are young but growing rapidly.	newspapers and specialised magazines, the World Wide Web, sectorial lists, industrial associations, scientific parks brochures, districts and incubators for small firms

Table 2.3 Equity market's function of evaluating innovation

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel A Literature studied how the equity market evaluate innovation in terms of R&D investment				
Lev and Sougiannis (1996)	1975-1991	US	There is a significant positive relationship between firms' R&D spending and subsequent stock returns.	NBER
Toivanen et al. (2002)	1988-1995	UK	Frim R&D spending can significantly improve subsequent stock returns.	Extel's Financial Company Analysis
Hall and Oriani (2006)	1989-1998	France, Germany, Italy, UK and US	There is a significantly positive relationship between R&D investment and market value of firms in France, Germany, the UK and the US, but not in Italy.	ANBERD database
Booth et al. (2006)	1991-2001	10 industrial countries	Stock market evaluation function of R&D spending can be improved by a higher degree of market-based financial system rather than a higher overall level of financial development.	Compustat Global Vantage database

Kallunki et al. (2009)	1993–2006	US	Technology-oriented M&As could improve the impact of the acquirer firm's R&D expenditures on its current stock market value and future profitability.	Worldscope

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel B Literature studied how equity market evaluate innovation in terms of innovation announcement				
Woolridge and Snow (1990)	1973-1983	US	The R&D announcement is positive associated with the stock market return	Wall Street Journal
Sood and Tellis (2009)	1977-2006	US	The positive reaction of stock market to innovation announcement.	FACTIVA (which includes the Wall Street Journal), Lexis-Nexis, and company websites for press releases/announcements on technological innovations, all newswire services such as PR Newswire,

				Business Newswire, and Reuters.
Adcock et al. (2014)	2007-2012	27 European countries	Higher innovation-intensive countries experience better market reactions to negative news during the global financial crisis.	Eurostat

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel C Literature studied how the equity market evaluate innovation in terms of patent-based indicators				
Hall et al. (2005)	1963-1995	US	A firm's patent citations could be capitalised in its market value.	USPTO; Compustat
Hsu (2009)	US (1977Q1–2007Q4, 1991Q2–2006Q4) Canada (1982Q2–2007Q4), China (1993Q1–2007Q4), France (1989Q1–	US, China, Canada, Germany, India, Italy, Japan,	Technology innovation would increase the expected real and excess return of stock index in global area.	USPTO databases, Hall, Jaffe, and Trajtenberg's (2001) data set, Compustat database, National Science Foundation (2005): US; SIPO: China; OECD

	2007Q4), Germany (1981Q3–2007Q4), India (2000Q4–2007Q4), Italy (1994Q2–2007Q4), Japan (1985Q2–2007Q4), U.K. (1984Q3–2007Q4)	French and UK		Factbook 2008: Canada, Germany, India, Italy, Japan, French and U.K
Hirshleifer et al. (2017)	1981-2006	US	Innovative originality can predict subsequent firm's profitability and abnormal stock market returns.	NBER (Hall, Jaffe, and Trajtenberg, 2001); Harvard Business School U.S. patent inventor database (Li et al. 2014)
Hirshleifer et al. (2013)	1981-2006	US	A new innovative efficiency measures which is positively associated with contemporaneous	NBER

			market valuation and firm's future stock returns and future operating performance.	
Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel D Literature studied on impact of innovation on stock return volatilities				
Chan et al. (2001)	1975-1995	US	Firms with a higher ratio of R&D to sales generate larger monthly volatility of return than firms without R&D.	Compustat Active and Research files
Gharbi et al. (2014)	2002–2011	French	R&D intensity positively affects stock return volatility.	Thomson Reuters
Ladner and Veronesi (2009)	1831-1858	US	Uncertainty about the average productivity of new technologies attributes to the high volatility and bubble-like stock prices of firms which improve innovation during technological revolutions.	No
Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel E Literature studied on whether equity market fully evaluates firm innovation or not				

Chan et al. (2001)	1975-1995	US	Full benefits of R&D spending are incorporated by stock price on average in several R&D-intensive industries during the period from 1975 to 1995.	Compustat Active and Research files
Cohen et al. (2013)	1980-2009	US	Stock market tend to ignore the information about R&D success which embedded in past track records, even this information is expectable, stability and simple to compute.	Compustat; NBER
Gu (2005)	1983-1999	US	Changes of patent citation impact have strong relationship with firms' real earnings, which is ignored by investors.	NBER
Eberhart et al. (2004)	1951-2001	US	R&D increases are beneficial investment; however, the market would like to slowly recognise the extent of them.	COMPUSTAT
Dong et al. (2017)	1976-2012	US	Stock market overvaluation is positively related with both quality and quantity of firms' innovation activities.	Kogan et al. (2016)
Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation

Panel F Literature studied the reason why the stock market misvalues firm innovation				
Chambers et al. (2002)	1979–1998	US	The measured excess returns to R&D-intensive firms due to compensation of risk-bearing rather than mispricing.	Compustat
Hirshleifer et al. (2013)	1981-2006	US	The positive relationship between innovation efficiency (IE) and current (and future) market valuations cannot be entirely explained by risk and mispricing, even though IE is incremental to other innovation-related variables.	NBER

Table 2.4 The relation between trading in the equity market on innovation

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel A Literature studied the relation between market manipulation (i.e., insider trading, end-of-day dislocation) and innovation				
Cumming et al. (2016)	2003-2010	9 countries	The end-of-day manipulation is found to significantly decrease patenting; however, insider trading is not observed to significantly impact subsequent patenting.	PATSTAT
Levine et al. (2015)	1976-2006	94 economies	Enforcement of insider trading laws improves innovation.	PATSTAT
Aboody and Lev (2000)	1985-1997	US	R&D makes a great contribution to asymmetric information between corporate insiders and normal investors, which leads to insider trading and gains.	Compustat

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel B Literature studied the influence of takeover on innovation				

Atanassov (2013)	1976-2000	US	Hostile takeovers are helpful for corporate innovation	NBER (Hall, Jaffe and Trajtenberg, 2001)
Chemmanur and Tian (2018)	1990–2006	US	The positive, causal influence of antitakeover provisions (ATPs) on innovation.	NBER (Hall, Jaffe and Trajtenberg, 2001)
Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Panel C Literature studied on impact of trading by institutional investors in the equity market on firm innovation				
Bushee (1998)	1983-1994	US	When institutional investors, as major shareholders, heavily trade based on current earning news, firms tend to focus on managers tend to myopic investment rather than R&D investment; otherwise, they improve R&D projects.	the 1995 Compustat PST, Full Coverage and Research
Abdioglu et al. (2015)	1998-2009	US	Sarbanes-Oxley Act improves institutional investment in firms' R&D expenditures.	Compustat Fundamentals Annual database.

Table 2.5 The impact of equity market microstructure on innovation

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Fang et al. (2014)	1994-2005	US	Stock liquidity impedes firm innovation.	NBER (Hall, Jaffe and Trajtenberg, 2001)
Dass et al. (2017)	1994-2006	US	There is no significant relation between Stock liquidity and firm innovation	NBER (Li et al.,2014)
Wen et al. (2017)	2006-2013	China	Stock liquidity improves innovation in state-owned enterprises, but not in non-state-owned enterprise.	Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE)
Tadesse (2006)	1980-1995	34 countries	Stock market liquidity positively impacts innovation which represented by the rate of technological progress for each industry in each country.	UNIDO database
Cumming *et al.* (2020)	2003-2010	9 countries	Sock liquidity will positively affect subsequent patenting. However, this effect tends to be mitigated by the presence of end-of-day manipulation.	PATSTAT

Table 2.6 The relation between other financial markets and firm innovation

Reference	Period of study	Country (s) studied	Main finding (Effects on Innovation)	What database they use for innovation
Blanco and Wehrheim (2017)	1996 -2004	US	An increasing options trading volume encourages firm innovation in R&D-intensive industries.	NBER
Chang *et al.* (2015)	1998-003	US	Non-executive employee stock options will improve corporate innovation.	NBER
Chang *et al.* (2019)	1997-2008	US	Trading of credit default swaps (CDS) to lenders is positively associated with the borrowing firm's innovative success.	Noah Stoffman's website; Harvard Business School (HBS) Patent Network Dataverse

Chapter 3 Matching PATSTAT applications to Datastream financial data

3.1 Introduction

Technology innovation is widely regarded as a vital driver for a nation's long-term economic growth (Solow, 1956; Grossman and Helpman, 1991; Aghion and Howitt, 1992) and its competitive advantage (Porter, 1998). Extensive literature in this field employs patent-based measurements to represent innovation performance. This chapter aims to provide a more accessible dataset to study firm innovation from an international perspective. With this in mind, we have created a list of company names that links the patent data from the PATSTAT database with firms' account information from the Datastream database across 44 countries from 1990 to 2010.

Studies in this area are mainly focused on the US market (for example, Fang *et al.*, 2014; Chemmanur and Tian, 2018). They extract patent data from the National Bureau of Economic Research's (NBER) Patent and Citation Database, which only covers patents that are granted by the US Patent & Trademark Office (USPTO) (Moshirian *et al.*, 2015). Other literature in this area is generally more relevant to individual countries (Lotti and Marin, 2013; Martinsson and Lööf, 2013) or countries in specific regions (Thoma and Torrisi, 2007; Macartney, 2009). Some studies represent a firm's innovative activity through the Research and Development (R&D) investment. However, the R&D investment is more likely to describe a firm's innovation input rather than its innovation performance (Ashwin *et al.*, 2015; Wen *et al.*, 2018). While the Orbis platform can identify companies from external datasets through the "batch search", it usually only covers data from the previous ten years of the current year.[8] Although

[8] For a detail introduction of Orbis platform, see https://www.bvdinfo.com/en-gb/our-products/data/international/orbis.

the Orbis database can offer company account data from 10 years ago and consolidate patent data from the PATSTAT database, it is not accessible to most institutions and too expensive for individual researchers to afford.

Regarding the disadvantages of previous literature, we link the worldwide patent database (PATSTAT) with one of the most widely used firm accounting information databases (Datastream) by modifying the code of Macartney (2009) and Lotti and Marin (2013). Overall, we have created a list of 11,371 company names across 44 countries between 1990 and 2010. This covers around 42.04% of patents from the PATSTAT database and 14.43% of equities from the Datastream database. Three countries/regions merged more than 50% of patents from PATSTAT with their firm account data from Datastream; Ten countries merged more than 30% of patent applications, and twenty-five countries merged more than 10% of patent applications.

In this chapter, we provide a more accessible dataset by which to investigate the relationship between financial markets and firm innovation from an international perspective. Compared with previous researches, this dataset includes patents from patent authorities worldwide rather than just USPTO. Thus, it is less like to underestimate the number of patents per company in non-US countries. In addition, we collect and calculate patent data in different countries with the same standard, which provides a basis for global innovation research through innovation outputs.

In the remainder of this chapter we review existing databases and describe their advantages and disadvantages in section 2. We introduce the characteristics of the matched dataset in section 3. Section 4 concludes.

3.2 Review of existing databases

This section describes previous literature that links a firm's patent-based measures with their account information. First we introduce the NBER Patent and Citation Database, as it is widely employed to study the US market. However, this dataset restricts international researches on firm innovation outcomes (i.e., patent-based measures). We then demonstrate several studies that merge PATSTAT applicants with firms in different databases, which generally focuses on individual countries or regions. The Orbis platform contains the firm's account information and can identify companies from an external dataset through "batch search". However, it generally only covers the data ten years previous to the current year. Although individuals/institutions can take out a subscription to access date from more than 10 years ago, the fee is expensive for individual researchers. Compared with this, this chapter can perhaps provide a more accessible opportunity for international studies regarding a firm's innovation performance.

3.2.1 NBER and US financial data

Previous studies have incorporated patent-based data (the number of patent applications, the number of patent citations) and merged it with a firm's account information. The Patent and Citation Database is one of researchers' most used databases, such as Pakes and Griliches (1980), Hausman *et al.* (1984), Hall *et al.* (1986) and Griliches *et al.* (1986). It covers the patents granted by USPTO and provides data regarding technological class, assignee, and citations (*Dass et al.*, 2017).[9] The patent data from the NBER database is linked to a firm's account data from different databases.

The first systematic attempt is NBER's productivity program from 1978 through to 1988 (Bound *et al.*, 1982; Hall *et al.*, 1986b). It covers around 2,600 large listed companies in the US manufacturing industry in Compustat and then merges this with around 300,000 patent applications in the USPTO during the period between 1965 and 1981. 'Harmonisation' and visual matching remove incorrect results. The matching between USPTO applicants and companies in Compustat has been updated by Hall *et al.* (2001), Cockburn *et al.* (2009), Li *et al.* (2014) and Arora *et al.* (2021). Although this matching procedure is effective, Lotti and Marin (2013) suggest that it is costly (in money and time) and difficult to extend databases to include small and medium-sized enterprises.

The second example is from Balasubramanian and Sivadasan (2010), which merged assignees in the NBER Patent and Citation Database with the firms on the Business Register (BR) of the Census Bureau. They extended the coverage offered by Hall *et al.* (2001). Because the link between the datasets of Hall *et al.* (2001) is based on the 1989 Compustat universe of firms, and the ownership changes before or after 1989 it could not reflect the matching result accurately. The US Census Bureau spends large sums of money tracking ownership changes and thus provides a research opportunity to not only study smaller and unlisted firms but also to consider the changes in ownership among patent assignees. However, they only cover the US assignees that were not individuals or governments.

[9] Except NEBR patent database, KPSS patent dataset, which was constructed by Kogan *et al.* (2017), also covers the information of patents granted by USPTO (Wang, 2017). While the NBER patent database covers a shorter time period between 1976 and 2006, the KPSS patent dataset covers the time period from 1926 to 2010.

Although the NBER Patent and Citation Database is widely used in the literature on intellectual property and technological progress, it only covers the patents that are filed in the US and granted by the USPTO (Moshirian *et al.*, 2015). A range of research assumes the USPTO records all important granted patents around the world, as the US is and has been the largest technology consumption market over the past few decades (Hsu *et al.*, 2014). However, Chang *et al.* (2015) argue that many emerging countries do not submit patent applications to the USPTO. Luong *et al.* (2017) found that USPTO does not record about 25% of Japanese patents and around 17% of patents from Germany and other countries. Thus, international research which uses USPTO tends to underestimate the number of applications per company for non-US firms. Namely, it restricts international studies which focus on firm innovation performance (i.e., patent-based measures), and researchers have to use R&D instead.

3.2.2 PATSTAT and European data

The PATSTAT database contains more than 80 million patent documents from 100 patent offices over the world (Levine *et al.*, 2017). It was created by the European Patent Office (EPO) based on the requirements of the Patent Statistics Task Force, which is led by the Organisation for Economic Co-operation and Development (OECD). The PATSTAT database is published biannually, and we use the PATSTAT 2016 Autumn Edition.

Lotti *et al.* (2005) matched the European Patent Office (EPO) patent applications to around 115,000 EU15 companies on the AMADEUS database by taking exact matches and visually-checked matches based on the SOUNDEX algorithm.[10] They acknowledge that the data on the

[10] The SOUNDEX algorithm 'produces matches for strings using a weighting scheme, according to which each component of the string is assigned a certain weight and matches are produced accordingly' (Lotti *et al.*, 2005).

location of firms and applicants were not exploited to improve precision. In addition, the possibility of different firms having the same name is neglected both with AMADEUS and the patent database.

For other researches that link corporate account information to the patent data from the PATSTAT database, Thoma and Torrisi (2007) merged 2,197 listed European firms and their subsidiaries from the AMADEUS database to the patent applications at the EPO.[11] In addition, the dataset of Macartney (2009) matches corporate applicants across the 15 selected European countries to firm account data from AMADEUS from 1978 to 2004. Compared to these, the Datastream database only covers the listed companies and their current subsidiaries, but the account information is far more detailed than that on AMADEUS and has longer time series variation (Macartney, 2009). In addition, the dataset of Martinsson and Lööf (2013) consists of patent data and companies registered in the Statistics Sweden dataset from 1997 to 2005. Lotti and Marin (2013) merged the patent data with Italian firms on the AIDA database during the period 1977 and 2009.[12] Compared with them, our dataset contains 44 countries around the world until 2010.

In addition, compared with other methods that match databases through their original name on PATSTAT, we utilise the standardised name created by the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) Database (Du Plessis *et al.*, 2009; Magerman *et al.*, 2009; Peeters *et al.*, 2010). The EEE-PPAT dataset was made available in 2010 and presented the standardised name and sector allocation for all entities in PATSTAT. Using this dataset allows us to overcome two problems during the analysis: One of them is

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[11] The Amadeus (Bureau van Dijk) database includes the financial and business information of the 520,000 biggest public and private companies across 43 European countries.

[12] AIDA is the dataset that contains comprehensive information on companies in Italy, with up to ten years of history.

undercounting or overcounting. In other words, some applicants' and inventors' names do not remain in PATSTAT even though they are recorded in most patents. In addition, one entity tends to appear with different names in different patent documents in the patent filing process. EEE-PPAT identifies and unifies the names of these entities, which increases the accuracy of each entity's patent information. However, they did not thoroughly standardise all names. Additionally, the format of the name record in EEE-PPAT is not the same as on the Datastream database. We further standardised the company name and made it more suitable for combining other datasets, especially the Datastream databases.

3.2.3 Orbis Intellectual Property data

The Orbis database contains firm data from around the world. It can identify companies from external datasets through "batch search". However, this platform only covers data from ten years previous to the current year. The time interval available for research is shorter if the delay between filing and grant or refusal of patents is taken into account. Although the Orbis database offers company account data from more than ten years ago, and consolidates patent data from the PATSTAT database, it is not accessible for most institutions around the world and too expensive for individual researchers. Compared with the Orbis database, the Datastream database is widely accessed by institutions and covers the data of public companies around the world.

In conclusion, compared with previous literature, this research links one of the largest patent-based databases around the world, the PATSTAT database, and one of the most widely used firm account information databases, the Datastream database. It provides a more accessible approach to enhance one's understanding of the relationship between financial markets and innovation.

We demonstrate the matching procedure in Appendix3.[13] And then, we describe and analyse the matching results in section 3.

[13] We describe the process of recording patent applications on PATSTAT in Appendix 1 and measure the number of patent applications for each company in Appendix 2.

3.3 The matched dataset

In this section, we describe the matching results and analyse the company being merged during the matching procedure. In summary, we successfully matched 11,371 listed companies from Datastream with their patent-based data from PATSTAT for 44 countries between 1990 and 2010. It covers around 42.04% of patents on PATSTAT and 14.43% of the universe of firm records on Datastream for these countries during the period.

3.3.1 The number of patents and applicants before/after matching

In Table 3.1, we show the number of patents and applicants in each country before and after matching procedures from 1990 to 2012.

*** Table 3.1 ***

In order to summarise the matching results, we merged around 42.04% of patents for these countries from PATSTAT from 1990 to 2010. Among them, 3 countries/regions merged more than 50% of patent applications at PATSTAT with their firm account data on Datastream; 10 countries merged more than 30% of patent applications, and 25 countries merged more than 10% of patent applications. Japan was the country with the highest percentage of matched patent applications. 62.70% of patent applications in Japan were successfully merged with their corporate account information on Datastream.

It is worth noting that while column (4) shows the number of patents for both private and public companies, column (5) only covers this for public companies. Thus, the higher percentage in column (6) represents the fact that more patents were applied for by public companies in the countries/regions. This is especially true for Japan, Taiwan, and South Korea, where listed companies applied for more than half the patents. This means public companies are behind more inventions (measured by the number of patents) than private companies in these countries/regions from 1990 to 2010.

The United States covers more than 4,000 companies, namely, contains the highest number of merged patent applicants during the whole period. It is followed by Japan, China, Taiwan, and South Korea, which merged more than 900 corporate applicants from PATSTAT. Column (8) shows the number of all corporate applicants in each country, while column (9) only contains the corporate patent applicants as listed companies. Column (10) represents the proportion of listed companies in all companies which applied for at least one patent over the period 1990 to 2010. This is generally below 10% for most countries. Moreover, it is around just 6% even for Japan which merged the highest percentage of patents among all the countries considered. It shows that most of the companies applying for patents are *not* listed companies.

We show the map of public companies' innovative activities around the world in Figure 3.1 based on the data in column (9) of Table 3.1. This covers all matched companies across these 44 countries and represents innovative ability by the number of patents submitted from 1990 to 2010.

*** Figure 3.1 ***

In Table 3.2, we demonstrate the number of applicants that have been matched in different steps. There are 11,371 corporate applicants merged in this chapter. It shows that most companies are merged through the "full strings" company name and country code, this amounts to 4,731. 4,703 follows and this is the number of corporate applicants been merged by original name and country codes. In addition, 1,883 firms were merged through the "stem sting" company name and address information, 54 firms were added to the dataset through the manual match process.

*** Table 3.2 ***

3.3.2 The contribution of the top ten percent of applicants

In Figure 3.2, we present the distribution of the number of applications by matched companies from 1990 to 2010.[14] On average, each company made 163 applications during the period. According to the figure, however, the number of applications from 90% of applicants is less or equal to 152. Namely, most of the patents come from the top 10% of corporate applicants. Regarding this, we draw particular attention to the contribution of the top 10% of applicants to the total number of applications in each country.

*** Figure 3.2 ***

In Figure 3.3, we demonstrate the percentage of the number of applications from the top 10% applicants with the total number of applications in each country.[15] [16] The vertical axis is the percentage of the number of patents applied for by each type of patent applicants to the total number of applications in each country. The horizontal axis represents the name of each country. The columns are ordered by the percentage of applications from the top10% applicants

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[14] See the descriptive statistics of the full sample that is analysed in this thesis in subsection 5.3.3 Descriptive Statistics. In this chapter, we describe the method that matches corporate applicants on PATSTAT with firm accounting information on Datastream. We report the number of matched applications and corporate applicants in each country in row 5 and 9 in Table 3.1. They are different from the full sample analysed in the Chapter 5. It is because we restrict our dataset created in this chapter and produce the sample analysed in Chapter 4 and 5. For example, we restrict dataset to companies located and listed in the domestic country, and exclude the corporate applicants if they applied for fewer than 3 applications from 1990 to 2010 (see detailed restrictions in subsection 4.3.1 Data and sample selection).

[15] It is a 100% stacked column chart, which is employed to compare the percentages that each value contributes to a total.

[16] We define "Top 10% applicants of a country" as the top ten percent of companies with the largest number of patent applications in a country.

to the applications from whole applicants in each country. The higher the proportion of patents filed by the top 10% of corporate applicants to the total patents is a country, the more to the left the country is in the histogram.

*** Figure 3.3 ***

Using the country furthest to the left of the histogram, Japan, as an example, the white and light grey area represents the percentage of applications applied from the top10% applicants in Japan from 1990 to 2010. This amounts to 807,285 applications and covers 93.90% of applications in Japan.[17] Among them, the white area represents the percentage of applications applied by matched applicants. It is about twice the light grey area, which shows the percentage of applications which failed to merge with the firm account information on Datastream. While the top 10% of corporate applicants apply for more than 90% of patents in Japan, the remaining 90% of applicants applied for 6.10% of applications, which represented by grey and dark grey areas. The grey area shows the percentage of applications from matched applicants (0.40% of total applications), and dark grey represents the percentage of applications from unmatched applicants (5.7% of total applications).

Except for Egypt, Malaysia, Chile, Portugal, the Philippines, Colombia, Indonesia and Morocco, the top 10% of applicants contribute more than 50% of patents across the country in question. In addition, most successfully merged applications come from the top 10% of applicants in each country. In other words, for public companies, the contribution of the top 10% of applicants on a country's innovation performance is much more significant than the remaining 90% of applicants in the country.

[17] The detailed data is listed in Table 3.21 in the Appendix.

3.3.3 The number of applications per year

In Figure 3.4, we present the number of patents applied for by all corporate applicants and merged applicants from 1990 to 2010. The straight line in this figure represents the number of applications from all corporate applicants in the dataset. It is the sum of patents filed by both private and public companies. The dotted line is the number of patents applied for that have been matched with firm account information on Datastream. In other words, it represents the number of patents filed by public companies. The correlation between the straight line and the dotted line is 0.8146. This high correlation means that the innovation ability of public companies can represent the innovation ability of all companies.

*** Figure 3.4 ***

In Figure 3.3, in the Appendix, we show the number of applications from all companies and merged companies in each country.[18] These figures are ordered by the number of applications filed by all firms in each country (i.e., the blue line). The closer the straight and dotted lines are, the fewer patents (in the country in question) are filed by private companies. We also list the trend of merged companies' innovation outputs within each country in Table 3.22 in the Appendix. The number of applications submitted by merged companies is indexed to equal 1000 in 1990.

*** Figure A3.3 ***

*** Table A3.22 ***

[18] The meaning of the line in this figure is as same as the lines in Figure 3.3.

3.3.4 The number of patents per industry

In Table 3.3, we display the total patents between 1990 and 2010 classified by country and the 2-digital Standard Industrial Classification (hereafter, SIC) code for all matched corporate applicants. Column (1) represents the country name based on the two-letter alphabetic codes according to the WIPO Standard ST.3. Columns (2) to (11) show the number of patents applied for by companies in each industry. For example, the value 63 in the first row and fourth column means companies in the Austrian construction industry successfully applied for a total of 63 patents between 1990 and 2010. In this table, 117 corporate applicants (relevant to 1901 patent applications) have not recorded any industry information on Datastream. Excepting this, most patents come from the manufacturing industry, around 1.6 million. Among them, the number of patents applied for by US and Japanese listed companies, number 476,313 and 467,507 respectively and far exceeds the number of patents applied for by companies in other countries.

*** Table 3.3 ***

In Figure 3.5, we show the distribution of the number of patents applied for by companies in different industries. These figures also demonstrate the number of companies and the mean/minimum/median/maximum number of patents applied for by the companies at the top right of the histogram for each industry division. Companies in the manufacturing industry applied for an average of 198 patents, the most across all industries. Almost half of the companies in this industry applied for fewer than 10 patents between 1990 and 2010. ‘Samsung Electronics’ is the company with the most patents in the manufacturing industry, which filed 70,641 applications over the period.

*** Figure 3.5 ***

These tables show that most of the corporate applicants apply for a small number of patents during the whole period. This is because, excepting manufacturing companies, the median number of companies applying for patents in the remaining industries is less than or equal to 5. It shows that while most of the corporate applicants apply for a small number of patents, a few companies apply for a large number of patents.

In Figure 3.6, we introduce the condition of patent and R&D for companies in the manufacturing industry. We classify companies in the manufacturing industry into 20 major industry groups (i.e., the 2-digit SIC code).[19] For each major industry group, the orange bar represents the average R&D investment of the companies, and the blue bar shows the average number of patents received by the companies. The major industry group is ordered by the average number of patents obtained by the companies. Namely, the higher the average number of patents filed by companies in this industry, the higher the position of this industry on the table. Using the "Transportation Equipment" industry group as an example, companies belonging to this industry group invest an average of 3.3 million dollars in R&D projects and obtain an average of 451 patents from 1990 to 2010. It is the highest number of patents among these industry groups, and thus, it is on the left of Figure 3.6.

*** Figure 3.6 ***

The industry on the left and second positions of this figure is "Electronic and Other Electrical Equipment and Components, Except Computer Equipment". Although companies in this industry group obtain slightly fewer than average patents compared to companies in the "Transportation Equipment" industry group, they invest much less in R&D projects. It means

[19] For example, a company recorded with a 4-digit SIC code '3711' is classified as being in the 'Motor Vehicles and Passenger Car Bodies' industry. It in turn is included by industry group 371 (a 3-digit SIC code, representing 'Motor Vehicles and Motor Vehicle Equipment'), major group 37 (a 2-digit SIC code, representing 'Transportation Equipment') and Manufacturing Division.

companies in this industry group have a higher ability to transform the R&D investment into patents compared with the companies in the “Transportation Equipment” industry group.

3.4 Chapter Conclusion

In this chapter, we created a list of 11,371 company names that merged the patent data from PATSTAT with firm account information from Datastream across 44 countries from 1990 to 2010. It covers around 42.04% of patents from PATSTAT and 14.43% of equities on Datastream. Overall, we demonstrate a high correlation between the number of patents applied for matched companies with total companies. 3 countries/regions merged more than 50% of patents on PATSTAT with their firm account data on DataStream; 10 countries merged more than 30% of patent applications, and 25 countries merged more than 10% of patent applications. We show that the top 10% of applicants applied for most of the patents from 1990 to 2010. In addition, the US and the manufacturing industry are separately the country and the industry which contribute most of the patents in our sample.

We link the worldwide patent database, PATSTAT, with one of the most widely used firm accounting information databases, Datastream, through company name. This chapter provides a basis for global research by which to investigate the relationship between financial markets and a firm’s innovation performance.

Table 3.1 The number of patents and applicants in each country from 1990 to 2010

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AUSTRIA	AT	427,122	22,967	1,448	6.31%	4,923	4,095	45	1.10%
AUSTRALIA	AU	397,849	28,015	3,634	12.97%	8,113	6,803	165	2.43%
BELGIUM	BE	419,852	17,234	4,854	28.17%	2,834	2,034	39	1.92%
BRAZIL	BR	458,193	2,567	608	23.69%	1,295	1,018	41	4.03%
CANADA	CA	932,701	51,780	18,079	34.92%	12,844	10,848	422	3.89%
SWITZERLAND	CH	1,076,278	72,131	15,462	21.44%	11,124	8,463	89	1.05%
CHILE	CL	9,557	248	21	8.47%	167	140	2	1.43%
CHINA	CN	1,687,877	322,167	47,367	14.70%	65,269	60,256	992	1.65%
COLOMBIA	CO	144,173	52	0	0.00%	94	39	0	0.00%
CZECH REPUBLIC	CZ	146,685	3,758	394	10.48%	1,788	1,247	27	2.17%
GERMANY	DE	2,033,580	462,422	160,972	34.81%	50,792	45,420	406	0.89%
DENMARK	DK	332,700	15,155	4,998	32.98%	3,640	2,936	56	1.91%
EGYPT	EG	37,789	53	5	9.43%	36	28	2	7.14%
SPAIN	ES	457,768	21,471	740	3.45%	9,312	8,491	59	0.70%
FINLAND	FI	467,601	32,098	2,505	7.80%	4,090	3,491	63	1.81%
FRANCE	FR	1,606,855	186,484	52,750	28.29%	22,840	18,657	421	2.26%
UNITED KINGDOM	GB	1,823,774	97,657	20,514	21.01%	25,065	20,090	353	1.76%
GREECE	GR	44,294	446	49	10.99%	216	156	5	3.21%

HONG KONG	HK	144,413	6,815	1,839	26.99%	2,302	1,461	10	0.68%
HUNGARY	HU	225,079	3,173	342	10.78%	1,398	1,181	3	0.25%
INDONESIA	ID	31,734	27	1	3.70%	40	17	1	5.88%
IRELAND	IE	315,034	7,365	26	0.35%	2,248	1,869	5	0.27%
INDIA	IN	376,226	4,071	1,506	36.99%	1,038	837	92	10.99%
ITALY	IT	1,177,875	85,509	4,637	5.42%	23,430	20,374	165	0.81%
JAPAN	JP	2,491,555	859,755	539,099	62.70%	27,277	24,028	1,466	6.10%
SOUTH KOREA	KR	1,880,957	308,915	181,446	58.74%	30,114	24,639	959	3.89%
MOROCCO	MA	39,776	204	4	1.96%	194	125	2	1.60%
MEXICO	MX	51,537	693	15	2.17%	345	293	4	1.37%
MALAYSIA	MY	48,960	1,234	48	3.89%	808	718	11	1.53%
NETHERLANDS	NL	898,455	61,452	17,770	28.92%	12,222	10,742	31	0.29%
NORWAY	NO	196,288	9,675	1,009	10.43%	3,304	2,669	62	2.32%
NEW ZEALAND	NZ	48,213	3,159	400	12.66%	1,305	1,034	20	1.93%
PERU	PE	138	6	0	0.00%	19	3	0	0.00%
PHILIPPINES	PH	19,828	72	5	6.94%	58	35	1	2.86%
POLAND	PL	155,335	6,200	128	2.07%	1,976	1,748	49	2.80%
PORTUGAL	PT	56,361	792	3	0.38%	509	465	2	0.43%
RUSSIA	RU	348,256	38,990	1,390	3.57%	10,433	9,878	46	0.47%
SWEDEN	SE	705,749	52,080	18,705	35.92%	8,838	7,370	186	2.52%

SINGAPORE	SG	298,165	9,154	2,152	23.51%	1,331	1,015	31	3.05%
THAILAND	TH	12,670	332	119	35.84%	135	102	5	4.90%
TURKEY	TR	98,833	1,125	1	0.09%	319	282	1	0.36%
TAIWAN	TW	956,315	190,907	118,492	62.07%	12,124	10,085	968	9.60%
UNITED STATES	US	3,959,054	1,427,425	627,682	43.97%	141,634	125,407	4,039	3.22%
SOUTH AFRICA	ZA	224,758	5,588	393	7.03%	1,678	1,454	25	1.72%

Data source: PATSTAT - 2016 Autumn Edition.

Note: (1) refers to the country name. (2) refers to the "PERSON_CTRY_CODE" variable, namely, the corporate applicants' country code. It represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf). This is the country part of the correspondence address of applicants and inventors on PATSTAT. (3) refers to the number of patents per country before any processing. The number of patents per country in this column is relevant to private and public companies. However, the number of them in this column is overestimated than real data. It is because a corporate applicant may be recorded with more than one country on PATSTAT (See detailed explanation in Appendix 3.2 Measuring the number of applications and number of citations). By using "Harvard University" (in Table 3.9 in the Appendix) as an example. Harvard University is a famous private university in the United States; however, it is recorded along with Italy and United States in the database and identified as a company. Around 10% of corporate applicants are recorded with more than one country code before processing (see detailed information in Table 3.10 in the Appendix). (4) represents the number of patents per country after matching and removing extra country codes. The number of patents in this column is relevant to private and public companies. Compared with column (3), the number in column (4) is closer to the real data. It is because there is only less than 1% of the corporate applicants are associated with more than one country code after processing (see detailed information in Table 3.10 in the Appendix). In other words, most of the corporate applicants are associated with one country code after processing. In this column, the number of patents applied by Harvard University is only recorded in the United States. It is because although Harvard University is not a company, it is classified by PATSTAT into the company sector. Besides, we remove the link between it and Italy by subsection "A3.4.5 Remove extra country codes". (5) is the number of matched patents per country after matching. The number of patents in this column is only relevant to the public companies because Datastream only includes public companies. In this column, the number of patents applied by Harvard University is not recorded in the United States. This is because Harvard Univeristy is not a public company and it is not matched with firm accounting information on Datastream. (6) is the percentage of matched patents to the total patents after matching and removing extra country codes (i.e., (5)/ (4)). (7) shows the number of applicants per country before any processing. (8) is the number of applicants per country after matching and removing extra country codes. (9) is the number of matched applicants per country after matching. (10) represents the percentage of the matched applicant to the total applicant after matching and removing extra country codes (i.e., (9)/ (8)).

Table 3.2 The number of corporate applicants matched by each method

(1)	(2)	(3)	(4)	(5)	(6)
AT	14	16	15	0	45
AU	61	33	70	1	165
BE	16	15	8	0	39
BR	9	32	0	0	41
CA	177	151	94	0	422
CH	38	25	25	1	89
CL	2	0	0	0	2
CN	75	912	5	0	992
CZ	27	0	0	0	27
DE	143	166	93	4	406
DK	17	26	13	0	56
EG	0	2	0	0	2
ES	34	13	12	0	59
FI	29	19	14	1	63
FR	337	53	28	3	421
GB	125	71	157	0	353
GR	1	2	2	0	5
HK	2	7	0	1	10
HU	0	0	3	0	3
ID	0	1	0	0	1
IE	1	4	0	0	5
IN	25	29	38	0	92
IT	110	26	29	0	165
JP	566	878	0	22	1,466
KR	192	763	3	1	959
MA	1	1	0	0	2
MX	1	3	0	0	4
MY	7	3	1	0	11
NL	16	9	5	1	31

NO	41	9	12	0	62
NZ	7	10	3	0	20
PH	1	0	0	0	1
PL	13	36	0	0	49
PT	0	2	0	0	2
RU	31	13	2	0	46
SE	91	62	32	1	186
SG	10	10	11	0	31
TH	0	5	0	0	5
TR	0	1	0	0	1
TW	431	529	0	8	968
US	2,043	787	1,199	10	4,039
ZA	9	7	9	0	25
Total	4,703	4,731	1,883	54	11,371

Note: (1) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. The representation of strings in this column can be seen in Table 3.1. (2) refers to the number of applicants at PATSTAT successfully merged with their firm account information at the Datastream through the original name. (3) refers to the number of applicants at PATSTAT successfully merged with their firm account information at the Datastream through the full name. (4) refers to the number of applicants at PATSTAT, which is successfully merged with their firm account information at the Datastream through stem name. (5) refers to the number of applicants at PATSTAT is successfully merged with their firm account information at the Datastream through the manual match. (6) refers to the total number of applicants at PATSTAT is successfully merged with their firm account information at the Datastream (i.e., (2) + (3) + (4) + (5)).

Table 3.3 Country-Industry Breakdown of matched patents 1990-2010

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AT	.	.	63	1,350	14	13	2	6	.	.
AU	1	86	.	1,429	140	46	.	17	288	1,416
BE	.	3	1	4,743	.	.	.	4	101	.
BR	1	29	.	567	9	1	.	.	1	.
CA	11	498	.	15,417	535	94	.	460	1,014	.
CH	.	.	.	15,200	106	3	1	4	148	.
CL	.	20	.	1	.	.	.	.	.	.
CN	58	480	262	45,176	707	39	8	21	616	.
CZ	.	4	6	330	1	.	.	.	.	.
DE	25	172	242	151,008	2,957	474	46	1,758	4,289	.
DK	2	2	1	4,572	273	3	6	1	138	.
EG	.	.	2	3	.	.	.	.	.	.
ES	.	16	22	368	186	16	2	7	123	.
FI	5	.	316	1,821	81	210	.	3	69	.
FR	30	51	286	46,829	3,002	1,221	9	46	1,267	.
GB	1	255	141	17,646	1,683	29	28	66	665	.
GR	5	11	.	33	.	.	.	.	.	.
HK	.	5	1	1,824	.	.	.	.	9	.
HU	.	.	.	342	.	.	.	.	.	.
ID	.	.	.	1	.	.	.	.	.	.
IE	.	.	.	1	.	.	.	.	25	.
IN	.	67	10	1,041	2	.	.	23	363	.
IT	.	344	1	4,073	69	39	12	40	59	.
JP	27	279	3,674	467,507	4,509	4,012	1,107	62	57,916	.
KR	38	6	889	171,789	6,185	1,224	34	78	1,124	.
MA	.	.	.	.	3	1	.	.	.	.
MX	.	.	.	14	.	1	.	.	.	.
MY	.	31	.	7	1	.	.	1	8	.

NL	.	16	32	17,681	3	2	.	2	34	.
NO	.	296	13	593	53	12	.	1	41	.
NZ	29	.	1	296	10	.	1	.	63	.
PH	.	.	.	5	.	.	.	.	.	.
PL	.	15	7	97	2	2	1	.	1	.
PT	.	.	.	2	1	.	.	.	.	.
RU	.	414	52	732	154	11	5	5	.	.
SE	.	1	14	18,212	13	1	8	68	372	2
SG	.	3	1	2,109	20	.	4	1	14	.
TH	.	3	.	115	.	.	.	.	1	.
TR	.	.	.	1	.	.	.	.	.	.
TW	.	.	54	115,566	892	690	119	274	889	.
US	385	1,771	136	476,313	8,844	2,076	614	3,457	132,637	24
ZA	.	68	.	213	59	14	.	10	6	.
Total	618	4,946	6,227	1,585,027	30,514	10,234	2,007	6,415	202,281	1,442

Note: (1) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. The representation of strings in this column can be seen in Table 3.1. Column (2)-(11) are the industry division based on the 2-digit SIC code. (2) represents the "Agriculture, Forestry, and Fishing" industry division. (3) represents the "Mining" industry division. (4) represents the "Construction" industry division. (5) represents the "Manufacturing" industry division. (6) represents the "Transportation, Communications, Electric, Gas, and Sanitary Services" industry division. (7) represents the "Wholesale Trade" industry division. (8) represents the "Retail Trade" industry division. (9) represents the "Finance, Insurance, and Real Estate" industry division. (10) represents the "Services" industry division. (11) represents the "Public Administration" industry division.

Figure 3.1 Innovative activity of public company around the world from 1990 to 2010 using all Matched data

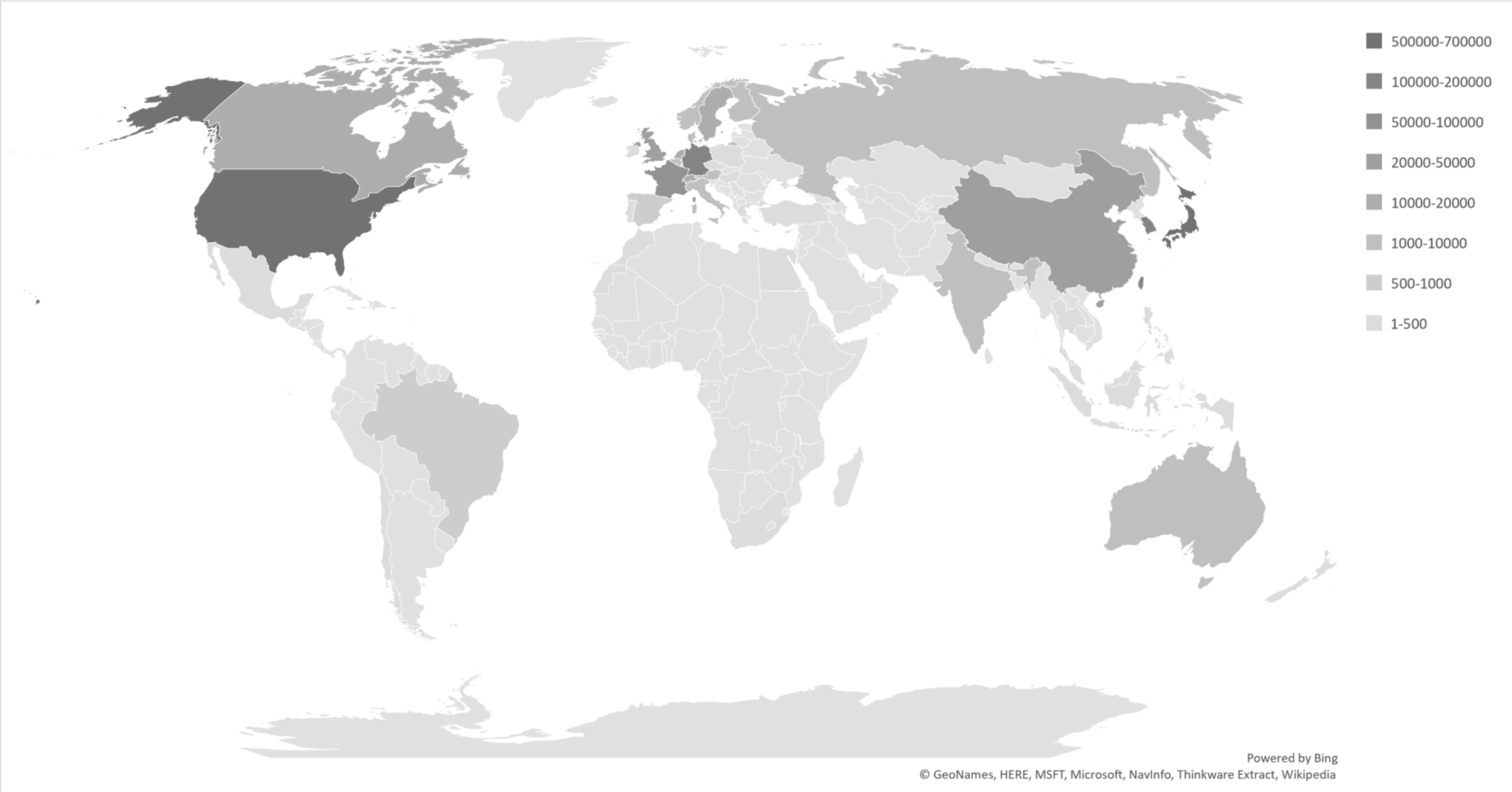


Figure 3.2 Distribution of matched applications

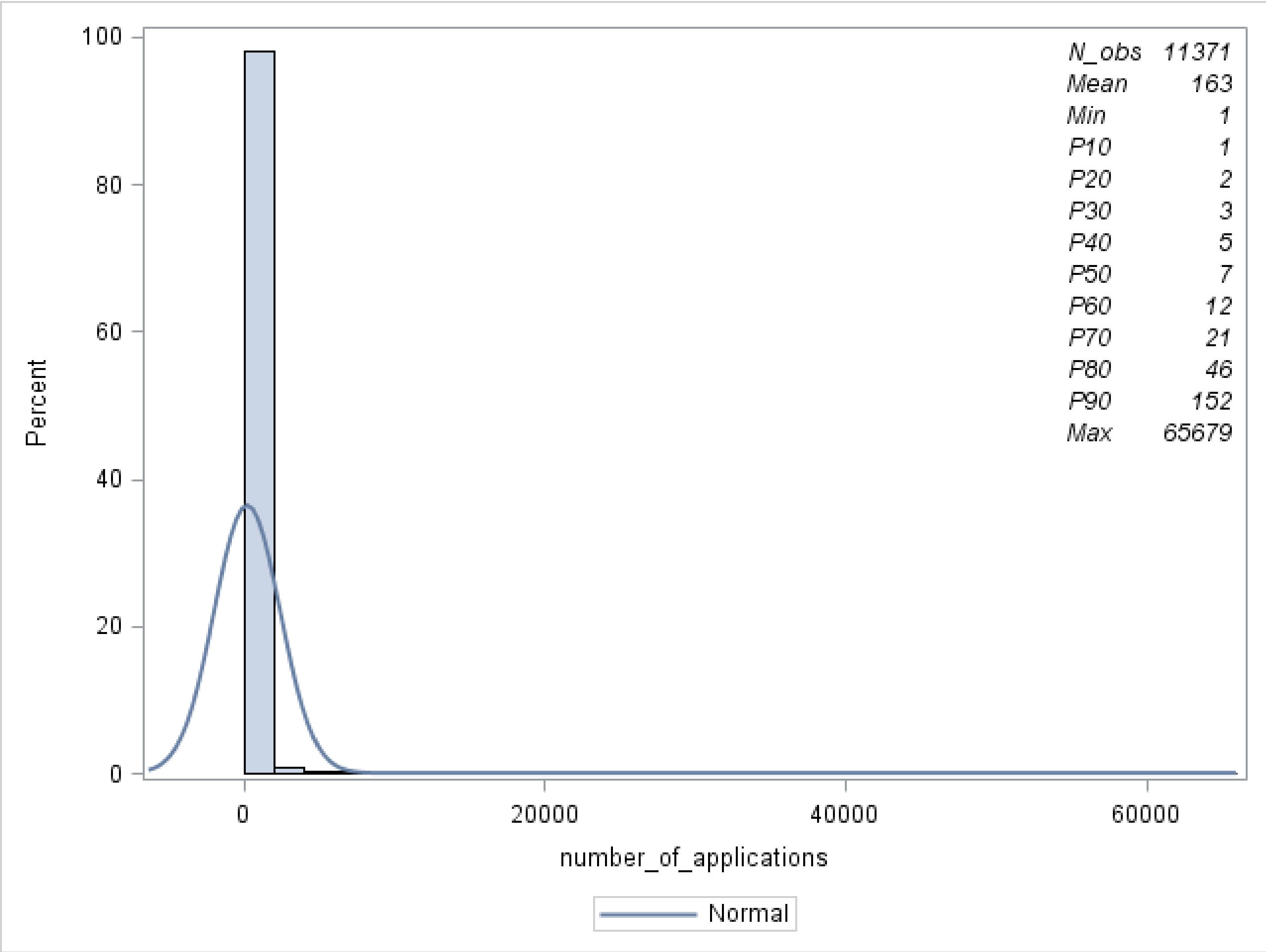


Figure 3.3 The percentage of the number of patents applied by the Top10% corporate applicants to that applied by all corporate applicants in each country

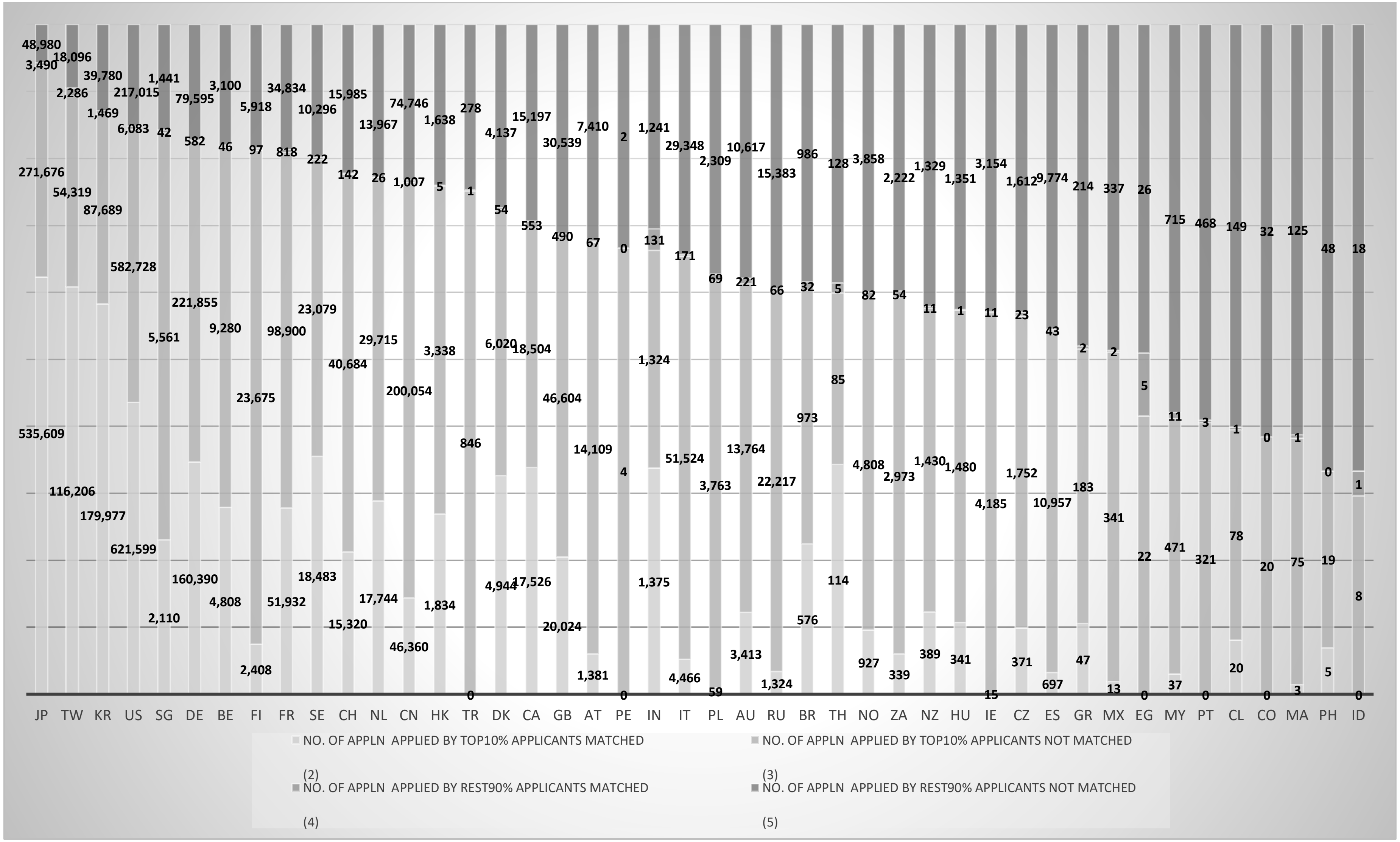
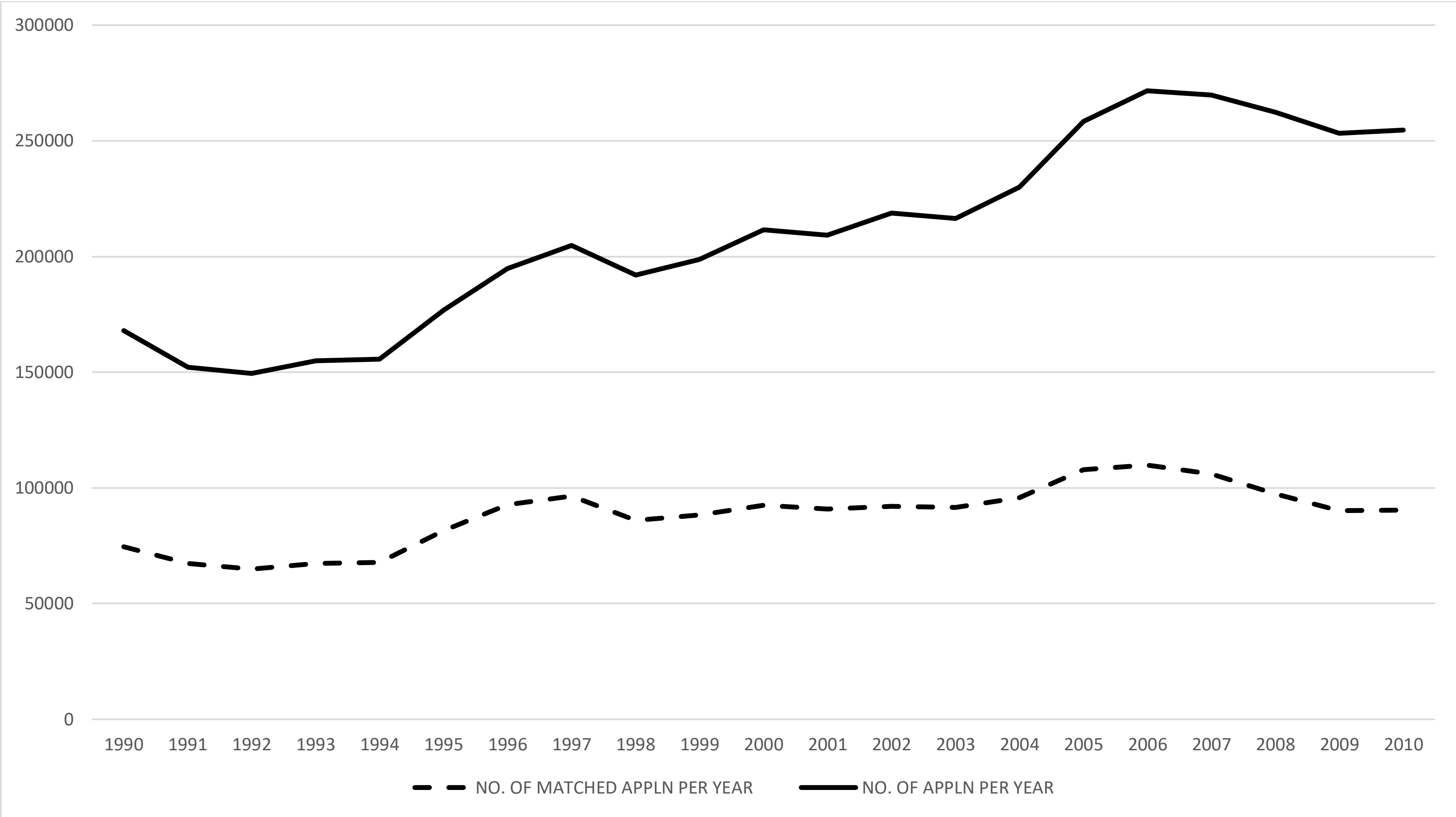
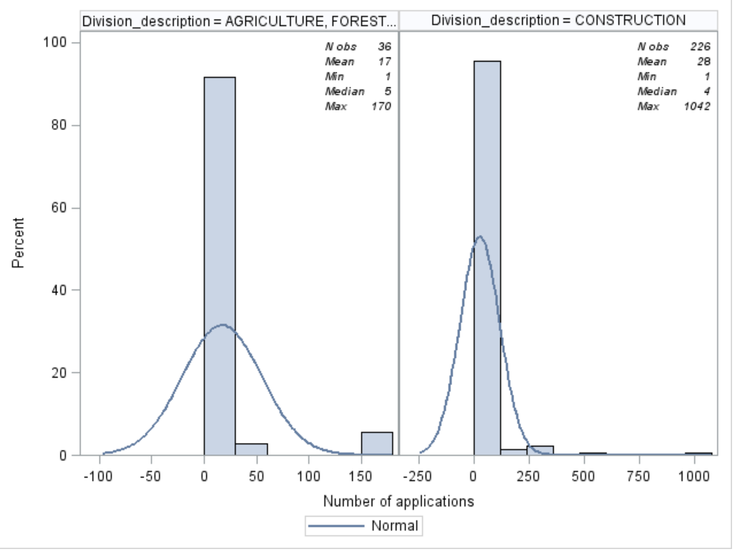

JP TW KR US SG DE BE FI FR SE CH NL CN HK TR DK CA GB AT PE IN IT PL AU RU BR TH NO ZA NZ HU IE CZ ES GR MX EG MY PT CL CO MA PH ID
NO. OF APPLN APPLIED BY TOP10% APPLICANTS MATCHED (2)
NO. OF APPLN APPLIED BY TOP10% APPLICANTS NOT MATCHED (3)
NO. OF APPLN APPLIED BY REST90% APPLICANTS MATCHED (4)
NO. OF APPLN APPLIED BY REST90% APPLICANTS NOT MATCHED (5)

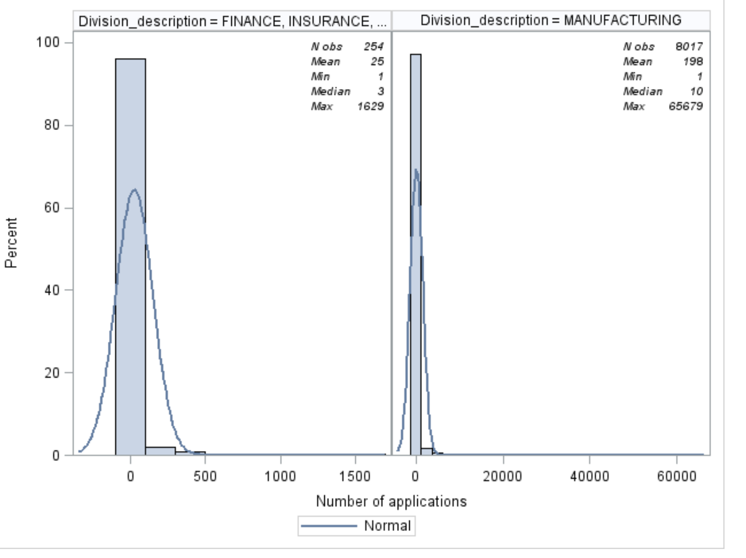
Figure 3.4 The number of applications applied by all companies and matched companies in the dataset from 1990 to 2010

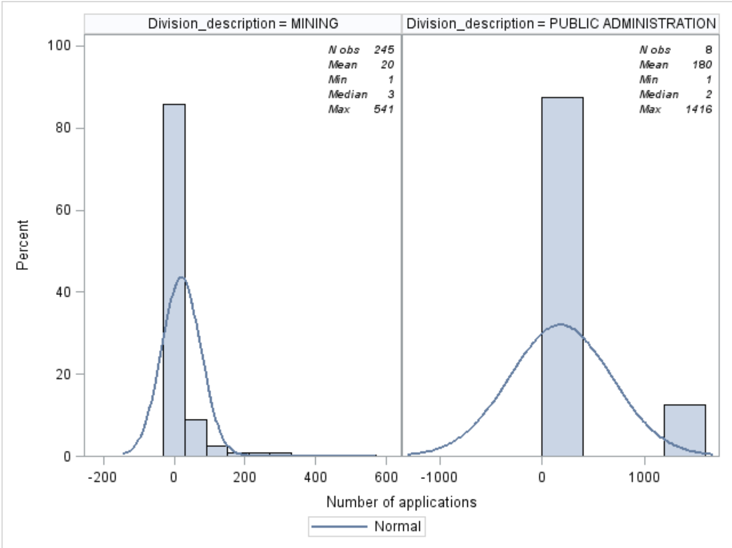


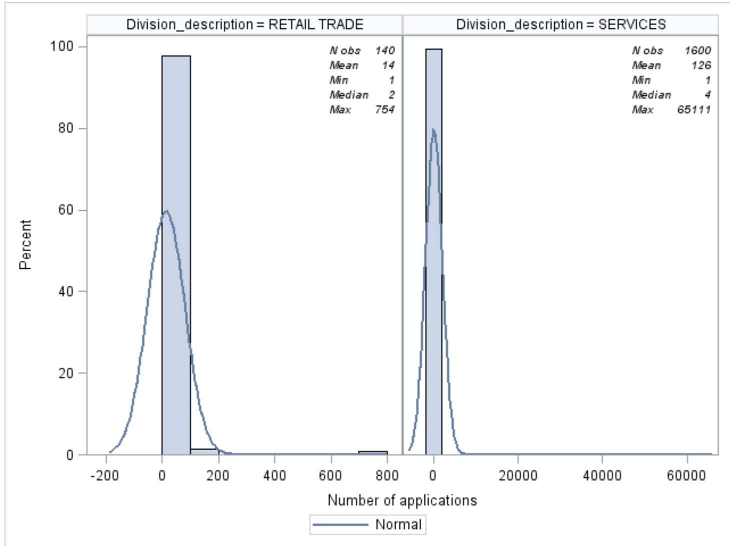
Note: The vertical axis is the number of patents applied by all corporate applicants in the dataset. The horizontal axis represents each year during the period from 1990 to 2010. The blue line is the number of applications applied by all corporate applicants in the dataset. It is the sum of patents filed by both private and public companies. The orange line represents the number of patents applied by applicants that have been matched with firm account information in Datastream.

Figure 3.5 Distribution of the number of patents applied by companies in different industries






Division_description = MINING
Division_description = PUBLIC ADMINISTRATION
N obs 245
Mean 20
Min 1
Median 3
Max 541
N obs 8
Mean 180
Min 1
Median 2
Max 1416
Percent
Number of applications
Normal


Division_description = RETAIL TRADE
Division_description = SERVICES
N obs 140
Mean 14
Min 1
Median 2
Max 754
N obs 1600
Mean 126
Min 1
Median 4
Max 65111
Percent
Number of applications
Normal

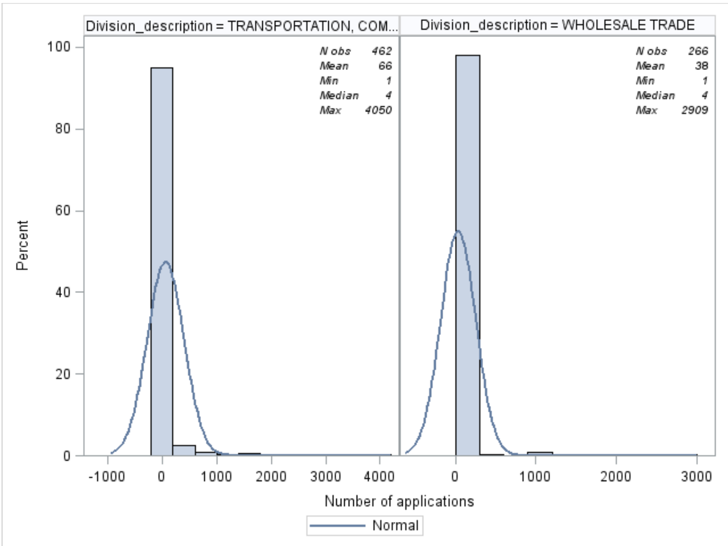
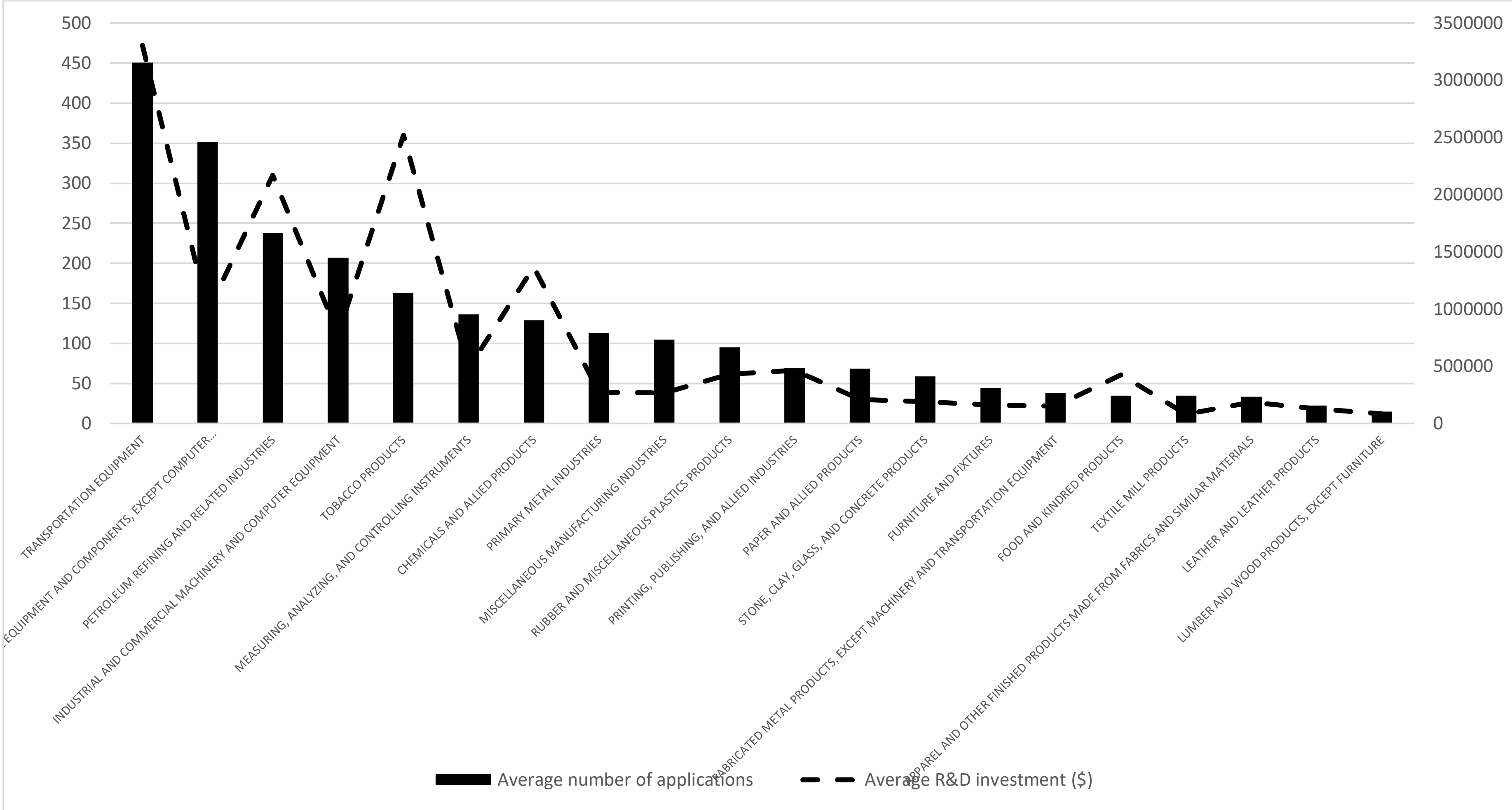

Division_description = TRANSPORTATION, COM...
Division_description = WHOLESALE TRADE
N obs 462
Mean 66
Min 1
Median 4
Max 4050
N obs 266
Mean 38
Min 1
Median 4
Max 2909
Percent
Number of applications
Normal

Figure 3.6 Patent and R&D for companies in the manufacturing industry



Appendix to Chapter 3

Appendix 3.1 Recording patent applications on the PATSTAT database

In this section, we describe a process by which the PATSTAT database records a patent application after it is submitted to the patent authority. According to Zuniga *et al.* (2009), there are four steps in the application and recording procedure:

1. When the individual/institution decides to protect their inventions through patents, they will file the applications with patent authorities and expect to eventually obtain the patent right to their invention. In this step, the individual/institution that submits the patent application is the patent applicant; the date they submit the application to a patent authority is the application filing date. Additionally, the patent authority is the office that checks whether the invention conforms to the relevant laws and regulations and decides to grant the patent right or reject the application accordingly.

2. The patent office will start to search and examine whether the invention is qualified for the granting of a patent after the application is filed and will generally publish the application 18 months later.[20] The period between filing and the granting or refusing of patents ranges from two to eight years, and this is substantially different across patent offices. In this step, the date that the application goes public is the publication date. There is a series of publications for an application. Among them, the publication date of the earliest publication is the earliest publication date of that application.

[20] On November 29, 2000, the American Inventors Protection Act (AIPA) reduced the default publication time of patents at the United States Patent and Trademark Office (USPTO) to 18 months (Baruffaldi and Simeth, 2020).

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3. If the application is ultimately granted as a patent, it will be labelled as "Granted". The first publication that makes the "Granted" announcement is known as the first granted publication.

4. The applicant submits patent applications for an invention to different countries to protect their invention globally. Because patents are territorial, patent laws and examination processes are different from country to country. A set of applications that protect the same invention belong to a patent family. The earliest of them is the earliest application, and the application date is the earliest application date.

In Figure A3.1, we show the front page of a published patent application from USPTO. We can identify the following information: the application authority, the title of the application, the investors' names and their correspondence address, assignee name and address, the application number, application filing date, publication number, publication date, other related patent applications, foreign application priority date, patent classification and abstract of application. [21]

*** Figure A3.1 ***

We use one invention (i.e., identify by DOCDB_FAMILY_ID=3822559) recorded on PATSTAT as an example (in Table A3.1). This invention is called 'Unsupervised scene segmentation'. It is the title of the patent applications recorded in the

[21] The NBER database has been widely used in the innovation literature (e.g., Hall *et al.*, 2005; Aghion *et al.*, 2013), it covers the patents that are filed in the US and granted by the USPTO (Moshirian *et al.*, 2015). IIP Patent Database is developed based on patents filed with Japan Patent Office (JPO) (Goto and Motohashi, 2007).

TLS202_APPLN_TITLE.[22] In addition to this, PATSTAT records the abstract of these applications in the TLS202_APPLN_ ABSTR.[23]

*** Table A3.1 ***

In Table A3.1, we observe that this invention's first application was filed with the Australian Patent Authority on 30/06/2000, and recorded with the application ID 2502166. It was published by the patent authority on 27/07/2000 through the publication ID 382921116. This publication contains ten applicants (i.e., NB_APPLICANTS=10) and zero investors (i.e., NB_INVENTORS=0).[24] This application is the earliest application filed for this invention (i.e., DOCDB patent family). Therefore, this application is titled as the priority filing (or earliest filing) with the priority filing date (or earliest filing date), namely, 30/06/2000. EARLIEST_FILING_ID and EARLIEST_FILING_DATE are the same for all applications that belong to the same DOCDB patent family.

[22] TLS202_APPLN_TITLE is a dataset which contains the title of the application when available. It is not been introduced in detail in this chapter as the title of an application is less relevant to our research. Table 3.1 in the Appendix lists all applications belonging to the DOCDB_FAMILY_ID =3822559 in TLS202_APPLN_TITLE.

[23] TLS202_APPLN_ ABSTR is a dataset which contains the English language abstract when available. We list all abstracts of this invention in Table 3.3 in the Appendix. We do not introduce it in detail in this chapter because the title of an application is less relevant to our research.

[24] The five applicants are universities (UNIVERSITY OF ADELAIDE, UNIVERSITY OF SOUTH AUSTRALIA, UNIVERSITY OF MELBOURNE, FLINDERS UNIVERSITY, UNIVERSITY OF QUEENSLAND) one is non-profit governance institution (i.e., COMMONWEALTH OF AUSTRALIA (DEFENCE SCIENCE & TECHNOLOGY ORGANISATION) and four are companies (i.e., TELSTRA CORPORATION, COMPAQ COMPUTER AUSTRALIA, RLM SYSTEMS, CEA TECHNOLOGIES). The detailed information of applicants published via PAT_PUBLN_ID "382921116" is listed in Table 3.4 in the Appendix. The remaining applicants relevant to application family can be emailed on request.

The second application was filed with the Australian Patent Authority on 28/06/2001 through application 1395187, which is in the international phase.[25] It was published by the World Intellectual Property Organization (WIPO) on 10/01/2002 via publication 290186427 and includes twelve applicants and two inventors.

The other six applications were filed with Patent Authorities on 28/06/2001 through applications 1395187, 2199353, 2521129, 4785747, 15871796, 37959530, 273925312 and 49522367. Three of them were finally awarded patents, namely applications 2199353, 15871796 and 49522367. For the application 15871796, three documents were published by the European Patent Office (EP). The first and second publications are 290186429 and 387625969, which were published separately on 14/05/2003 and 21/01/2009. The patent office announces that the application is granted through the third publication 290186433 on the date 16/12/2009.

In summary, PATSTAT records the entire process around the application for the patenting of an invention from submission, to examination, to the eventual granting or refusal of the application. It shows that more than one application may be submitted to protect an invention, and more than one publication may be announced for an application. The patent applicants recorded on each publication may not be the same. We cannot measure a firm's innovative ability and link it with the account information from Datastream in these instances. It is more likely that we will be able to measure a firm's ability to submit applications rather than create

[25] PATSTAT database records the routes of an application through the value of attributes INT_PHASE, REG_PHASE and NAT_PHASE. The details can be seen in section 6.57 "INT_PHASE" of Data Catalog of PATSTAT - 2016 Autumn Edition (). We do not introduce it in this chapter as the routes of an application are less relevant with our research.

an invention when we compute only the number of applications of a company. We describe how to calculate the number of patents for each applicant in Appendix 3.2.

Appendix 3.2 Measuring the number of applications and number of citations

This section describes how to compute the number of patent applications and citations for each corporate applicant on PATSTAT. We do this in the following way:

Step 1 We include global patents and their applicants from 1990 to 2010.[26] Although PATSTAT (2016 Autumn Edition) covers the patent-based data until 2016, we exclude the final six years of the sample to ensure the data is relatively free of truncation-bias as the period between filing and granting of patents ranges substantially across patent offices (see Zuniga *et al.*, 2009; Dass *et al.*, 2017). Truncation-bias exists in the patent database because of the significant lag between a patent's application date and its publication date. Especially for the NBER database, the patent appears in this database *only* if it is granted (Fang *et al.*, 2014). Papers, such as Fang *et al.* (2014), He and Tian (2013) and Acharya *et al.* (2014), correct the truncation-bias associated with the NBER-2006 patent database (which records the patent-based date until 2006) following Hall et al. (2001, 2005)'s method which estimates the number of applications at the end of the sample. However, by comparing this with the real patent data at the NBER-2010 database (which extends the time range to 2010), Dass *et al.* (2017) found that this adjustment performed poorly towards the end of the NBER-2006 sample. Therefore, we set a 20-year window between 1990 and 2010 to avoid the truncation-bias problem. In addition, we aim to measure a company's innovation ability. Thus, we only include

[26] The number of all "utility patent" applications submitted to the patent authority from 1990 to 2010 are shown in Figure 2 in the Appendix. It includes all applications of "utility patents" no matter whether it is finally granted a patent or not.

the applications that are finally patented even though PATSTAT covers the application whether or not it is granted.

Step 2 Computing the number of patent applications and patent citations at family-level rather than application-level. The patent family is designed to bundle the same invention into different patent documents (Kang and Tarasconi, 2016). This is because patents are territorial. Applications for an invention that have been filed in one country must be filed again in another country as patent laws and the examination processes vary among countries. If the innovation performance is measured using the number of patent applications, regardless of whether they are relevant to one invention or not, we are more likely to be able to calculate a firm's ability to make patent applications rather than its ability to innovate. Therefore, we calculate firm innovation at family-level, which means an invention is calculated just once no matter how many applications are made for it (Levine *et al.*, 2017). Regarding this, we also compute the number of patent citations at family-family level. This means patent Family A will be cited only one time by Family B no matter how many patents in Family A are cited by patents in Family B.

We use the patent family identifier which links all directly related patent applications on PATSTAT. The applications in this patent family have the same priorities; members of the family refer to the same invention.[27] PATSTAT provides another patent family identifier that includes, directly and indirectly, patent applications. However, we do not

[27] According to the Data Catalog of PATSTAT - 2016 Autumn Edition, if two applications claim exactly the same prior applications as priorities (these can be, for example, Paris Convention priorities or technical relation priorities – for details see Section 4.4.1 "Application replenishment for priorities"), then they are defined by the EPO as belonging to the same DOCDB simple family.

use this identifier because it includes a set of inventions and cannot display the company's innovation ability. [28]

Step3 We identify the first time an invention (i.e. with the same patent family identifier) is patented and record the patent applicants in that publication (Levine *et al.*, 2017). This is because data from patent applications in a patent family may be different. Using patent family 3822559 in Table 3.1 in the Appendix as an example, 1) The number of patent applications applied for an invention is uncertain (e.g., it contains 9 applications submitted to 6 patent authorities). 2) The number of patent applications ultimately granted in a patent family is uncertain (e.g., while 3 applications are eventually granted, the rest are not). 3) The number of publications for a patent application is uncertain (e.g., there are three publications for application 15871796, two publications for application 49522367). 4) The applicants recorded in different publications for a patent application may be different (e.g., while applicant 47837215 is recorded in publication 290186433, it is not recorded in publication 290186429 and 387625969).[29] Regarding these, it would better to confirm a specific application in the patent family, thereby avoiding the potential bias in extracting information about applicants.

Following Levine *et al.* (2017), we identify the first time an invention (i.e. with the same DOCDB patent family identifier) is patented and then use this patent to record the country of residence of its primary assignee (i.e., owner) and the country of the invention. By using patent family 3822559 in Table 3.1 in the Appendix as an example,

[28] An example of these two patent family identifier are listed in Table 3.5 in the Appendix, application 27081238 (APPLN_ID=27081238) and 28809634 (APPLN_ID=28809634) which have different priorities (i.e., the priority application and date for application 27081238 are 27081238 and 06/03/1991, and them for application 28809634 are 28809634 and 12/03/1991) belong to different DOCDB patent families but the same INPADOC patent family (i.e., INPADOC_FAMILY_ID=12564081).

[29] The information of patent applicants recoded with application 15871796 is listed in Table 3.6 in the Appendix.

only publication 382935566, which was published on 13/10/2005, will be included in the sample. First, applications which were eventually not patented are excluded from the sample (i.e., row 1,2,3,5,9 and 10 are ignored by this research because of GRANTED=0 in these rows). Second, publications will be excluded from the sample when they do not make the first announcement that the invention is granted by the patent authority through the certain application (i.e., row 7,8 and 11 are excluded from the sample as PUBLN_FIRST_GRANT=0 in these rows). Finally, publications are excluded from this sample if they are published later than others (i.e., row 8 and 12 are excluded from the sample as the PUBLN_DATE of both is later than 13/10/2005).

Step 4 This chapter uses the earliest filing date of the patent family to represent the date of the invention. Levine *et al.* (2017) use the application date of the first granted patent in the family to record the date of an invention. However, the earliest filing date is closer to the date when an invention occurred than the application date of the first granted patent. By using the first granted patent 2521129 in Table 3.1 as an example, this application was submitted to protect the invention on 28/06/2001; however, the first application to protect this invention was submitted on 30/06/2000. Compared with 28/06/2001, the date 30/06/2000 is closer to the date when invention occurred. In addition, all patent applications in the same patent family have the same earliest filing date. Therefore, we chose the earliest filing date of the patent family to record the date of invention.

Step 5 We only follow patent literature and focus on utility patents, like Levine *et al.* (2017). Excepting the utility patent, PATSTAT contains two other minor types of intellectual property rights, namely, utility model and design patent. 1) According to the US Patent & Trademark Office (2018), utility model and design patent follow different rules compared to a utility patent. For instance, the term of a design patent is 14 years measured from the date of grant, while the duration of a utility patent is 20 years. 2) By only focusing on the utility patent, this study will be consistent with most of the other papers involved in this area because they generally extract innovation data from the NBER database, which only covers utility patents.

Step 6 We follow Blanco and Wehrheim (2017) and count each patent for each firm even if the patent is filed by multiple applicants. Most literature in this area extracts innovation data from the NBER database (He and Tian, 2013; Fang *et al.*, 2014). To the best of our knowledge, for papers that extract innovation data from the NBER database, there are two methods by which to measure patenting activity for each company when it contains multiple applicants. The first is provided by the NBER database, which calculates fractional patent ownership of each patent family by multiple $\frac{1}{Number\ of\ appliants}$ (NBER, 2010). The second methods are provided by Blanco and Wehrheim (2017), who count each patent for each firm even if the patent is filed by multiple assignees. According to the current PATSTAT database, we have not found any variable by which to discern how much contribution is made by each applicant to patents, nor how many benefits they will receive from the patent. In terms of this, we follow Blanco and Wehrheim (2017) and count each patent for each firm.

Step 7 The number of self-citations will be excluded from the sample. According to Hall *et al.* (2005), self-citations are defined as citations that comes from patents assigned to the same firm as that which holds the cited patent. It tends to be treated differently to external citations in many cases (Jaffe *et al.*, 1993; Jaffe and Trajtenberg, 2002). First of all, as self-citations occur within the same economic unit, they cannot be regarded as the representing spillover based on their common definition (Hall *et al.*, 2005). In addition, self-citations tend to be affected by firms' differential knowledge and incentives with respect to internal versus external citations because the decision made by a patent examiner is partly based on information provided by the applicant and occurs in the process of negotiation with the applicant's lawyers. Therefore, the accuracy of the investigation tends to be affected by these self-citations.

Step 8 Patent citations which occur three years after the earliest publication date of an invention will be excluded from the sample.[30] Where a patent application was published in 1990, and another was published in 2000, it is unfair to compare the quality of their innovation through the number of patent citations without setting a time window. The earlier application tends to be cited more than the later applications because it has existed for longer. Therefore, we set a three-year moving window for counting the number of patent citations.

Step 9 According to our research target, we exclude the patent inventors (i.e., APPLT_SEQ_NR > 0) and focus on institutions which belong to "company" sector (i.e., SECTOR ="COMPANY", "COMPANY GOV NON-PROFIT", "COMPANY GOV NON-PROFIT UNIVERSITY", "COMPANY HOSPITAL", "COMPANY UNIVERSITY"). As stated by the EEE-PPAT database, the sector codes are sometimes not unique because an entity can belong to multiple sectors. For example, a "COMPANY UNIVERSITY" is a company owned by the university but earns profits and with limited liability.

Step 10 The sample will only include companies from the following 44 countries/regions. We expect to merge patent-based data with a public firm's account

[30] Patents start to receive citations after they are awarded or their publications are published (Bena *et al.*, 2014).

information. However, not all countries have stock exchanges. Therefore, we cover certain countries by following the suggestion of Ince and Porter (2006), Griffin *et al.* (2010), Hanauer (2014), and Schmidt *et al.* (2015). [31]

The total number of patent applicants, applications, and citations relevant to each selected country/region before processing are shown separately in columns 2, 3 and 4 of Table 3.8 in the Appendix. However, these figures are likely to be overestimated when comparing them with real data. This is because sometimes the standardised company name produced by the EEE-PPAT database is associated with several countries and is not a company. We use "Harvard University" (in Table 3.9 in the Appendix) as an example. Harvard University is a famous private university in the United States; however, it is recorded along with Italy and United States in the database and identified as a company. For the current dataset, 401,480 companies are only related to a single country which covers more than 90% of the companies in this database (in Table 3.10 in the Appendix).

*** Table A3.8 ***

*** Table A3.9 ***

*** Table A3.10 ***

[31] The country's name and constituent lists are listed in Table 3.7 in the Appendix.

Appendix 3.3 Introduction to Datastream

Datastream is a historical financial and macroeconomic database. It contains data on equities, stock market indices, company fundamentals, key economic indicators, fixed income securities and currencies for 175 countries and 60 markets. It focuses on public companies and their current subsidiaries.

Following Hanauer's list (2014), the initial dataset includes both active and inactive companies in 23 developed countries/regions and 21 emerging countries/regions.[32] Our initial sample includes companies that were listed between 1990 and 2010. It is set based on the time interval of the patent-based dataset from the PATSTAT database.

Datastream includes different financial instruments, such as the American Depository Receipt, the Closed-End Fund and Stock Equity.[33] We focus on stock equities that cover more than 96% of the records in the initial dataset.

A firm may issue its equity shares on more than one exchange in the domestic country or abroad for many reasons. For example, to improve information disclosure, to have better investor protection or to overcome international investment barriers (Roosenboom and Van Dijk, 2009). Moreover, Datastream records each equity with a single unique ID; in other words, Datastream may include more than one record for an individual listed company. This will lead to a multiple matching problem. We eliminate this kind of problem by using the "ISINID" and "MAJOR" variables. We introduce the detail of this step in "Appendix3.4.4 Resolving Multiple matches".

[32] The list of both active and inactive companies in 23 developed markets and 21 emerging markets is reported in Table 3.7 in the Appendix.

[33] The detailed information can be seen in the Table 3.11 in the Appendix.

For each unique ID in Datastream, five different name variables are recorded. This dataset includes four of them (i.e., WC06001, CNAME, PNAME and ECNAME) to avoid missing corporate applicants on the PATSTAT database.[34] In Table 3.12 in the Appendix, we demonstrate the description of each named variable and use US company “@POS.COM” (which can be identified through the unique ID “360125” on the Datastream database) as an example. Its “NAME” is “@POS.COM DEAD - DELIST 19/09/02”, which consists of the stem company name “@POS.COM”, its equity status “DEAD”, and its inactive date “19/09/02”.[35] The “WC06001” name and “ECNAME” name of the company are “@POS.COM, INC.” and “@POS.COM INCO”. They consist of the stem name and two different kinds of abbreviated company suffixes of “INCORPORATED”. The “PNAME” name is “ATPOS.COM”, and the “ECNAME” is “@POS.COM INCORPORATED”. We extracted these four company names from the Datastream database and merged them with corporate applicants on the PATSTAT database.

*** Table A3.12 ***

Datastream also includes the address information for each unique Datastream ID. Unlike address information on PATSTAT which are recorded in one variable, Datastream contains the address data through different variables, and these are country (GEOGN), state (WC06024),

[34] The company name from ‘NAME’ list is not processed in this paper, although it is a ‘three-star’ name variable and available for all institutions. According to the introduction from the Datastream database, it represents the name of the equity/company or equity list which is sorted in the database. The relevant information of the equity/company, such as current status, event date and share type, are also written in the latter part of the variable. However, in order to include these comments, the company name in the ‘NAME’ list tends to be abbreviated. There is no obvious sign to separate the abbreviated company name and remark information. Therefore, the company name in the ‘NAME’ list is excluded from this dataset to avoid the possible errors.

[35] Stem name is the company name that has removed the corporate extensions. For instance, the stem name of company “@POS.COM INCORPORATED” is “@POS COM” which removes the company extensions “INCORPORATED”.

city (WC06023), street (WC06022) and postcode (WC06025). We employ this address information to identify the corporate applicants where corporate applicants on PATSTAT and companies on Datastream can be matched by stem name in the automatic matching procedure. It is also used to identify a unique company in order to solve the multiple matching problem.

PATSTAT focuses on the patent-based information rather than on the account data of corporate applicants. In contrast, Datastream covers public companies’ account information rather than patent-based data. In this case, this research aims to link the PATSTAT database with the Datastream database through company names. We face the following two challenges in this chapter, 1) Stings in the name variable of these two databases include not only the company name but also the company’s address, explanation and stock status. 2) as we try to process companies' names across 44 countries, we need to consider the conversion of language and company suffixes in terms of different countries' conditions. We describe how to overcome these challenges in Appendix 4.

Appendix 3.4 Steps taken in matching

In this section, we create a dataset which matches corporate applicant name on the PATSTAT database with their unique ID on the Datastream database. To do that, we 1) standardise the company names from PATSTAT and Datastream separately, and then 2) match them together using automated and manual matching procedures. The automated matching procedure includes merging standardised "full string" and "stem string" company names in both databases. The "full string" company name represents the company names that are standardised and stripped out spaces, and the "stem string" company name is the company names that are standardised, the corporate extensions removed and then stripped out spaces. By using the company name "3DS FAMILY COMPANY" as an example, it is converted to the "full string" company name "3DSFAMCO" and "stem string" name "3DSFAM". After doing that, 3) we manually match the names of companies that applied for at least 700 patents during the period 1990 to 2010.

To obtain accurate results, the matched companies from both databases are required to belong to the same country if they are merged by the "full string" company names. Additionally, the matched companies are required to belong to the same country and same address (i.e., state, city, street or zip code) if they are matched by "stem string" company names.

A3.4.1 Name standardisation

We divide the name standardisation procedures into three main steps, namely, word standardisation (Step1-Step3), name standardisation (Step4-Step5), and creating full/stem names (Step6, Step7). Except for some special cases, the name standardisation procedures are the same for company names on both databases.

Step 1: Converting to upper case characters. For example, the lower character "a" is converted to the "A".

Step2 Replacing accented characters as non-accented characters. For example, "Æ" is replaced with "A.E.", all words like "ÀÁÂÃÄÅ" becomes "A" and strings like "{UMLAUT OVER (X)}" is converted to "X".

Step3 Unifying the word "AND" of each country to "&". The conversion of the strings "AND" in non-English languages (such as, "UND", "ET" and "Y") is identified based on the official languages of each country and Google Translate. For example, as the official language of Germany is German, the "AND" is translated as "UND" from English to German by Google Translate. Regarding this, for any German company, we convert strings "UND" in name variables to “&”.

Step4 Cleaning extra strings at the ending of the value. The strings recorded in most of the name variables is just company name. However, in part of the name variables, they include not only a company’s name but also the company’s information, such as their address/explanation and status. In Table 3.13 in Appendix, we show the structure of strings recorded at the name variable.

*** Table A3.13 ***

Especially regarding the PATSTAT database, strings in name variables have three structures, and they are "Company name", "Company Name + address/explanation" and "Company Name + Company Name".

1) "Company name" represents the strings recorded at name variable and only contains the company name, such as "21ST CENTURY PLASTICS CORPORATION". In most cases, the

string in the name variable only contains the company name. No action is required for this type of variable in this step.

2) "Company name + address/explanation" is the name variable which consists of the company name and its address/explanation, such as 'BODE CHEMIE & COMPANY 22525 HAMBURG' and 'AGE SCIENCES CORPORATION, A UTAH CORPORATION'. For this kind of name, we exclude the address/explanations which follow the company suffix, thereby getting the new variable as 'BODE CHEMIE & COMPANY' and 'AGE SCIENCES CORPORATION'.

3) "Company Name + Company Name" means the strings in the company name variable includes two company names. This kind of name variable can be identified and split by the keyword. Using a record "BENZ COMPANIES, INC., D/B/A BENZ AIRBORNE SYSTEMS" as an example, it includes two company names, which are "BENZ COMPANIES, INC.,", "BENZ AIRBORNE SYSTEMS", and a keyword "D/B/A", which means "doing business as". Therefore, the strings recorded in the name variable means "BENZ COMPANIES, INC.," doing business as "BENZ AIRBORNE SYSTEMS". We identify this name variable by the "D/B/A", and spilt it into two new name variables, which are "BENZ COMPANIES, INC.," and "BENZ AIRBORNE SYSTEMS".

For the Datastream database, there are two structures of strings in name variables, which are "Company Name" and "Company Name + status/explanation". While the "Company Name" variable does not need to be processed, the "Company Name + status/explanation" variable consists of the company's name and its status/explanation. By using "CENTAUR MINING AND EXPLORATION LTD- A.D.R." as an example, "CENTAUR MINING AND EXPLORATION LTD" is the name of the company, the "A.D.R." represents "American depositary receipt" which is the status of the company/equity. We exclude the "status/explanation" of this type of name variable, thereby getting the new variable.

Step5 Splitting based on single brackets. In some cases, the unabbreviated company name is enclosed in single brackets. It exists after the abbreviation company name in the name variable, such as "3COM CORP (COMPUTERS COMMUNICATION COMPATIBILITY CORP)". It consists of the abbreviated name "3COM CORP" and the expanded name "COMPUTERS COMMUNICATION COMPATIBILITY CORP". However, in other cases, the strings in the single brackets are only part of the company name, such as "3CSCAN (BEIJING) TECHNOLOGY CO". To cover all "correct" company names, we retain all original company names, the strings within the single brackets, and without parentheses in this step (in Table 3.14 in the Appendix). We manually check each of them if the companies in the databases are matched based on the strings within/without the single brackets.

*** Table A3.14 ***

Step6 Cleaning punctuations. We substitute all punctuation except "&" with a blank in this step. For example, the variable "3D-VIZ.COM "converts to "3D VIZ COM ".

Step7 Name cleaning. We standardise corporate name by replacing the company suffix with their commonly used acronyms. For example, replace "PUBLIC COMPANY LIMITED" with "PLC", "LIMITED LIABILITY COMPANY" with "LLC". We also standardise the name based on the abbreviated words on the Datastream database. As an example, "ALUMINIUM" and "ALUMINUM" are replaced with "ALUM", "COUNTRY" and "COUNTRIES" are replaced with "CTRY". By doing this, we get the standardised full company name.

Step8 Creating the stem name. This is created by removing the corporate legal identifier from the standardised full company name. For instance, the standardised full company name "3DS FAMILY CO" is produced as a standardised stem name "3DS FAMILY" by removing the company suffix "CO".

Step9 Striping out spaces. As the final step, we strip out spaces from the standardised full company name and standardised stem name. As mentioned above, the company name "3DS FAMILY COMPANY" is converted to the "full sting" company name "3DSFAMCO" and "stem string" company name "3DSFAM".

We create four lists of name variables after doing the name standardisation procedures at both databases, which are "full string" and "stem string" company name from the PATSTAT database, as well as the "full string" and "stem string" company name from Datastream database.

A3.4.2 Automatic matching

We produce automatic matching after the "full string" and "stem string" company names have been created on both databases separately. Table 3.15 in the Appendix indicates lists of the company name that are going to be merged in each step and the requirements for it. We divide the automatic matching procedure into three steps, namely, matching based on the original company name, "full sting" company name and "stem string" company name separately.

*** Table A3.15 ***

For original name matching, we match the companies on both databases by the capitalised name and the country code. The original name is defined as a corporate name that is not processed except been capitalised. Although the names of most applicants on the PATSTAT database and listed companies' names on the Datastream have been capitalised, we still add this step to ensure that no characters are missing. The corporate applicants are successfully merged with company names if they have the same original name and are in the same country. For example, the applicant "SHARP CORPORATION" on PATSTAT is successfully linked to the ID "906288" on Datastream, as the strings of this ID's name variable (i.e., WC06001 and ECNAME) are also "SHARP CORPORATION". Besides, they are both recorded with the same country code "JP" (i.e., Japan). In terms of the same original name and country code, they are regarded as a pair of the successfully merged company name.

For full name matching, when companies on PATSTAT and Datastream are merged through the full name, they have to be recorded within the same country/region, otherwise, they will not be defined as a matched company. By using the three observations in Table 3.16 in the Appendix as an example, the applicant "STEYR-DAIMLER-PUCH AG, WIEN" on PATSTAT and "ADAM OPEL AG" on Datastream are not matched as they do not have the same full name string. For the second rows, although the applicant “ "SKY LTD. " ” and the company “SKY LTD" have the same full name string, they do not belong to the same country. Only the applicant "A. G. V. PRODUCTS CORPORATION" and the company "A.G.V. PRODUCTS CORP" satisfies the criterion, because they the same full name string and are recorded within the same country/region, namely "TW" (i.e., TAIWAN).

*** Table A3.16 ***

For the stem name matching, the merged companies must not only be in the same country/region but also be recorded within the same street (i.e., WC06022) /city (i.e., WC06023) /state (i.e., WC06024) /postcode (i.e., WC06025). In other words, the value of at least one of these four variables on Datastream should tally with part of strings in the variable "PERSON_ADDESS" at PATSTAT. For example, in Table 3.7 in the Appendix, the applicant

"MOBILE MINI" on PATSTAT and company "130042" on Datastream, which records the same stem name and country code, are not defined as matched. This is because the value of street, city, state or postcode does not match the part of strings in the "PERSON_ADDESS" variable. However, the applicant "ESPIAL GROUP" and company "50547J" in the second observation is merged successfully in terms of the same stem name, country code, city and state and postcode.

*** Table A3.17 ***

A3.4.3 Manual matching

In this step, we manually check corporate applicants who have not successfully merged through automatic matching but have filed at least 700 applications to the patent authorities. Firstly, we manually search the applicant's name on Datastream and check their address information. We then perform an internet search and include observations only when we can confirm that these companies are the same. For example, the company "JOHN DEERE" on PATSTAT was manually matched with "DEERE & COMPANY" (Datastream ID= 906189) on the Datastream database. This is because John Deere is the brand name of Deere & Company. In this way, we ensure that the dataset includes all large corporate applicants who are listed companies.

A3.4.4 Resolving Multiple matches

One patent applicant can be matched with more than one record on Datastream for the following reasons:

1) A company can list and trade its equities in the different financial markets (or even over the counter) in different countries. Therefore, a company on Datastream may have more than one record. By using the matching result of corporate applicant "ACE HARDWARE CORPORATION" (in Table 3.18 in the Appendix) as an example, this is matched with three different IDs on Datastream, namely, "28145X", "878063" and "878064". We excluded duplicate Datastream company observations like these through ISINID and MAJOR variables on Datastream separately.[36] By setting primary equity (i.e., ISINID= "P") and major security (i.e., MAJOR= "Y"), the dataset excludes the observation "878063" and "878064", namely, the applicant "ACE HARDWARE CORPORATION" at PATSTAT is linked to "28145X" on Datastream.

*** Table A3.18 ***

2) Different IDs on Datastream can have the same standard name or stem name. For instance, in Table 3.19 in the Appendix, the entries "86523W" and "902317" have the same standard name "PECOENERGYCO". It is as same as the standardised name of the corporate applicant on PATSTAT. We identify the unique Datastream ID by matching the address information. In this example, "86523W" is in the same city as the patent applicant company. Therefore, we exclude the company "902317" from the dataset.

*** Table A3.19 ***

The Unresolved multiple matches are excluded from the final output.

[36] ISINID is the primary/secondary flag. It returns “P” or “S” when the equity record is the primary/secondary one (i.e., the domestic/foreign listing of the share or depository receipt or certificate). MAJOR is the major security flag. It returns “Y” or “N” to indicate whether the security is the one with the most significant market capitalization and liquidity of the primary quotation of that security.

A record on Datastream can also be matched with more than one patent applicant on PATSTAT. By using the Datastream company "905047" as an example, it links two patent applicants, which are "R. R. DONNELLEY & SONS COMPANY" and "R. R. DONNELLEY AND SONS COMPANY". We add the number of the patent application and the number of patent citations of these two applicants together.

A3.4.5 Remove extra country codes

We delete the country data of patent applicants by following two steps:

1. We exclude the country code if it does not include any address information.

2. We count the distinct number of address information for each applicant in a specific country. We then include the most frequently appearing countries for each applicant in the dataset.

Using the applicant "02 MICRO" in Table 3.20 in the Appendix as an example, row 2 is removed because its address information is empty. For the rest observations, "02 MICRO" is relevant to PERSON_CTRY_CODE "TW", and "US". Among them, the "US" which appears 6 times, is the most common country name for applicant "02 MICRO". Therefore, the "02 MICRO" is recorded with "US" in the new dataset. It is worth noting that both country codes will be recorded if they appear the same number of times. It is not helpful to merge more applicants on PATSTAT to the firm account information on Datastream but it is useful to understand what percentage of companies are merged within a country. More than 99% of companies on PATSTAT are only recorded with one country after the removal of the extra country codes. The detail of this result is listed in column (4) and column (5) in Table 3.10 in the Appendix.

*** Table A3.20***

Table A3.1 Applicants data belong to DOCDB_FAMILY_ID =3822559

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
1	2502166	AU	30/06/2000	N	N	Y	30/06/2000	2502166	27/07/2000	382921116	0	3822559	9	10	0	382921116	AU	0	27/07/2000
2	1395187	AU	28/06/2001	Y	N	N	30/06/2000	2502166	10/01/2002	290186427	0	3822559	9	12	2	290186427	WO	0	10/01/2002
3	4785747	CA	28/06/2001	Y	N	Y	30/06/2000	2502166	10/01/2002	335049588	0	3822559	9	10	2	335049588	CA	0	10/01/2002
4	2199353	AU	28/06/2001	Y	N	Y	30/06/2000	2502166	14/01/2002	290186428	0	3822559	9	10	2	290186428	AU	0	14/01/2002
5	37959530	JP	28/06/2001	Y	N	Y	30/06/2000	2502166	22/01/2004	290186431	0	3822559	9	0	0	290186431	JP	0	22/01/2004
6	2521129	AU	28/06/2001	Y	N	Y	30/06/2000	2502166	13/10/2005	382935566	1	3822559	9	**10**	2	**382935566**	AU	1	13/10/2005
7	15871796	EP	28/06/2001	Y	Y	N	30/06/2000	2502166	14/05/2003	290186429	1	3822559	9	6	2	290186429	EP	0	14/05/2003
7	15871796	EP	28/06/2001	Y	Y	N	30/06/2000	2502166	14/05/2003	290186429	1	3822559	9	6	2	387625969	EP	0	21/01/2009
7	15871796	EP	28/06/2001	Y	Y	N	30/06/2000	2502166	14/05/2003	290186429	1	3822559	9	6	2	290186433	EP	1	16/12/2009
8	273925312	DE	28/06/2001	Y	Y	Y	30/06/2000	2502166	28/01/2010	317783195	0	3822559	9	6	2	317783195	DE	0	28/01/2010
9	49522367	US	06/02/2003	Y	N	Y	30/06/2000	2502166	11/09/2003	290186430	1	3822559	9	1	2	290186430	US	0	11/09/2003
9	49522367	US	06/02/2003	Y	N	Y	30/06/2000	2502166	11/09/2003	290186430	1	3822559	9	1	2	290186432	US	1	28/11/2006

Data Source: PATSTAT - 2016 Autumn Edition

Note: (1) refers to the number of applications of this patent family. (2) refers to the "APPLN_ID" variable. It is application identification, representing a unique technical identifier (i.e., a unique patent application) on PATSTAT. (3) refers to the "APPLN_AUTH" variable. It is the application authority representing the office where the National, International or Regional application was filed. (4) refers to the "APPLN_FILING_DATE" variable; it is the application filing date, which shows the date on which the application was physically received at the Patent Authority. (5)-(7) represent the possible routes of an application, and the detail can be seen in the subsection "6.57 INT_PHASE" of "https://research-it.wharton.upenn.edu/wp-content/uploads/2016/11/DataCatalog_v5.08.pdf". (5) refers to the "INT_PHASE" variable; it indicates whether the application is or has been in the international phase. It covers all international filings at the receiving office as well as all applications based on these filings. (6) refers to the "REG_PHASE" variable; it indicates whether the application is or has been in the regional phase. (7) refers to the "NAT_PHASE" variable; it indicates that an application is in the national phase. (8) refers to the "EARLIEST_FILING_DATE" variable; it is the date of earliest filing of an invention (i.e., in the same Docdb patent family, only directly related applications are considered). (9) refers to the "EARLIEST_FILING_ID" variable, representing the application identification of the earliest filing. It represents the earliest filed application of a group of patent applications which directly related through technical relations and its application continuations. (10) refers to the "EARLIEST_PUBLN_DATE" variable; it is the date of the earliest publication of an application. (11) refers to the "EARLIEST_PAT_PUBLN_ID" variable; it is the identification of the earliest publication of an application. (12) is the " GRANTED " indicator; it equals "1" if there exists a publication of the grant; "0" otherwise. (13) refers to the "DOCDB_FAMILY_ID" variable. It is the identifier of a DOCDB simple family, which means that most probably the applications share specific the same priorities and generally refer to the same invention. (14) refers to the "DOCDB_FAMILY_SIZE" variable; it is the size of the DOCDB simple family, which shows the number of applications been covered by the DOCDB family. (15) refers to the "NB_APPLICANTS" variable; it is the number of applications of an application according to the most recent publication. (16) refers to the "NB_INVENTORS" variable; it is the number of inventors of an application according to the most recent publication. (17) refers to the "PAT_PUBLN_ID" variable, it is the patent publication identification. (18) refers to the "PUBLN_AUTH" variable, it is the patent authority that issued the publication of the application. (19) refers to the "PUBLN_FIRST_GRANT" variable, it equals "1" if the publication can be considered as the first publication of the grant of a given application. (20) refers to the "PUBLN_DATE" variable, it is the date on which the publication was made available to the public.

Table A3.2 Data for all applications belong to DOCDB_FAMILY_ID =3822559 in TLS202_APPLN_TITLE

(1)	(2)	(3)
1395187	en	UNSUPERVISED SCENE SEGMENTATION
2199353	en	Unsupervised scene segmentation
2502166	en	Unsupervised scene segmentation
2521129	en	Unsupervised scene segmentation
4785747	en	UNSUPERVISED SCENE SEGMENTATION
15871796	en	UNSUPERVISED SCENE SEGMENTATION
49522367	en	Unsupervised scene segmentation
273925312	de	UNÜBERWACHTE SZENENSEGMENTIERUNG

Data Source: TLS202_APPLN_TITLE, PATSTAT - 2016 Autumn Edition.

Note: (1) refers to application identification, representing a unique technical identifier (i.e., a unique patent application) on PATSTAT. (2) refers to the language of the title of the application selected for and loaded in PATSTAT. (3) refers to the title of the application.

Table A3.3 Data for all applications belong to DOCDB_FAMILY_ID =3822559 in TLS202_APPLN_ ABSTR

(1)	(2)	(3)
1395187	en	A method of segmenting objects in an image is described. The method applies a Top Hat algorithm to the image then constructs inner and outer markers for application to the original image in a Watershed algorithm. The inner marker is constructed using binary erosion. The outer marker is constructed using binary dilation and perimeterisation. The method finds particular application for first level segmentation of a cell nucleus prior to detailed analysis.
4785747	en	A method of segmenting objects in an image is described. The method applies a Top Hat algorithm to the image then constructs inner and outer markers for application to the original image in a Watershed algorithm. The inner marker is constructed using binary erosion. The outer marker is constructed using binary dilation and perimeterisation. The method finds particular applicatio n for first level segmentation of a cell nucleus prior to detailed analysis.</ SDOAB>
49522367	en	A method of segmenting objects in an image is described. The method applies a Top Hat algorithm to the image then constructs inner and outer markers for application to the original image in a Watershed algorithm. The inner marker is constructed using binary erosion. The outer marker is constructed using binary dilation and perimeterisation. The method finds particular application for first level segmentation of a cell nucleus prior to detailed analysis.

Data Source: TLS203_APPLN_ABSTR, PATSTAT - 2016 Autumn Edition.

Note: (1) refers to the "APPLN_ID" variable. It is application identification, representing a unique technical identifier (i.e., a unique patent application) on PATSTAT. (2) refers to the "APPLN_ABSTRACT_LG" variable, representing the language of the abstract of the application selected for and loaded in PATSTAT. (3) refers to the "APPLN_ABSTRACT" variable, representing the abstract of the application.

Table A3.4 Information of patent applicants recorded with PAT_PUBLN_ID =382921116

(1)	(2)	(3)	(4)	(5)	(6)
382921116	13764063	1	0	UNIVERSITY OF ADELAIDE	UNIVERSITY
382921116	13668410	2	0	UNIVERSITY OF SOUTH AUSTRALIA	UNIVERSITY
382921116	11233954	3	0	UNIVERSITY OF MELBOURNE	UNIVERSITY
382921116	13764068	4	0	FLINDERS UNIVERSITY	UNIVERSITY
382921116	13613804	5	0	UNIVERSITY OF QUEENSLAND	UNIVERSITY
382921116	14669183	6	0	COMMONWEALTH OF AUSTRALIA (DEFENCE SCIENCE & TECHNOLOGY ORGANISATION)	GOV NON-PROFIT
382921116	8807951	7	0	TELSTRA CORPORATION	COMPANY
382921116	14670546	8	0	COMPAQ COMPUTER AUSTRALIA	COMPANY
382921116	14670547	9	0	RLM SYSTEMS	COMPANY
382921116	13764066	10	0	CEA TECHNOLOGIES	COMPANY

Data Source: TLS203_APPLN_ABSTR, PATSTAT - 2016 Autumn Edition.

Note: (1) refers to "PAT_PUBLN_ID" variable, it is patent publication identification. (2) refers to the "PERSON_ID" variable, which is person identification. (3) refers to the "APPLT_SEQ_NR" variable, representing the sequence number of applicants. (4) refers to the "INVT_SEQ_NR" variable, representing the sequence number of inventors. (5) refers to the "HRM_L2" variable representing the standardised name created by the EEE-PPAT database. (6) refers to the "SECTOR" variable at the EEE-PPAT database representing the applicant's sector.

Table A3.5 Part Data for all applications belong to INPADOC_FAMILY_ID=12564081

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
27081238	JP	06/03/1991	06/03/1991	27081238	05/10/1992	393420303	1	12564081	7297826	1
28809634	JP	12/03/1991	12/03/1991	28809634	07/10/1992	393421563	1	13489253	7297826	1
34221362	JP	09/08/1991	09/08/1991	34221362	23/02/1993	393514199	1	16421334	7297826	1
35962935	JP	16/11/1990	16/11/1990	35962935	26/06/1992	393377683	0	17986774	7297826	1
53490507	US	18/11/1991	18/11/1991	53490507	18/01/1994	301123485	1	27460821	7297826	1

Data Source: PATSTAT - 2016 Autumn Edition

Note: (1) refers to the "APPLN_ID" variable. It is application identification, representing a unique technical identifier (i.e., a unique patent application) on PATSTAT. (2) refers to the "APPLN_AUTH" variable. It is the application authority, representing the office where the National, International or Regional application was filed. (3) refers to the "APPLN_FILING_DATE" variable. It is the application filing date, which shows the date on which the application was physically received at the Patent Authority. (4) refers to the "EARLIEST_FILING_ID" variable, which is the application identification of the earliest filing. It represents the earliest filed application of a group of patent applications which directly related through technical relations and its application continuations. (5) refers to the "EARLIEST_FILING_DATE" variable. It is the date of the earliest filing of an invention (i.e., in the same Docdb patent family, only directly related applications are considered). (6) refers to the "EARLIEST_PUBLN_DATE" variable. It is the date of the earliest publication of an application. (7) refers to the "EARLIEST_PAT_PUBLN_ID" variable. It is the identification of the earliest publication of an application. (8) is the " GRANTED " indicator; it equals "1" if there exists a publication of the grant; "0" otherwise. (9) refers to the "DOCDB_FAMILY_ID" variable. It is the identifier of a DOCDB simple family, which means that most probably the applications share specific the same priorities and generally refer to the same invention. (10) refers to the "INPADOC_FAMILY_ID" variable. It is the identifier of an INPADOC extended priority family. The INPADOC family generally covers one or more DOCDB families and covers a set of related inventions. (11) refers to the "DOCDB_FAMILY_SIZE" variable. It is the size of the DOCDB simple family, which shows the number of applications been covered by the DOCDB family.

Table A3.6 Information of patent applicants recorded with application 15871796

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
290186429	1142249	1	0	AU	UNIVERSITY OF ADELAIDE	UNIVERSITY	Adelaide, S.A. 5005
290186429	881138	2	0	AU	COMPAQ COMPUTER AUSTRALIA	COMPANY	139 Frome Street,Adelaide, SA 5000
290186429	881139	3	0	AU	RLM SYSTEMS	COMPANY	23 Lakeside Drive,Burwood East, VIC 3151
290186429	881140	4	0	AU	CEA TECHNOLOGIES	COMPANY	65 Gladstone Street,Fyshwick, ACT 2609
290186429	1142250	5	0	AU	THE COMMONWEALTH OF AUSTRALIA REPRESENTED BY DSTO	GOV NON-PROFIT	Salisbury S.A. 5108
290186429	73072	6	0	AU	UNIVERSITY OF SOUTH AUSTRALIA	UNIVERSITY	North Terrace,Adelaide, S.A. 5000
290186433	47837215	1	0	AU	UNIVERSITY OF ADELAIDE	UNIVERSITY	Adelaide,S.A. 5005
290186433	881138	2	0	AU	COMPAQ COMPUTER AUSTRALIA	COMPANY	139 Frome Street,Adelaide, SA 5000
290186433	881139	3	0	AU	RLM SYSTEMS	COMPANY	23 Lakeside Drive,Burwood East, VIC 3151
290186433	881140	4	0	AU	CEA TECHNOLOGIES	COMPANY	65 Gladstone Street,Fyshwick, ACT 2609
290186433	1142250	5	0	AU	THE COMMONWEALTH OF AUSTRALIA REPRESENTED BY DSTO	GOV NON-PROFIT	Salisbury S.A. 5108

290186433	73072	6	0	AU	UNIVERSITY OF SOUTH AUSTRALIA	UNIVERSITY	North Terrace,Adelaide, S.A. 5000
387625969	1142249	1	0	AU	UNIVERSITY OF ADELAIDE	UNIVERSITY	Adelaide, S.A. 5005
387625969	881138	2	0	AU	COMPAQ COMPUTER AUSTRALIA	COMPANY	139 Frome Street,Adelaide, SA 5000
387625969	881139	3	0	AU	RLM SYSTEMS	COMPANY	23 Lakeside Drive,Burwood East, VIC 3151
387625969	881140	4	0	AU	CEA TECHNOLOGIES	COMPANY	65 Gladstone Street,Fyshwick, ACT 2609
387625969	1142250	5	0	AU	THE COMMONWEALTH OF AUSTRALIA REPRESENTED BY DSTO	GOV NON-PROFIT	Salisbury S.A. 5108
387625969	73072	6	0	AU	UNIVERSITY OF SOUTH AUSTRALIA	UNIVERSITY	North Terrace,Adelaide, S.A. 5000

Note: (1) refers to "PAT_PUBLN_ID" variable, it is patent publication identification. (2) refers to the "PERSON_ID" variable, which is person identification. (3) refers to the "APPLT_SEQ_NR" variable, which is the sequence number of applicants. (4) refers to the "INVT_SEQ_NR" variable, which is the sequence number of inventors. (5) refers to the "PERSON_CTRY_CODE" variable. It is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. (6) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (7) refers to the "SECTOR" variable at the EEE-PPAT database, which is the sector of the applicant. (8) refers to the "PERSON_ADDRESS" variable, which is the person address of PERSON_ID.

Table A3.7 Constituent lists

Country	Lists	Country	Lists
Panel A Developed markets			
Australia	DEADAU	**Japan**	DEADJP
	WSCOPEAU		WSCOPEJP
	FAUS		FJAP
Austria	DEADOE		FTOKYO
	WSCOPEOE		FOSAKA
	FOST		FJASDAQ
Belgium	DEADBG	**Netherlands**	DEADNL
	WSCOPEBG		WSCOPENL
	FBDO		FHOL
	FBEL	**New Zealand**	DEADNZ
Canada	DEADCN1		WSCOPENZ
	DEADCN2		FNWZ
	WSCOPECN	**Norway**	DEADNW
	FVANC		WSCOPENW
	FTORO		FNOR
Denmark	DEADDK	**Portugal**	DEADPT
	WSCOPEDK		WSCOPEPT
	FDEN		FPOR
Finland	DEADFN		FPOM
	WSCOPEFN		FPSM
	FFIN	**Singapore**	DEADSG
France	DEADFR		WSCOPESG
	WSCOPEFR		FSIN
	FFRA		FSINQ

Germany	DEADBD1	**Spain**	DEADES
	DEADBD2		WSCOPEES
	DEADBD3		FSPN
	WSCOPEBD		FSPNQ
	FGERDOM		FSPDOM
Greece	DEADGR	**Sweden**	DEADSD
	WSCOPEGR		WSCOPESD
	FGRMM		FSWD
	FNEXA	**Switzerland**	DEADSW
	FGRPM		WSCOPESW
	FGREE		FSWS
Hong Kong	DEADHK		FSWA
	WSCOPEHK	**UNITED KINGDOM**	DEADUK
	FHK1		WSCOPEUK
	FHK2		FBRIT
	FHKQ	**UNITED STATES**	DEADUS1 - DEADUS6
Ireland	DEADIR		WSUS1 - WSUS20
	WSCOPEIR		FUSAA - FUSAG
	FIRL		
Italy	DEADIT		
	WSCOPEIT		
	FITA		

Country	**Lists**	**Country**	**Lists**
Panel B Developing markets			
Brazil	DEADBRA	**Morocco**	DEADMOR
	WSCOPEBR		WSCOPEMC

	FBRA		FMOR
	DEADCHI	**Peru**	DEADP
Chile	WSCOPECL		WSCOPEPE
	FCHILE		FPERU
	DEADCH	**Philippines**	DEADPH
China	WSCOPECH		WSCOPEPH
	FCHINA		FPHI
Colombia	DEADCO		FPHIQ
	WSCOPECB	**Poland**	DEADPO
	FCOL		WSCOPEPO
Czech Republic	DEADCZ		FPOL
	WSCOPECZ	**Russia**	DEADRU
	FCZECH		WSCOPERS
Egypt	DEADEGY		FRUS
	WSCOPEEY	**South Africa**	DEADSAF
	FEGYPT		WSCOPESA
Hungary	DEADHU		FSAF
	WSCOPEHN	**South Korea**	DEADKO
	FHUN		WSCOPEKO
India	DEADIND		FKOR
	WSCOPEIN	**Taiwan**	DEADTW
	FINDIA		WSCOPETA
	DEADIDN		FTAI
Indonesia	WSCOPEID		FTAIQ
	FINO	**Thailand**	DEADTH
Malaysia	DEADMY		WSCOPETH

	WSCOPEMY		FTHA
	FMAL		FTHAQ
	FMALQ	**Turkey**	DEADTK
Mexico	DEADME		WSCOPETK
	WSCOPEMX		FTURK
	FMEX		

Source: Hanauer (2014) Lists includes companies that were listed or are listed in the country.

Table A3.8 The number of applications and citations for the selected countries/regions before processing

(1)	(2)	(3)	(4)
AT	4,923	427,122	173,668
AU	8,113	397,849	151,696
BE	2,834	419,852	173,191
BR	1,295	458,193	166,810
CA	12,844	932,701	384,966
CH	11,124	1,076,278	371,913
CL	167	9,557	4,110
CN	65,269	1,687,877	487,802
CO	94	144,173	34,781
CZ	1,788	146,685	46,427
DE	50,792	2,033,580	712,529
DK	3,640	332,700	135,662
EG	36	37,789	10,214
ES	9,312	457,768	181,754
FI	4,090	467,601	179,689
FR	22,840	1,606,855	545,609
GB	25,065	1,823,774	658,570
GR	216	44,294	17,549
HK	2,302	144,413	50,128
HU	1,398	225,079	68,957
ID	40	31,734	23,157
IE	2,248	315,034	144,778
IN	1,038	376,226	157,057
IT	23,430	1,177,875	420,142

JP	27,277	2,491,555	819,878
KR	30,114	1,880,957	594,147
MA	194	39,776	12,434
MX	345	51,537	17,014
MY	808	48,960	13,284
NL	12,222	898,455	336,352
NO	3,304	196,288	75,012
NZ	1,305	48,213	15,385
PE	19	138	17
PH	58	19,828	4,721
PL	1,976	155,335	57,192
PT	509	56,361	18,875
RU	10,433	348,256	91,399
SE	8,838	705,749	281,004
SG	1,331	298,165	122,221
TH	135	12,670	4,231
TR	319	98,833	28,109
TW	12,124	956,315	278,004
US	141,634	3,959,054	1,313,642
ZA	1,678	224,758	97,152

Data source: PATSTAT - 2016 Autumn Edition

Note: (1) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. (2) refers to the total number of applicants for each selected country/region before the matching process. (3) refers to the total number of patent applications for each selected countries/region before the matching process. (4) refers to the total number of patent citations for each selected countries/region before the matching process.

Table A3.9 "HARVARD UNIVERSITY" in EEE-PPAT database

(1)	(2)	(3)
IT	HARVARD UNIVERSITY	COMPANY
US	HARVARD UNIVERSITY	COMPANY
US	HARVARD UNIVERSITY	COMPANY HOSPITAL
US	HARVARD UNIVERSITY	COMPANY GOV NON-PROFIT

Data source: PATSTAT - 2016 Autumn Edition

Note: (1) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. (2) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (3) refers to the "SECTOR" variable at the EEE-PPAT database, which is the sector of the applicant.

Table A3.10 How many countries an HRM_L2 related to

(1)	(2)	(3)	(4)	(5)
1	401,480	90.31%	435,374	99.26%
2	31,238	7.03%	3,072	0.70%
3	7,079	1.59%	163	0.04%
4	2,487	0.56%	4	0.00%
5	1,085	0.24%	4	0.00%
6	532	0.12%	0	0.00%
7	279	0.06%	0	0.00%
8	154	0.03%	0	0.00%
9	84	0.02%	0	0.00%
10	60	0.01%	0	0.00%
11	25	0.01%	0	0.00%
12	21	0.00%	0	0.00%
13	12	0.00%	0	0.00%
14	9	0.00%	0	0.00%
15	6	0.00%	0	0.00%
16	3	0.00%	0	0.00%
17	1	0.00%	0	0.00%
18	2	0.00%	0	0.00%
19	1	0.00%	0	0.00%
20	1	0.00%	0	0.00%
21	5	0.00%	0	0.00%
24	1	0.00%	0	0.00%

25	1	0.00%	0	0.00%
29	1	0.00%	0	0.00%

Data source: PATSTAT - 2016 Autumn Edition

Note: (1) is the number of countries an applicant related to. (2) is the number of companies is related to the specific number of countries before any processing. For example, observation 1 means 401,480 companies are only associated with one country in the initial dataset. (3) is the percentage of companies in the initial dataset that is relevant to a specific number of countries before any processing. For example, observation 1 is 90.31% of applicants are related to one country before any processing at the initial dataset. (4) is the number of companies is related to the specific number of countries after matching and removing extra country codes. (5) is the percentage of companies at the initial dataset is relevant to a specific number of countries after matching and removing extra country codes.

Table A3.11 The number of financial instruments for each country between 1990 to 2012

Country	STOCK_TYPE									
	American Depository Receipt	Closed End Fund	Exchange Traded Funds	Exchange-traded Commodity	Exchange-traded Notes	Global Depositary Receipt	Investment Trust	Unit Trust	Equity	Total
AUSTRALIA	145	96	3	1	0	0	0	1	4542	4788
AUSTRIA	18	2	0	0	0	0	0	0	411	431
BELGIUM	8	17	0	0	0	0	0	0	517	542
BRAZIL	106	26	1	0	0	1	0	23	1772	1929
CANADA	0	105	4	1	0	0	0	5	10349	10464
CHILE	25	1	0	0	0	0	0	0	392	418
CHINA	32	5	0	0	0	0	0	0	5096	5133
COLOMBIA	13	0	0	0	0	0	0	0	144	157
CZECH REPUBLIC	0	0	0	0	0	0	0	0	153	153
DENMARK	11	19	0	0	0	0	0	115	611	756
EGYPT	1	1	0	0	0	0	0	0	327	329
FINLAND	9	1	0	0	0	0	0	0	436	446

FRANCE	64	19	1	0	0	5	0	1	2617	2707
GERMANY	54	11	0	0	0	1	0	0	2962	3028
GREECE	3	29	0	0	0	0	0	0	537	569
HONG KONG	102	14	8	0	0	0	0	2	3597	3723
HUNGARY	4	6	0	0	0	0	0	25	157	192
INDIA	12	7	1	0	0	2	0	0	5496	5518
INDONESIA	7	1	0	0	0	0	0	0	864	872
IRELAND	14	4	4	0	0	0	0	2	309	333
ITALY	24	3	1	0	0	0	0	0	1234	1262
JAPAN	91	5	193	0	0	1	0	0	6434	6724
MALAYSIA	15	4	1	0	0	0	0	0	1600	1620
MEXICO	75	0	1	0	0	5	0	0	687	768
MOROCCO	0	0	0	0	0	0	0	0	93	93
NETHERLANDS	33	21	0	0	23	2	2	15	637	733
NEW ZEALAND	11	6	5	0	0	0	2	0	441	465
NORWAY	29	3	0	0	0	0	0	3	936	971
PERU	9	2	0	0	0	0	0	0	336	347

PHILIPPINES	7	1	0	0	0	0	0	0	482	490
POLAND	2	3	0	0	0	0	0	1	1044	1050
PORTUGAL	3	1	0	0	0	0	0	0	231	235
RUSSIA	36	0	0	0	0	1	0	0	1031	1068
SINGAPORE	21	10	1	0	0	0	0	0	1414	1446
SOUTH AFRICA	56	40	2	0	1	0	2	9	1284	1394
SOUTH KOREA	12	8	2	0	0	0	3	0	3104	3129
SPAIN	20	3	0	0	0	0	0	0	702	725
SWEDEN	32	10	0	0	0	0	0	0	1899	1941
SWITZERLAND	17	63	2	0	0	0	0	0	943	1025
TAIWAN	10	0	0	0	0	1	0	0	2527	2538
THAILAND	6	0	5	0	0	0	0	19	2294	2324
TURKEY	12	14	0	0	0	0	0	0	522	548
UNITED KINGDOM	201	69	0	0	0	9	778	4	6613	7674
UNITED STATES	249	595	15	0	1	7	2	2	27206	28077
Total	1599	1225	250	2	25	35	789	227	104983	109135

Note: Country is the name of the country. STOCK_TYPE indicates the type of instrument requested.

Table A3.12 Description and strings of name variables of ID "360125" on Datastream

(1)	(2)	(3)
Name	The name of the equity/company or equity list which sorted in the database.	@POS.COM DEAD - DELIST 19/09/02
WC06001	The legal name of the company as reported in the 10-K for US companies, and the annual report for non-US companies.	@POS.COM, INC.
CNAME	The name of the equity/company as stored on Datastream databases	@POS.COM INCO.
PNAME	Previous name	ATPOS.COM
ECNAME	The expanded (unabbreviated) name of the equity/company.	@POS.COM INCORPORATED

Data source: Datastream database

Note: (1) refers to the "NAME" variable on Datastream. It is the name of the equity/company or equity list, as stored on Datastream databases. It is available for all instruments. (2) refers to the description of the "NAME" variable. (3) refers to the strings in the "NAME" variable of ID "360125" as an example.

Table A3.13 Structure of strings recorded at name variable

(1)	(2)	(3)	(4)
Company Name	21ST CENTURY PLASTICS CORPORATION	21ST CENTURY PLASTICS CORPORATION	PATSTAT, Datastream
Company Name + address	BODE CHEMIE & COMPANY 22525 HAMBURG	BODE CHEMIE & COMPANY	PATSTAT
Company Name + explanation	AGE SCIENCES CORPORATION, A UTAH CORPORATION	AGE SCIENCES CORPORATION	PATSTAT, Datastream
Company Name + status	CENTAUR MINING AND EXPLORATION LTD- ADR	CENTAUR MINING AND EXPLORATION LTD	Datastream
Company Name + Company Name	BENZ COMPANIES, INC., D/B/A BENZ AIRBORNE SYSTEMS	BENZ COMPANIES, INC., BENZ AIRBORNE SYSTEMS	PATSTAT

Data source: PATSTAT - 2016 Autumn Edition, Datastream database

Note: (1) refers to the structure of strings recorded in the name variable. (2) refers to the strings before processing. (3) refers to the strings after processing. (4) refers to which databases the strings exist in.

Table A3.14 The name variable splits based on single brackets

(1)	(2)
	3COM CORP (COMPUTERS COMMUNICATION COMPATIBILITY CORP)
3COM CORP (COMPUTERS COMMUNICATION COMPATIBILITY CORP)	3COM CORP
	(COMPUTERS COMMUNICATION COMPATIBILITY CORP)
	3CSCAN (BEIJING) TECHNOLOGY CO
3CSCAN (BEIJING) TECHNOLOGY CO	3CSCAN TECHNOLOGY CO
	(BEIJING)

Note: (1) refers to the original name variable, namely, the strings in the company name variable before the variable is split based on the single brackets. (2) refers to the new name variable, namely, the strings in the company name created after the variable is split based on the single brackets.

Table A3.15 Steps of Automatic matching procedure

(1)	(2)	(3)	(4)
Step1	Original company name	Original company name	Same original name, same country
Step2	"full string" company name	"full string" company name	Same "full string" name, same country
Step3	"stem string" company name	"stem string" company name	Same "stem string" name, same country, same address (i.e., state, city, street or zip code)

Note: (1) refers to steps of the automatic matching procedure. (2) refers to the specific kind of company name at the PATSTAT database. (3) refers to the specific kind of company name on Datastream. (4) refers to the requirement of matching company names at both databases.

Table A3.16 The sample of the automatic match by "Full string" company names at both databases

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
866893	ADAM OPEL AG	ADAM OPEL AG	ADAM OPEL AG		ADAM OPEL AG	DE	ADAMOPELAG	STEYRDAIMLERP UCHAG	STEYR-DAIMLER-PUCH AG, WIEN	AT
14562W	BRIT.SKY BCAST.GP. (XET) DEAD - 30/05/11	SKY LTD	SKY PLC.	BRIT.SKY BCAST. (XET)	SKY PUBLIC LIMITED COMPANY	GB	SKYLTD	SKYLTD	"SKY LTD."	RU
540309	AGV PRODUCTS	A.G.V. PRODUCTS CORP	AGV PRODUCTS CORP.		AGV PRODUCTS CORPORATION	TW	AGVPRODCORP	AGVPRODCORP	A. G. V. PRODUCTS CORPORATION	TW

Note: (1) represents Datastream ID, which is the unique ID of record on Datastream. (2) refers to the "NAME" variable on Datastream. It is the name of the equity/company or equity list, as stored on Datastream databases. It is available for all instruments. (3) refers to the "WC06001" variable on Datastream, which is the legal name of the company as reported in the 10-K for US companies and the annual report for non-US companies. (4) refer to the "CNAME" variable on Datastream, which is the name of the equity/company as stored on Datastream databases. (5) refers to the "PNAME" on Datastream, which is the previous name of the security. (6) refers to the "ECNAME" variable on Datastream, which is the expanded (unabbreviated) name of the equity/company. (7) refers to the "GEOGN" variable on Datastream, which is a geographical classification of company by name, which specifying the home or listing country of company security. (8) refers to the "full strings" company name created by name standardisation on Datastream. (9) refers to the "full strings" company name created by name standardisation at the PATSTAT database. (10) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (11) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. The representation of strings in this column can be seen in Table 3.1.

Table A3.17 A sample of resolving multiple matches when a Datastram ID is matched with more than one applicant

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
R. R. DONNELLEY & SONS COMPANY	US	905047	R R DONNELLEY & SONS	RR DONNELLEY & SONS CO	R R DONNELLEY & SONS CO.	DONNELLEY R R & SONS	R R DONNELLEY & SONS COMPANY	US	P	Y
R. R. DONNELLEY AND SONS COMPANY	US	905047	R R DONNELLEY & SONS	RR DONNELLEY & SONS CO	R R DONNELLEY & SONS CO.	DONNELLEY R R & SONS	R R DONNELLEY & SONS COMPANY	US	P	Y

Note: (1) refers to the "HRM_L2" variable, which is the standardised name created by EEE-PPAT database. (2) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. the representation of strings in this column can be seen in Table 3.2. (3) represents Datastream ID, which is the unique ID of record on Datastream. (4) refers to the "NAME" variable, it is the name of the equity/company or equity list, as stored on Datastream's databases. It is available for all instruments. (5) refers to the "WC06001" variable on Datastream, which is the legal name of the company as reported in the 10-K for US companies and the annual report for non-US companies. (6) refer to the "CNAME" variable on Datastream, which is the name of the equity/company as stored on Datastream databases. (7) refers to the "PNAME" on Datastream, which is the previous name of the security. (8) refers to the "ECNAME" variable on Datastream, which is the expanded (unabbreviated) name of the equity/company. (9) refers to the "GEOGN" variable on Datastream, which is a geographical classification of company by name, which specifying the home or listing country of a company security. (10) refers to the "ISINID" variable on Datastream, which is the primary/secondary flag. It returns "P" or "S" when the equity record is the primary/secondary one (i.e., the domestic/foreign listing of the share or depository receipt or certificate). (11) refers to the "MAJOR" variable on Datastream, which is the major security flag. It returns "Y" or "N" to indicate whether the security is the one with the most significant market capitalisation and liquidity of the primary quotation of that security.

Table A3.18 Sample of eliminating the multiple matching problem through "ISINID" and "MAJOR" variable

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ACE HARDWARE CORPORATION	US	28145X	ACE HARDWARE CORPORATION	ACE HARDWARE CORPORATION	ACE HARDWARE CORPORATION		ACE HARDWARE CORPORATION	US	P	Y	EQ
ACE HARDWARE CORPORATION	US	878063	ACE HARDWARE CL.B	ACE HARDWARE CORPORATION	ACE HARDWARE CORPORATION		ACE HARDWARE CORPORATION	US	P	N	EQ
ACE HARDWARE CORPORATION	US	878064	ACE HARDWARE CL.C	ACE HARDWARE CORPORATION	ACE HARDWARE CORPORATION		ACE HARDWARE CORPORATION	US	P	N	EQ

Note: (1) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (2) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. the meaning of strings in this column can be seen in Table 3.2. (3) represents Datastream ID, which is the unique ID of record on Datastream. (4) refers to the "NAME" variable on Datastream. It is the name of the equity/company or equity list, as stored on Datastream's databases. It is available for all instruments. (5) refers to the "WC06001" variable on Datastream, which is the legal name of the company as reported in the 10-K for US companies, and the annual report for non-US companies. (6) refer to the "CNAME" variable on Datastream, which is the name of the equity/company as stored on Datastream databases. (7) refers to the "PNAME" on Datastream, which is the previous name of the security. (8) refers to the "ECNAME" variable on Datastream, which is the expanded (unabbreviated) name of the equity/company. (9) refers to the "GEOGN" variable on Datastream, which is a geographical classification of a company by name, which specifying the home or listing country of company security. (10) refers to the "ISINID" variable on Datastream, which is the primary/secondary flag. It returns "P" or "S" when the equity record is the primary/secondary one (i.e., the domestic/foreign listing of the share or depository receipt or certificate). (11) refers to the "MAJOR" variable on Datastream, which is the major security flag. It returns "Y" or "N" to indicate whether the security is the one with the most significant market capitalisation and liquidity of the primary quotation of that security. (12) refers to the "STOCK_TYPE" variable on Datastream, indicates the type of instrument requested.

Table A3.19 A sample that a PATSTAT company is matched with more than one Datastream records

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PECO ENERGY COMPANY	US	86523W	PECO ENERGY COMPANY	PECO ENERGY COMPANY	PECO ENERGY COMPANY		PECO ENERGY COMPANY	US	P	Y		2301 MARKET ST	PHILADELPHIA	PENNSYLVANIA	19101
PECO ENERGY COMPANY	US	86523W	PECO ENERGY COMPANY	PECO ENERGY COMPANY	PECO ENERGY COMPANY		PECO ENERGY COMPANY	US	P	Y	PHILADELPHIA	2301 MARKET ST	PHILADELPHIA	PENNSYLVANIA	19101
PECO ENERGY COMPANY	US	902317	EXELON	EXELON CORPORATION	EXELON CORP.	PECO ENERGY CO.	EXELON CORPORATION	US	P	Y			CHICAGO	ILLINOIS	60680
PECO ENERGY COMPANY	US	902317	EXELON	EXELON CORPORATION	EXELON CORP.	PECO ENERGY CO.	EXELON CORPORATION	US	P	Y	PHILADELPHIA		CHICAGO	ILLINOIS	60680

Note: (1) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (2) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. The meaning of strings in this column can be seen in Table 3.1. (3) represents Datastream ID, which is the unique ID of record on Datastream. (4) refers to the "NAME" variable on Datastream, it is the name of the equity/company or equity list, as stored on Datastream databases. It is available for all instruments. (5) refers to the "WC06001" variable on Datastream, which is the legal name of the company as reported in the 10-K for US companies, and the annual report for non-US companies. (6) refer to the "CNAME" variable on Datastream, which is the name of the equity/company as stored on Datastream databases. (7) refers to the "PNAME" on Datastream, which is the previous name of the security. (8) refers to the "ECNAME" variable on Datastream, which is the expanded (unabbreviated) name of the equity/company. (9) refers to the "GEOGN" variable on Datastream, which is a geographical classification of a company by name, which specifying the home or listing country of company security. (10) refers to the "ISINID" variable on Datastream, which is the primary/secondary flag. It returns "P" or "S" when the equity record is the primary/secondary one (i.e., the domestic/foreign listing of the share or depository receipt or certificate). (11) refers to the "MAJOR" variable on Datastream, which is the major security flag. It returns "Y" or "N" to indicate whether the security is the one with the most significant market capitalisation and liquidity of the primary quotation of that security. (12) refers to the "PERSON_ADDRESS" variable. It is the address of corporate applicants at the PATSTAT database. Column (13)-(16) represent the location of the corporate offices of a company on Datastream. (13) refers to the "WC06022" variable on Datastream. It represents the street of the corporate offices of a company on Datastream. (14) refers to the "WC06023" variable on Datastream. It represents the city of the corporate offices of a company on Datastream. (15) refers to the

"WC06024" variable on Datastream. It represents the state of the corporate offices of a company on Datastream. (16) refers to the "WC06025" variable on Datastream. It represents the postcode of the corporate offices of a company on Datastream.

Table A3.20 Address information of HRM_L2 "02 MICRO" at PATSTAT database and EEE-PPAT database

(1)	(2)	(3)	(4)	(5)
02 MICRO	TW	15	1	Taipei
02 MICRO	US	15	1	
02 MICRO	US	15	1	3118 PATRICK HENRY DRIVE SANTA CLARA, CALIFORNIA 95054 U.S.A.
02 MICRO	US	15	1	3118 Patrick Henry Drive,Santa Clara, CA 95054
02 MICRO	US	15	1	Santa Clara
02 MICRO	US	15	1	Santa Clara,CA
02 MICRO	US	15	1	Santa Clra,CA
02 MICRO	US	15	1	Sunnyvale,CA

Note: (1) refers to the "HRM_L2" variable, which is the standardised name created by the EEE-PPAT database. (2) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. The meaning of strings in this column can be seen in Table 3.1. (3) refers to the number of applications applied by the specific company (i.e., 02 MICRO). (4) refers to the number of citations relevant to the specific company's applications. (5) refers to the "PERSON_ADDRESS" variable. It is the address of corporate applicants at the PATSTAT database.

Table A3.21 The number of applications contributed by the Top10% applicants

(1)	(2)	(3)	(4)	(5)	(2) + (3) (6)	(4) + (5) (7)	(6) + (7) (8)	(2) + (4) (9)	(6)/ (8) (10)
JP	535,609	271,676	3,490	48,980	807,285	52,470	859,755	539,099	93.90%
TW	116,206	54,319	2,286	18,096	170,525	20,382	190,907	118,492	89.32%
KR	179,977	87,689	1,469	39,780	267,666	41,249	308,915	181,446	86.65%
US	621,599	582,728	6,083	217,015	1,204,327	223,098	1,427,42 5	627,682	84.37%
SG	2,110	5,561	42	1,441	7,671	1,483	9,154	2,152	83.80%
DE	160,390	221,855	582	79,595	382,245	80,177	462,422	160,972	82.66%
BE	4,808	9,280	46	3,100	14,088	3,146	17,234	4,854	81.75%
FI	2,408	23,675	97	5,918	26,083	6,015	32,098	2,505	81.26%
FR	51,932	98,900	818	34,834	150,832	35,652	186,484	52,750	80.88%
SE	18,483	23,079	222	10,296	41,562	10,518	52,080	18,705	79.80%
CH	15,320	40,684	142	15,985	56,004	16,127	72,131	15,462	77.64%

NL	17,744	29,715	26	13,967	47,459	13,993	61,452	17,770	77.23%
CN	46,360	200,054	1,007	74,746	246,414	75,753	322,167	47,367	76.49%
HK	1,834	3,338	5	1,638	5,172	1,643	6,815	1,839	75.89%
TR	0	846	1	278	846	279	1,125	1	75.20%
DK	4,944	6,020	54	4,137	10,964	4,191	15,155	4,998	72.35%
CA	17,526	18,504	553	15,197	36,030	15,750	51,780	18,079	69.58%
GB	20,024	46,604	490	30,539	66,628	31,029	97,657	20,514	68.23%
AT	1,381	14,109	67	7,410	15,490	7,477	22,967	1,448	67.45%
PE	0	4	0	2	4	2	6	0	66.67%
IN	1,375	1,324	131	1,241	2,699	1,372	4,071	1,506	66.30%
IT	4,466	51,524	171	29,348	55,990	29,519	85,509	4,637	65.48%
PL	59	3,763	69	2,309	3,822	2,378	6,200	128	61.65%
AU	3,413	13,764	221	10,617	17,177	10,838	28,015	3,634	61.31%
RU	1,324	22,217	66	15,383	23,541	15,449	38,990	1,390	60.38%
BR	576	973	32	986	1,549	1,018	2,567	608	60.34%

TH	114	85	5	128	199	133	332	119	59.94%
NO	927	4,808	82	3,858	5,735	3,940	9,675	1,009	59.28%
ZA	339	2,973	54	2,222	3,312	2,276	5,588	393	59.27%
NZ	389	1,430	11	1,329	1,819	1,340	3,159	400	57.58%
HU	341	1,480	1	1,351	1,821	1,352	3,173	342	57.39%
IE	15	4,185	11	3,154	4,200	3,165	7,365	26	57.03%
CZ	371	1,752	23	1,612	2,123	1,635	3,758	394	56.49%
ES	697	10,957	43	9,774	11,654	9,817	21,471	740	54.28%
GR	47	183	2	214	230	216	446	49	51.57%
MX	13	341	2	337	354	339	693	15	51.08%
EG	0	22	5	26	22	31	53	5	41.51%
MY	37	471	11	715	508	726	1,234	48	41.17%
PT	0	321	3	468	321	471	792	3	40.53%
CL	20	78	1	149	98	150	248	21	39.52%
CO	0	20	0	32	20	32	52	0	38.46%

MA	3	75	1	125	78	126	204	4	38.24%
PH	5	19	0	48	24	48	72	5	33.33%
ID	0	8	1	18	8	19	27	1	29.63%

Note: (1) refers to the "PERSON_CTRY_CODE" variable, it is the corporate applicants' country code, which represents the country name based on the two-letter alphabetic codes of WIPO Standard ST.3 (http://www.wipo.int/export/sites/www/standards/en/pdf/03-30-01.pdf), this is the country part of the correspondence address of applicants and inventors on PATSTAT. the meaning of strings in this column can be seen in Table 2. (2) refers to the number of applications applied by top10% of applicants to total applicants at PATSTAT, which has been matched with companies on Datastream. (3) refers to the number of applications applied by top10% applicants at PATSTAT which not been matched. (4) refers to the number of applications applied by the rest of 90% applicants which has been matched with companies on Datastream. (5) refers to the number of applications applied by the rest of 90% applicants which is not matched. (6) refers to the number of applications applied by top10% applicants (i.e., column (2) + column (3)). (7) refers to the number of applications applied by the rest 90% of applicants (i.e., column (4) + column (5)). (8) refers to the number of applications per country after matching and removing extra country codes. (i.e., column (6) + column (7)). (9) is the number of matched applications per country after matching (i.e., column (2) + column (4)). (10) refers to the percentage of applications applied by the top 10% applicants to the total applications (i.e., Column (6)/ Column (8)).

Table A3.22 Trends in innovation within a country; index 1990=1000

PERSON CTRY CODE	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
AT	1000	955	773	955	1,061	1,379	727	864	909	924	1,121	1,424	1,045	1,136	939	939	939	1,591	1,136	985	1,136
AU	1000	1,182	1,007	1,063	1,189	1,280	1,238	1,189	895	1,497	1,378	1,189	1,678	1,364	965	1,007	986	1,490	1,503	1,203	1,112
BE	1000	1,509	1,901	1,845	1,944	2,093	2,087	2,584	2,292	1,776	1,820	1,559	1,702	1,000	994	758	745	652	795	578	516
BR	1000	810	619	1,238	905	524	1,429	1,381	1,381	1,476	952	1,333	1,238	1,381	2,381	2,381	1,762	2,000	2,095	1,762	905
CA	1000	815	888	1,006	1,055	1,334	1,881	3,316	3,781	3,793	4,046	3,179	2,848	2,705	3,608	3,438	3,696	3,185	2,532	3,210	3,635
CH	1000	818	756	690	742	652	741	727	811	982	1,144	1,088	1,081	1,053	1,060	1,102	1,174	1,015	835	814	709
CN	1000	739	1,391	1,609	2,348	2,522	4,435	8,957	10,000	13,000	18,391	26,130	39,957	55,913	69,783	106,304	172,478	300,435	324,217	426,739	473,087
CZ	1000	218	425	241	460	276	241	253	253	218	103	149	46	103	149	57	103	46	80	103	0
DE	1000	976	1,059	1,058	1,142	1,282	1,471	1,624	1,713	1,784	1,816	1,768	1,725	1,688	1,702	1,563	1,515	1,490	1,346	1,173	1,103
DK	1000	867	824	1,079	1,242	1,503	1,782	1,673	2,055	1,770	1,697	1,545	1,655	1,982	1,667	1,515	1,515	1,315	1,224	1,121	1,261
ES	1000	243	432	568	784	1,000	676	649	1,162	1,081	1,297	784	730	595	946	973	784	1,027	1,189	1,514	2,568
FI	1000	670	741	830	857	920	804	598	813	679	1,018	1,071	1,241	1,384	1,500	1,357	1,330	1,321	1,241	1,554	1,438
FR	1000	1,045	1,056	1,163	1,044	1,189	1,193	1,344	1,432	1,565	1,590	1,556	1,560	1,713	1,961	1,904	1,932	2,025	2,039	1,851	1,767
GB	1000	882	889	834	906	875	986	871	845	809	830	822	927	873	820	752	834	745	821	850	779
HK	1000	0	1,000	0	500	1,500	1,500	0	500	3,000	4,500	25,500	116,500	125,500	71,500	103,000	92,000	85,000	127,000	81,000	79,000

HU	1000	741	815	296	222	407	167	148	111	167	93	111	185	296	352	315	259	370	167	56	56
IN	1000	200	600	600	200	1,800	4,000	4,800	7,000	6,400	10,400	15,200	23,000	18,000	28,200	26,400	31,200	24,600	34,600	27,600	35,400
IT	1000	1,066	892	994	1,024	1,151	1,476	1,217	1,235	1,458	1,777	1,205	1,223	1,096	1,205	1,145	1,127	1,470	1,880	2,325	1,970
JP	1000	822	691	680	568	587	610	597	554	602	656	607	586	594	613	588	548	531	457	403	396
KR	1000	1,496	2,204	3,071	3,903	7,504	9,271	8,927	2,672	836	1,114	1,156	1,407	1,611	2,301	6,788	8,240	5,357	3,037	3,006	3,342
MY	1000	0	0	0	0	0	2,000	0	0	1,000	7,000	1,000	1,000	10,000	2,000	5,000	4,000	1,000	1,000	10,000	2,000
NL	1000	1,261	1,905	1,398	1,137	1,336	1,493	2,284	3,370	6,118	8,441	10,261	9,261	5,801	5,441	4,882	4,464	3,578	4,100	4,071	2,611
NO	1000	773	500	227	818	1,000	3,045	1,273	2,000	1,909	2,864	3,136	3,818	3,182	5,500	4,318	2,000	2,364	2,091	2,091	1,955
NZ	1000	778	1,000	444	667	1,444	2,222	2,556	3,111	4,778	5,000	2,333	3,444	2,333	2,333	2,222	1,556	1,778	1,556	1,889	2,000
PH	1000	0	0	0	0	0	0	0	0	1,000	0	0	1,000	1,000	1,000	0	0	0	0	0	0
PL	1000	167	1,333	500	1,000	833	2,000	1,000	1,833	1,000	500	500	0	833	0	333	500	2,167	2,333	2,500	1,000
SE	1000	1,000	1,284	1,767	2,265	3,158	5,302	6,665	6,735	6,707	6,000	4,860	3,228	3,233	3,577	3,847	4,060	5,140	5,800	5,209	6,163
SG	1000	4,000	8,000	8,000	12,000	22,000	62,000	52,000	65,000	180,000	190,000	99,000	106,000	93,000	103,000	169,000	223,000	217,000	234,000	143,000	161,000
TR	1000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TW	1000	1,449	2,090	4,436	9,538	10,859	19,885	20,000	41,872	58,782	49,833	74,628	88,359	105,385	115,654	139,782	146,564	158,462	166,026	159,026	145,462
US	1000	979	1,023	1,057	1,171	1,343	1,517	1,682	1,846	1,932	1,980	1,930	1,964	1,859	1,853	1,897	1,814	1,811	1,781	1,493	1,503
ZA	1000	1,414	724	1,034	966	448	1,034	1,069	1,034	1,069	793	172	310	172	207	310	310	241	379	241	621

Note: it excludes "CL", "CO", "EG","GR","ID", "IE","MA","MX","PE", "PT","RU","TH" because non application was submitted by merged companies in these countries.

Figure A3.1 The front page of a published patent application by USPTO

US 20120082102A1

(19) **United States**
(12) **Patent Application Publication**
Kang et al.

(10) **Pub. No.: US 2012/0082102 A1**
(43) **Pub. Date: Apr. 5, 2012**

(54) **METHOD FOR INDICATING PRECODING MATRIX INDICATOR IN UPLINK MIMO SYSTEM WITH BASED ON SC-FDMA**

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(73) Assignee: **LG ELECTRONICS INC.**, Seoul (KR)

(21) Appl. No.: **13/148,886**

(22) PCT Filed: **Feb. 19, 2010**

(86) PCT No.: **PCT/KR2010/001039**

§ 371 (c)(1), (2), (4) Date: **Nov. 14, 2011**

Related U.S. Application Data

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(30) **Foreign Application Priority Data**

Jul. 7, 2009 (KR) 10-2009-0061699

Publication Classification

(51) **Int. Cl.**
H04W 74/04 (2009.01)
H04W 72/04 (2009.01)

(52) **U.S. Cl.** **370/329**

(57) **ABSTRACT**

A method of transmitting PMI (precoding matrix indicator) information in an uplink MIMO system is disclosed. The present invention includes the steps of receiving channel information from a user equipment and transmitting information on a resource allocated to the user equipment in uplink transmission and PMI information indicating a precoding matrix to apply to a region of the resource among a plurality of precoding matrices to the user equipment based on the received channel information, wherein the resource allocated to the user equipment is allocated by a bundle unit of a prescribed number of subcarriers, wherein each of a plurality of the precoding matrices are applied to regions generated from dividing a whole frequency band into a prescribed number of regions, respectively, and wherein the precoding matrix applied to the resource among a plurality of the precoding matrices has a maximum area resulting from overlapping a frequency band occupied by the allocated resource with a frequency band having the precoding matrix applied thereto.

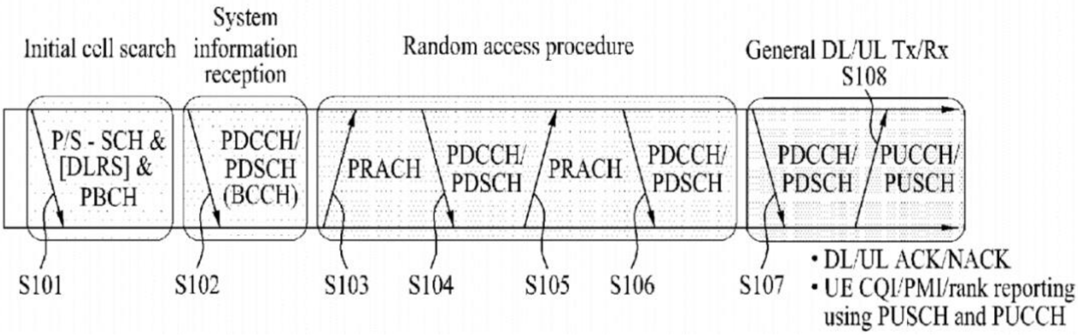


Figure A3.2 The number of patent applications submitted to patent authority from 1990 to 2010 at the PATSTAT database

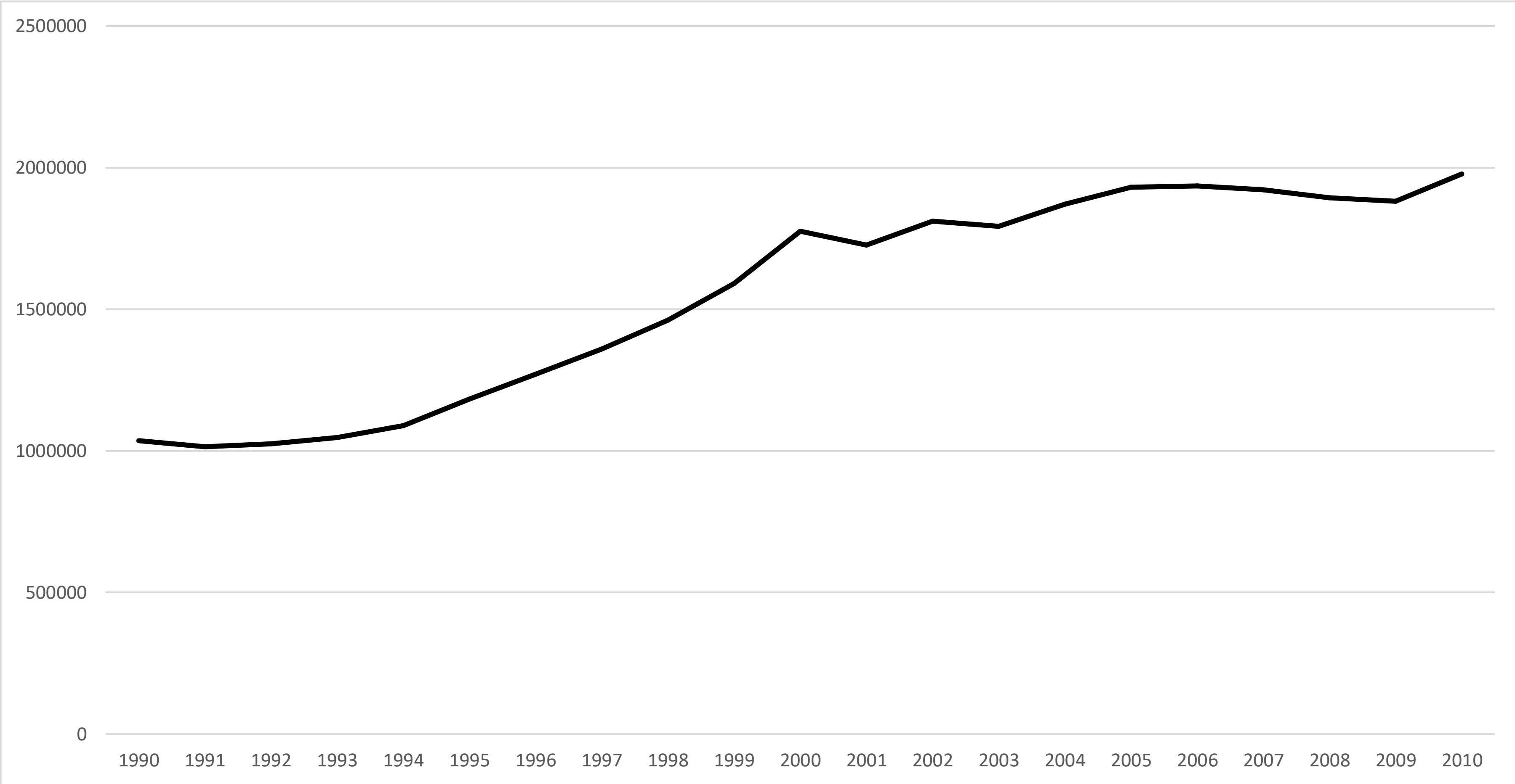
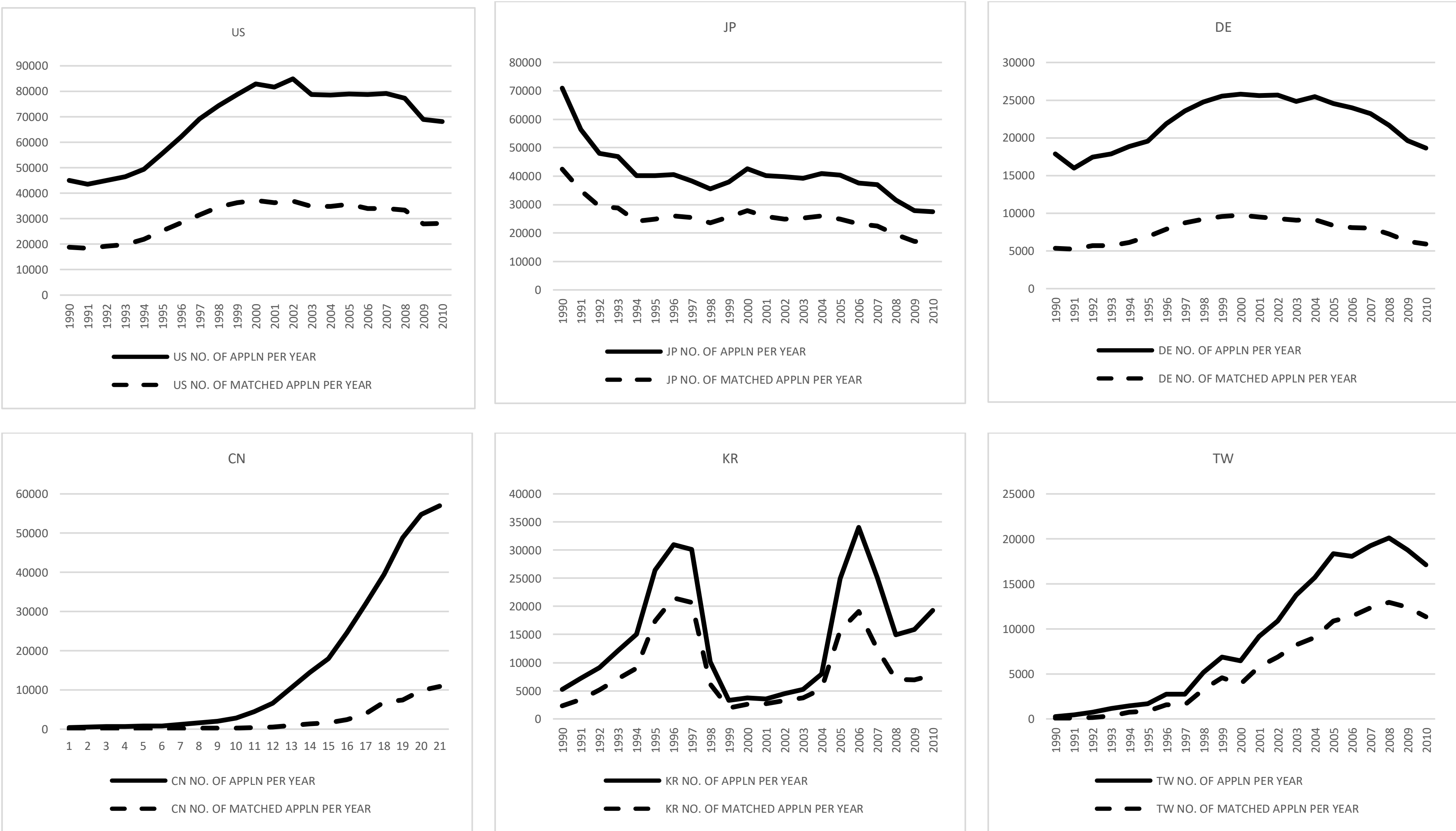
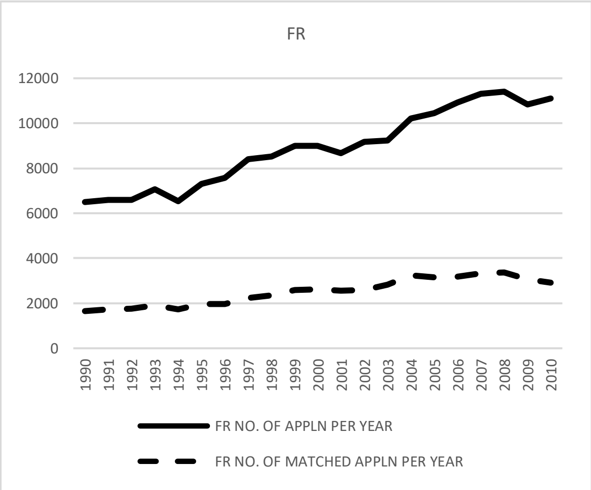


Figure A3.3 The number of applications applied by corporate applicants in each country from 1990 to 2010

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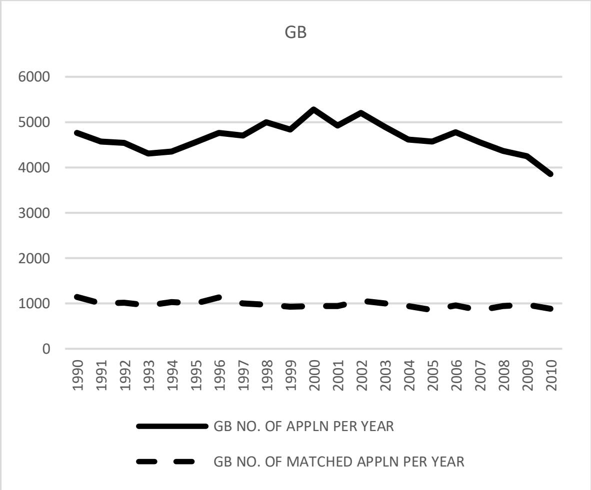
FR NO. OF MATCHED APPLN PER YEAR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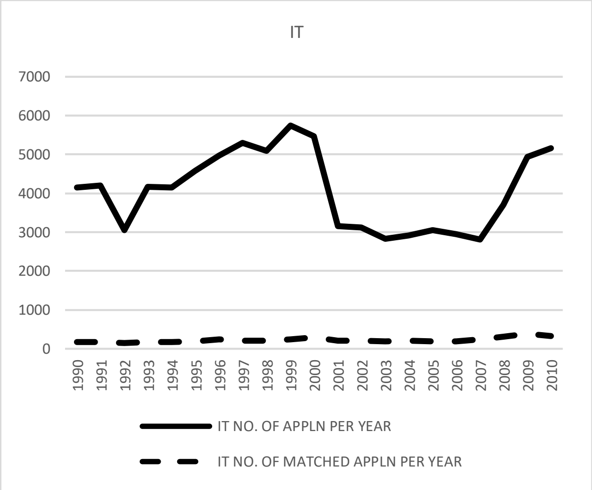
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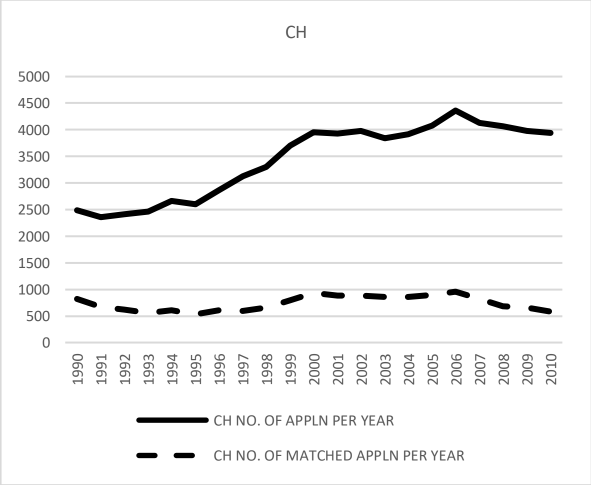
IT NO. OF MATCHED APPLN PER YEAR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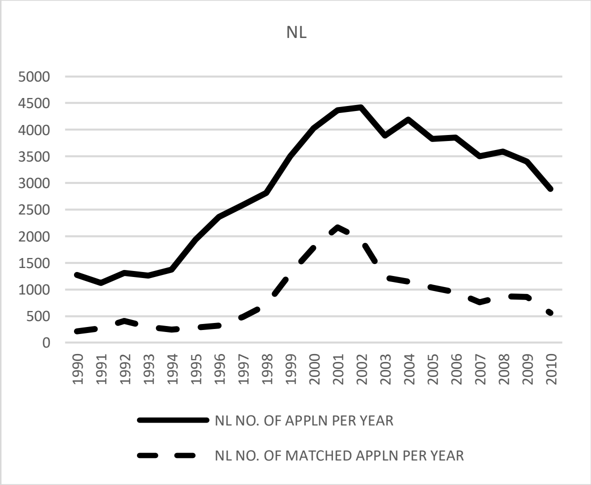
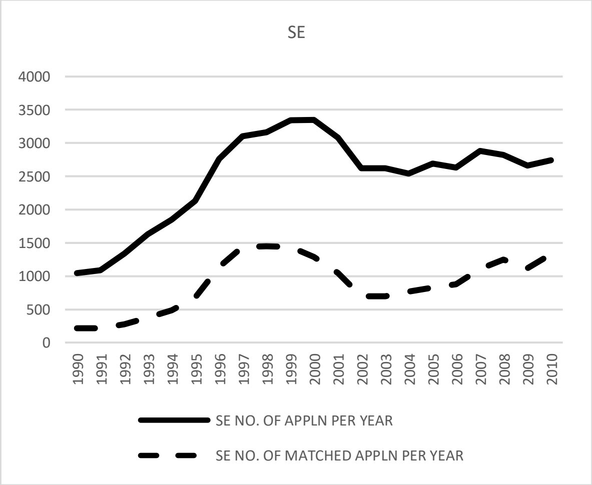
CH NO. OF MATCHED APPLN PER YEAR


NL
NL NO. OF APPLN PER YEAR
NL NO. OF MATCHED APPLN PER YEAR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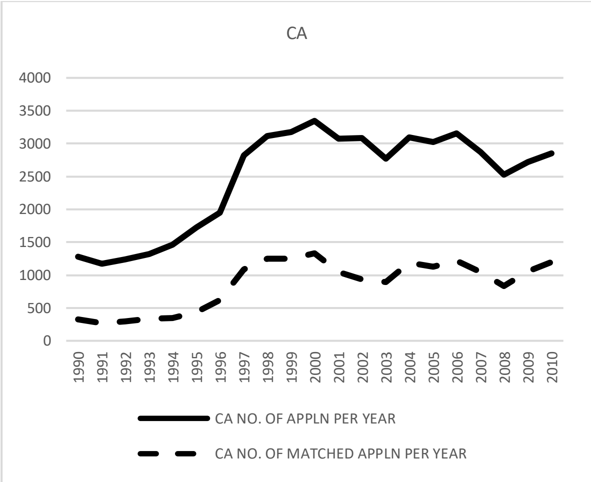
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3500
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2000
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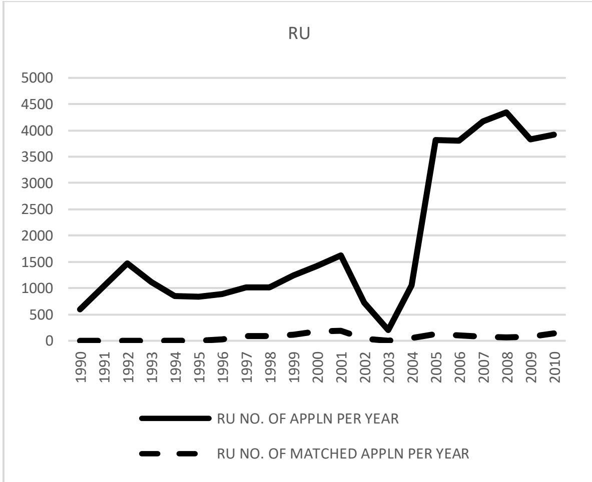
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010
CA NO. OF APPLN PER YEAR
CA NO. OF MATCHED APPLN PER YEAR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3500
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2500
2000
1500
1000
500
0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010
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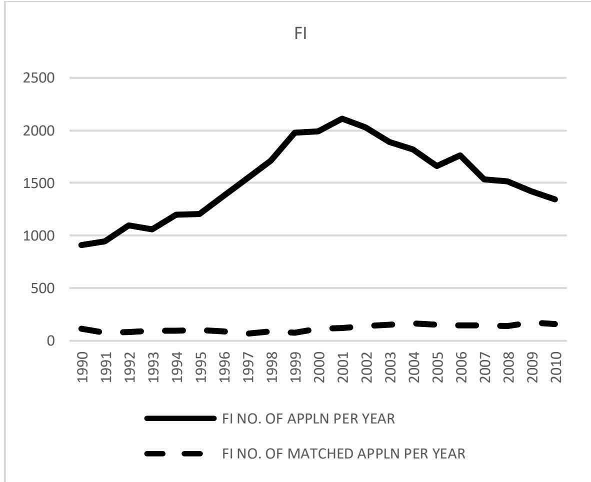
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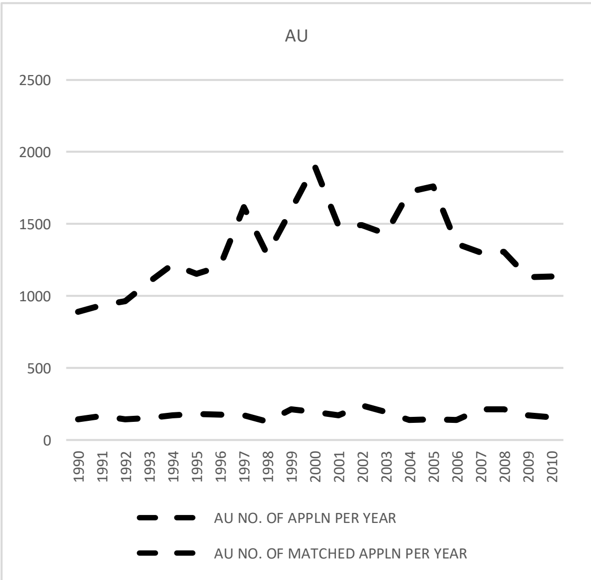
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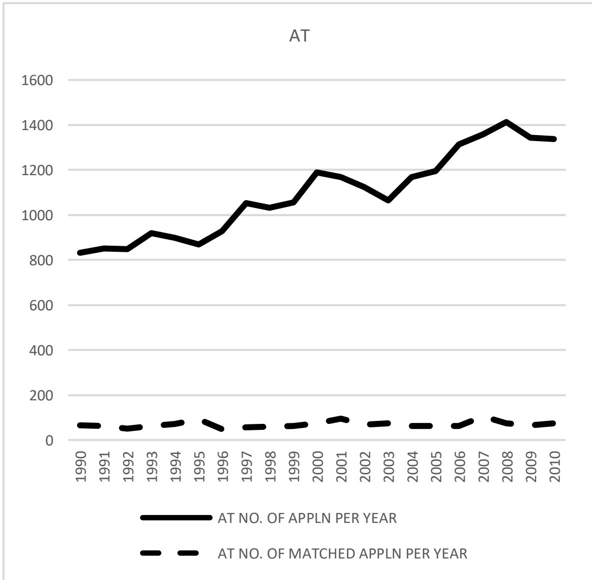
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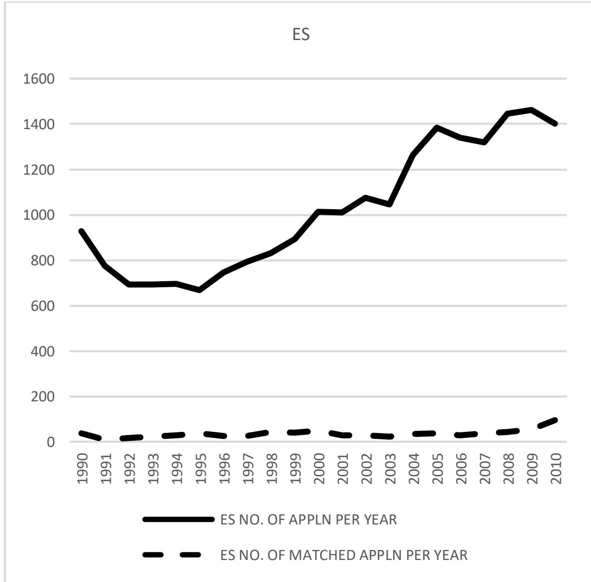
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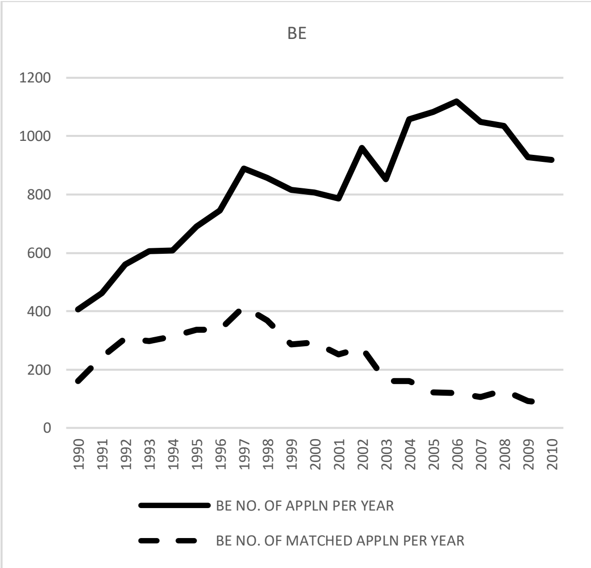
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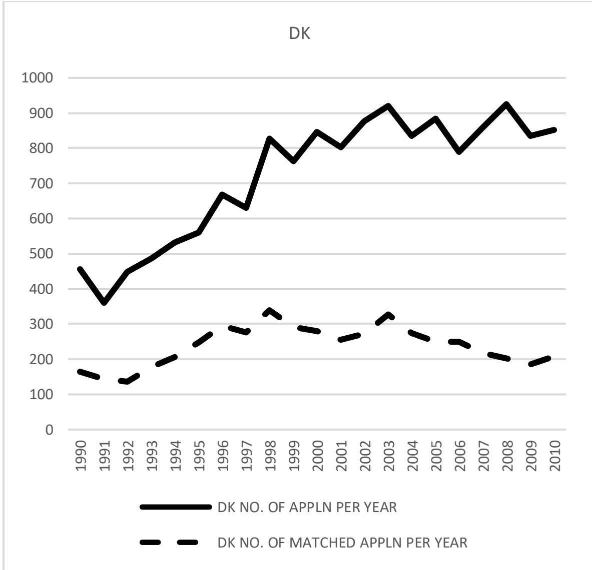
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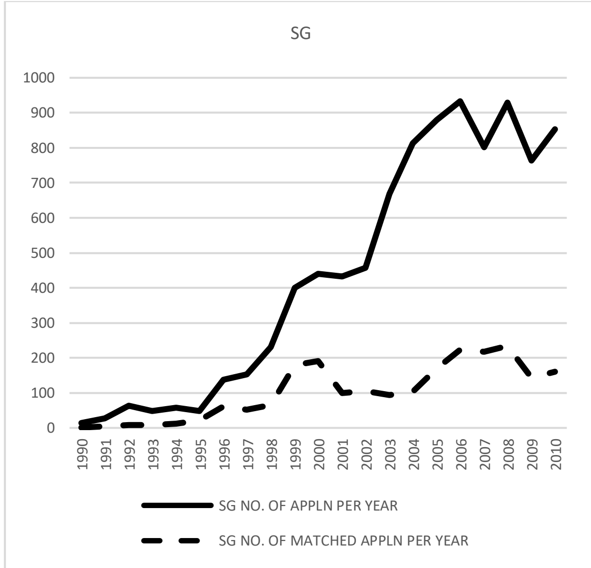
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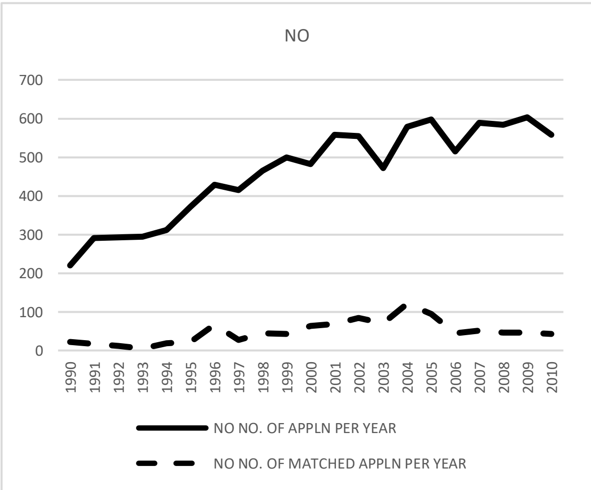
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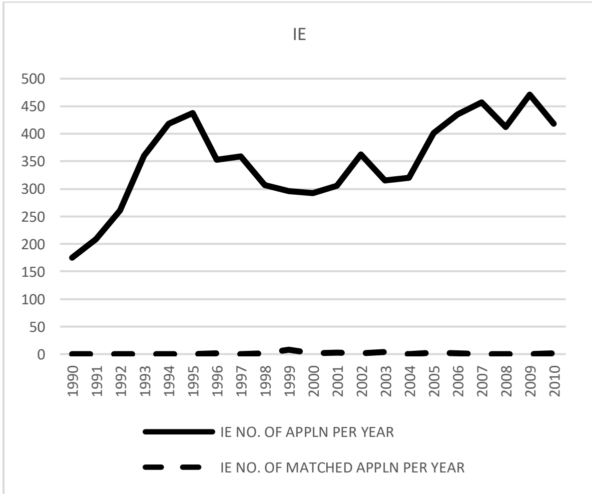
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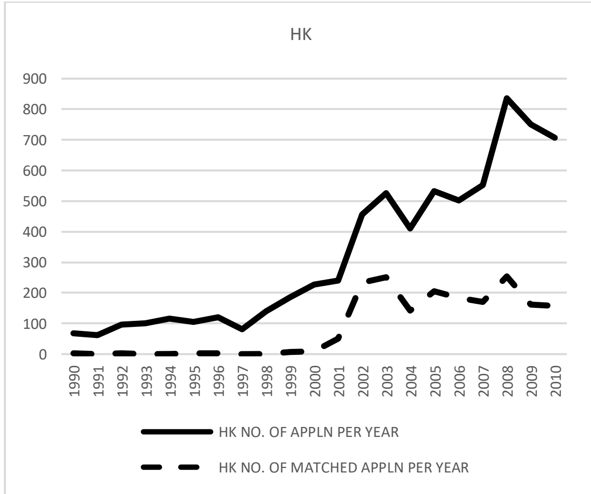
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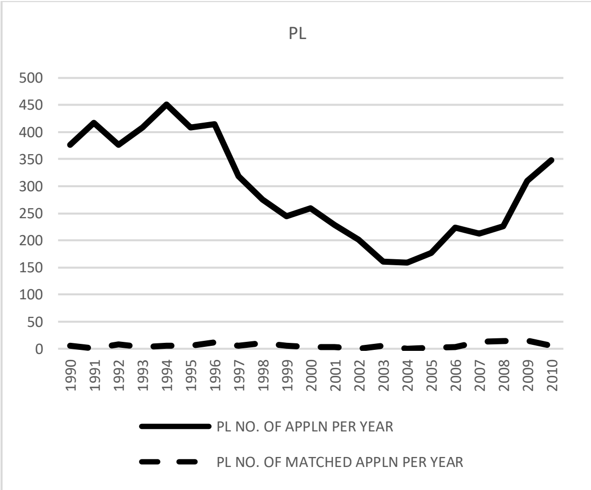
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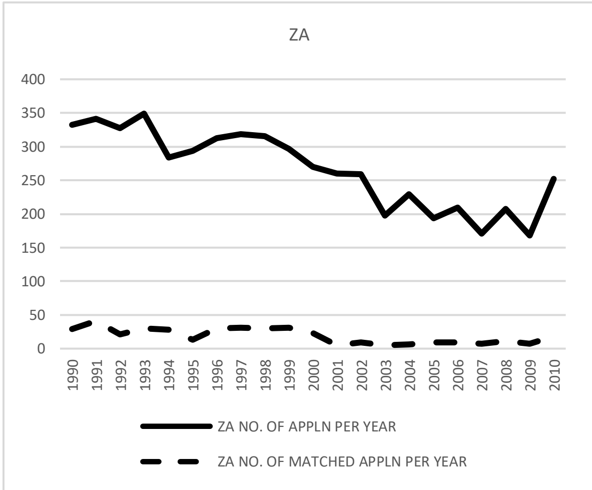
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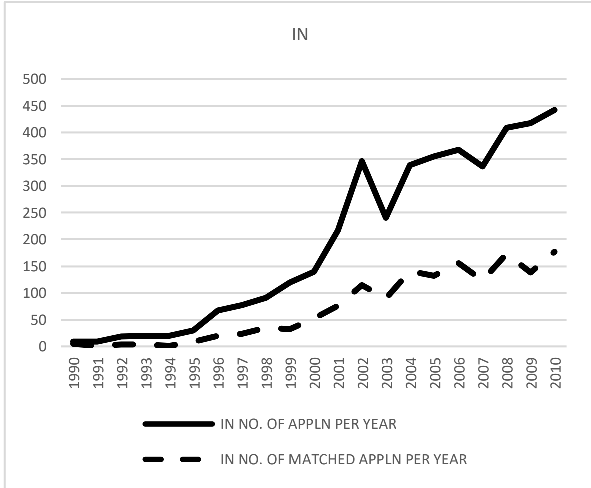
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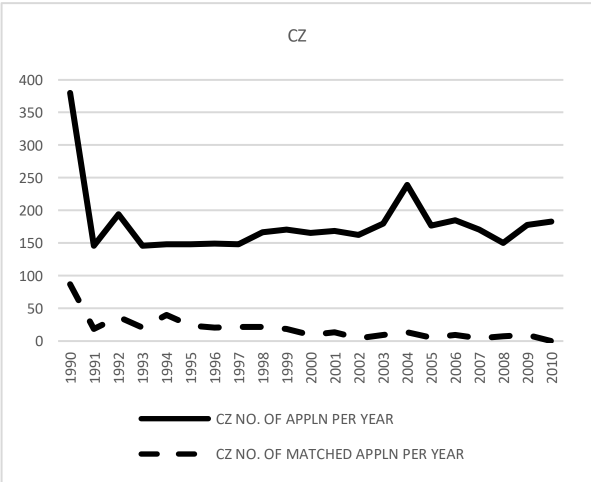
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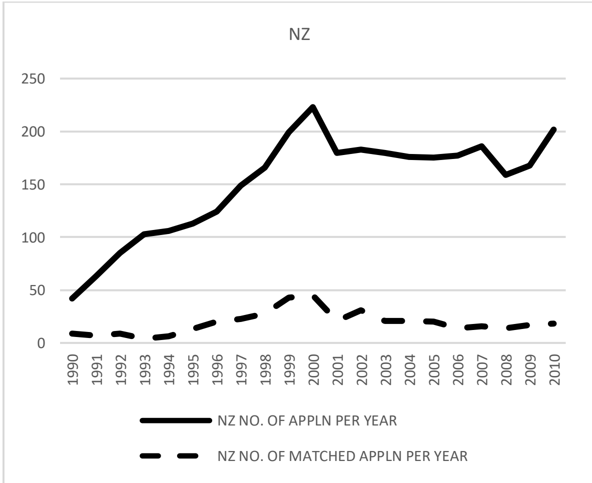
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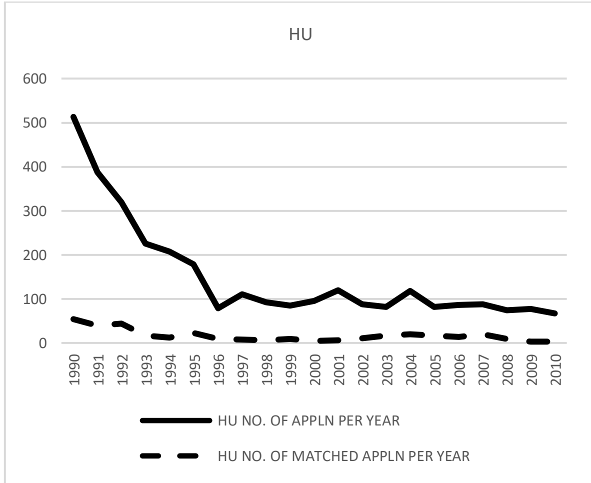
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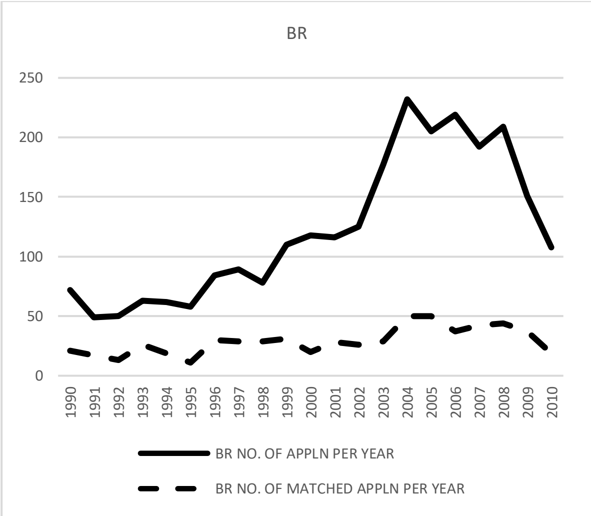
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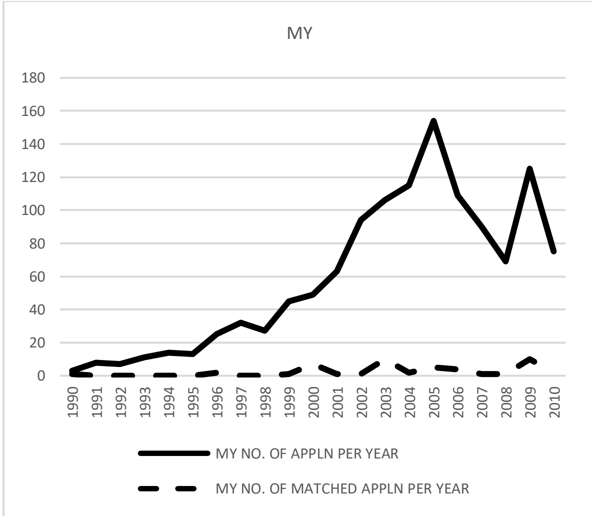
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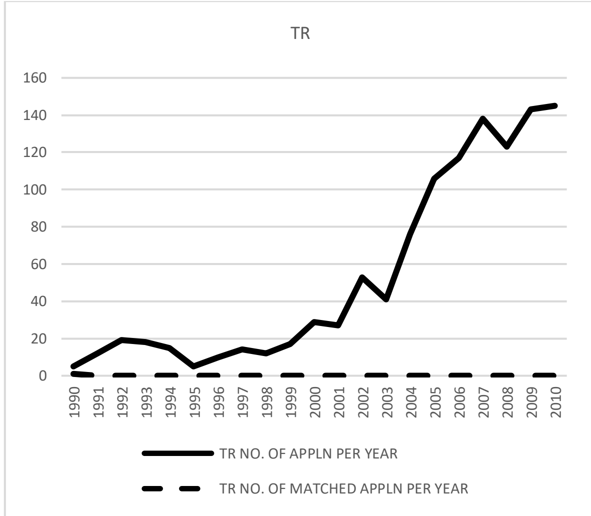
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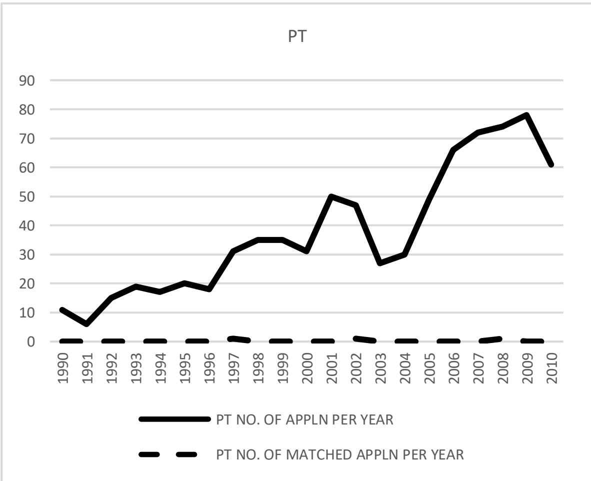
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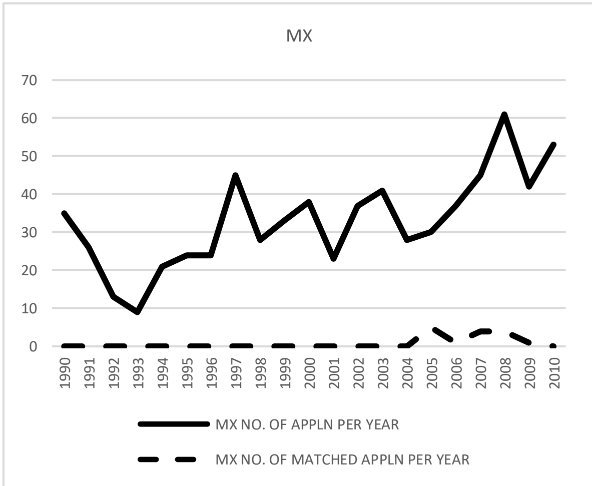
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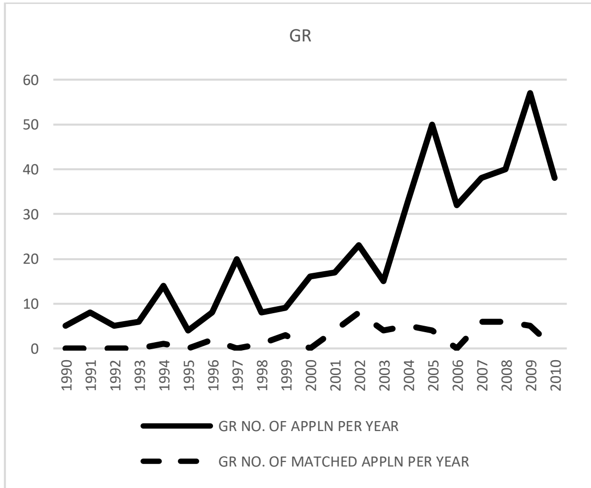
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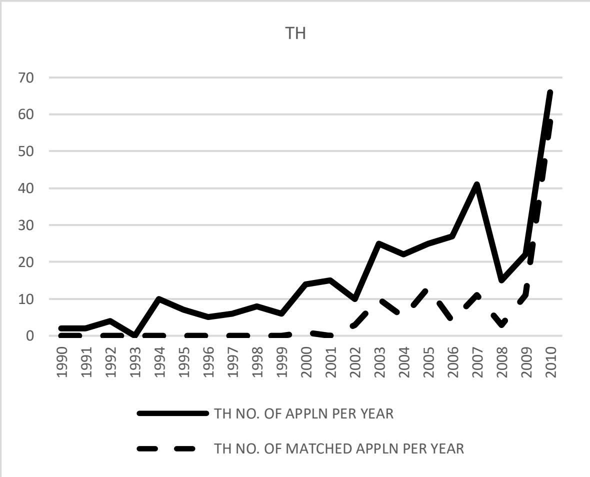
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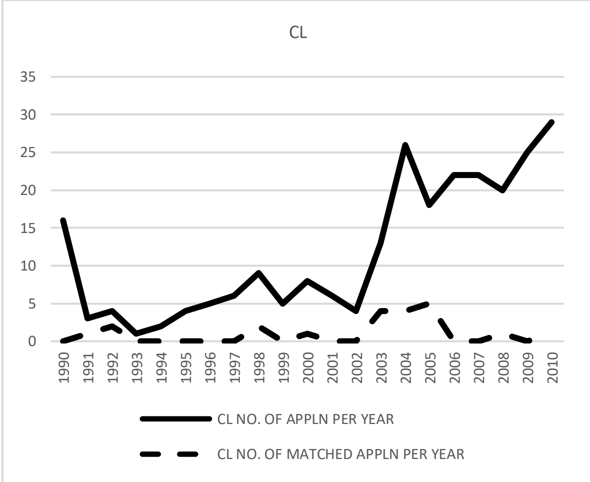
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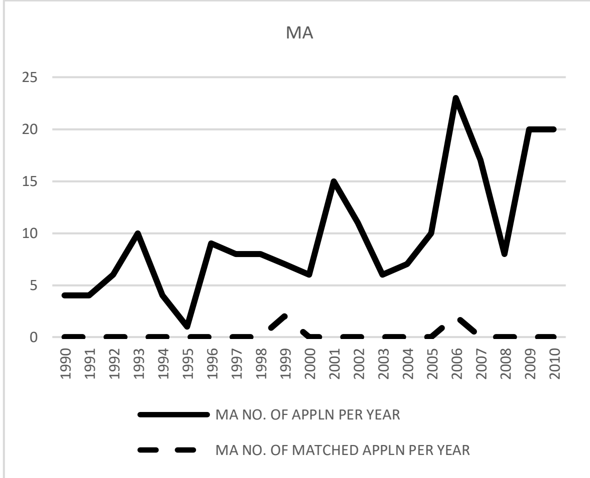
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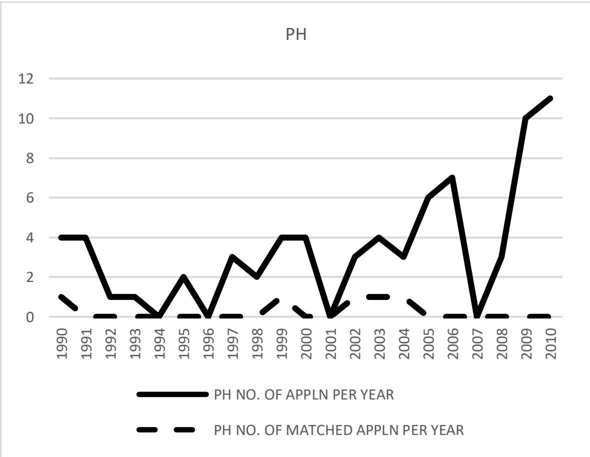
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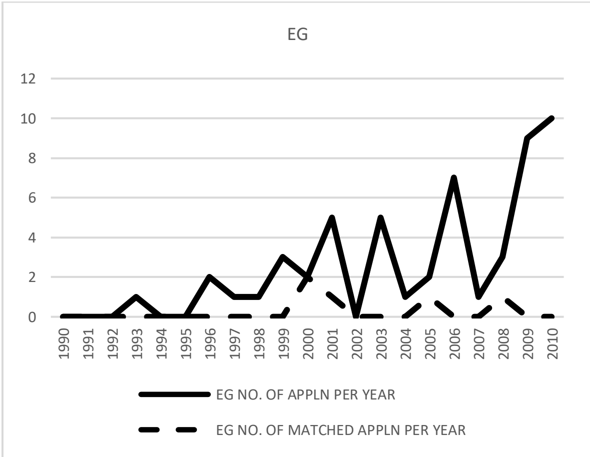
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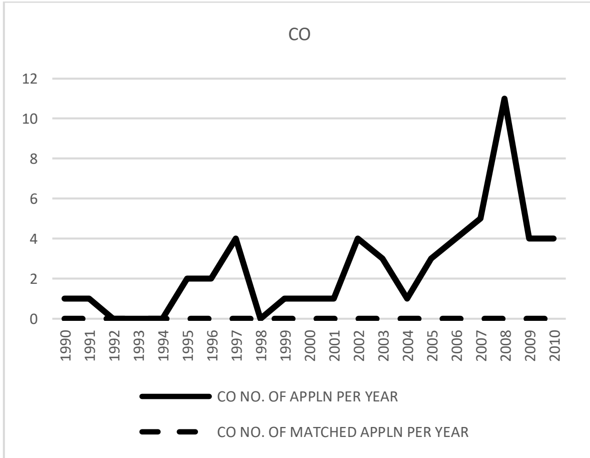
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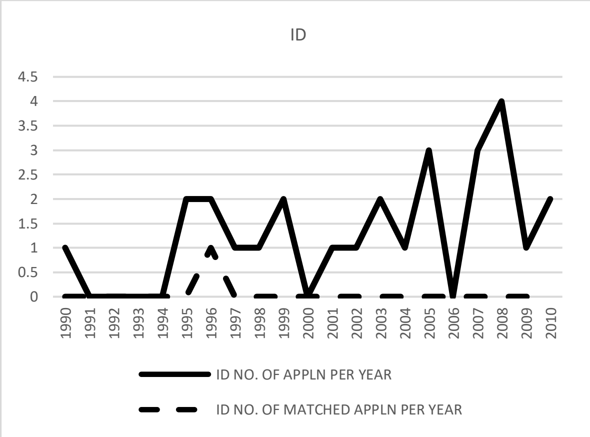
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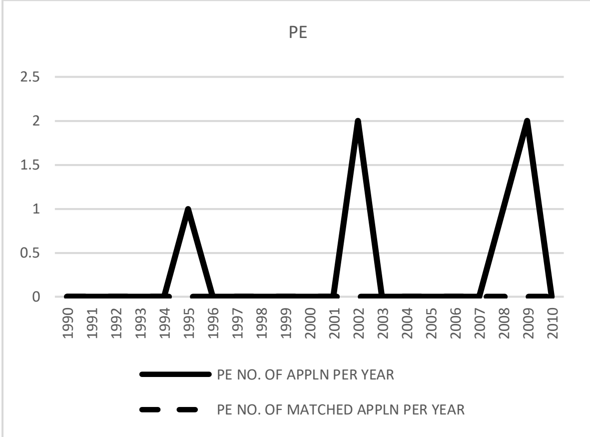
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Chapter 4 The Effect of Stock Liquidity on R&D-Innovation Relationship: A Structure Model Approach

4.1 Introduction

An extensive range of literature has investigated the relationship between R&D and patents. They represent different steps in the innovation process and contain different information about technological inventions. In this chapter, we study the R&D-patent relationship from the perspective of stock liquidity. Especially, we aim to understand whether stock liquidity affects innovation outputs through R&D investments.

A large amount of literature investigates the impact of liquidity in stock markets. The literature mainly focuses on the effect of stock liquidity on stock price and returns, the cost of raising capital, market efficiency and financial decisions. Excepting these, Fang *et al.* (2014) and Wen *et al.* (2018) study the relationship between stock liquidity and innovation outputs (i.e., patent-based data). However, they do not consider the possibility that stock liquidity affects innovation outputs through R&D investments.

R&D investments and patent-based indicators represent the different steps in the innovation process. In this chapter, we first propose that stock liquidity may indirectly affect firm innovation outputs through R&D investments. On the one hand, increased stock liquidity may improve R&D investment by reducing the cost of raising capital. On the other hand, it may impede R&D investment because of the potential threat of hostile takeovers and short-term institutional investors. Secondly, stock liquidity could directly affect firm innovation outputs. We propose that an increase in stock liquidity improves a firm’s innovation activities by reducing asymmetric information between investors and firm managers. In addition, it could facilitate the entry of long-term and/or strategic institutional investors, thereby improving a firm's innovation abilities.

This chapter is structured three equations to investigate the effects of stock liquidity on the R&D-patent relationship. We introduce the HFT start date as an exogenous shock to stock liquidity. HFT is a specific kind of Algorithmic Trading (AT) where orders are entered very quickly, usually in microseconds. As High-frequency traders mainly focus on high market value companies (Brogaard *et al.*, 2014), this chapter only includes the top 30 percentile of the largest public companies, by market capitalisation in each exchange.

We find that although stock liquidity can affect firm innovation through R&D investment, the greatest impact of stock liquidity on firm innovation comes from the direct impact of stock liquidity itself. While stock liquidity causes a significant but slight negative influence on a firm's R&D investment, it causes a much larger positive impact on firm innovation output directly. It means that increased stock liquidity mainly contributes to reducing asymmetric information and the entry of long-term and/or strategic institutional investors. It leads to the monitoring of firm managers and extra resources (for example, foreign technology), thereby improving both the quantity and quality of firm innovation.

More specifically, we show that while R&D investment causes larger impacts on firm innovation quantity than stock liquidity, it does not significantly improve other patent-based indicators. A possible reason is that companies change their innovation strategy after going public. These large companies tend to invest in incremental innovation projects and obtain disruptive innovation through acquisitions. It may also because our sample does not include the self-citations.

We observe that stock liquidity significantly improves the patent generality index and originality index. This could be an explanation of the positive relationship between stock liquidity and firm innovation quality. Increased stock liquidity facilitates the entry of long-term and/or strategic institutional investors, who bring extra resources, and who improve the patent originality index. Thus, they are more likely to be cited by other patents in different areas.

In this chapter, we make several potential contributions, outlined below. Firstly, we emphasise the importance of both stock liquidity and R&D investments on a firm's patent outputs. In particular, we show that while R&D leads to larger impacts on a firm's innovation outputs, increased stock liquidity could benefit firms in aiding the production of high-quality innovation.

In addition, we extend the empirical literature on the impact of stock liquidity on firm innovation. In this chapter, we find a positive relationship between stock liquidity and firm innovation outputs. In terms of this, we support the work Wen *et al.* (2018) based on an international sample. Fang *et al.* (2014) argue that firm managers tend to cut R&D investments when facing the potential threat of hostile takeovers and short-term institutional investors caused by increased stock liquidity. Although we observe a negative impact of stock liquidity on R&D investments, it is much lighter than the impact on firm innovation outputs.

In addition, we improve the understanding of the R&D-patents relationship from the perspective of stock liquidity. We provide a different explanation for their relationships. We show that while stock liquidity could indirectly improve firms innovation performance through R&D investments, so too it could directly encourage firm innovation activities.

The rest of the chapter is structured as follows: In section 4.2, we review the literature around the impacts of liquidity in stock markets, the R&D-patent relationship and we propose the hypothesis. In section 4.3, we describe the sample, variable construction, and estimation method. In section 4.4, we present and analyse the empirical results. In section 4.5, we describe the robustness results. In section 4.6, we present the conclusion.

4.2 Literature Review and Hypothesis

4.2.1 The impact of stock liquidity in financial markets

In this subsection, we review the literature around the impact of stock liquidity in financial markets. There is extensive literature around the impacts of stock liquidity on stock price (for example, Amihud and Mendelson, 1986, 1989; Amihud, 2002; Chordia *et al.*, 2005; Uddin, 2009). Amihud and Mendelson (1989) argued that a lower bid-ask spread (i.e., higher stock liquidity) reflects more information availability. Huang et al. (2013) showed that stock liquidity improves the informative stock price by promoting informed trading.

A series of papers demonstrate that firms can reduce the cost of raising capital by increasing their stock liquidity (Amihud and Mendelson, 1988, 2000; Butler *et al.*, 2005; Saad and Samet, 2017). This is the result of reducing trading costs (Brennan *et al.*, 1998). It is also the reason behind a decrease in the required illiquidity premium (Jacoby *et al*., 2000). Amihud and Mendelson (1988) found that investors prefer stock markets with higher liquidity because they can transfer their ownership efficiently. Butler *et al.* (2005) argued that investment banks tend to charge lower fees for firms with liquid stocks during the Follow on Public Offer (FPO).

Previous research demonstrates the interplay between stock liquidity and market efficiency (for example, Chordia et al., 2008; Ho and Njindan Iyke, 2017; Kelley and Tetlock, 2013). They argue that improved stock liquidity decreases frictions and encourages arbitrage activities, which in turn increases stock liquidity. In addition, the presence of illiquidity restricts market agents in setting up arbitrage trading even if they can identify an arbitrage opportunity.

Previous literature shows that stock liquidity affects financial decisions. Lipson and Mortal (2009) found that firms tend to have lower leverage and prefer to use equity finance to raise capital when they have more liquid shares. In addition, Brockman *et al.* (2008) and Jayaraman and Milbourn (2012) investigated the impacts of stock liquidity on managerial payout decisions. Banerjee *et al.* (2007) reported that investors are more (less) likely to receive cash dividends for less (more) liquid common stocks.

Additionally, Pástor and Stambaugh (2003), Acharya and Pedersen (2005) and Sadka (2006) present stock liquidity as a systematic and non-diversifiable risk measure. Pereira and Zhang (2010), Petkova *et al.* (2011) and Engle *et al.* (2012) investigated the relationship between volatility of liquidity and stock returns. Amihud *et al.* (1990), Lesmond (2005) and Yeyati *et al.* (2008) explored the impacts of illiquidity shocks on prices during crisis events.

Separately to the above literature, Fang *et al.* (2014) and Wen *et al.* (2018) investigated the impact of stock liquidity on firm innovation. However, they mainly focused on the relationship between stock liquidity and innovation outputs (i.e., patent-based data). Although they include the R&D investments as control variables, they do not consider the potential endogeneity between stock liquidity, R&D and innovation outcomes.

4.2.2 R&D and patents

In previous literature, innovation is often represented by two indicators: R&D investments and patent-based data (Becheikh *et al.*, 2006). The empirical studies which cover the relationship between R&D and patent-based indicators is headed by Schmookler (1966) and Scherer (1965). They showed positive links between these two variables. Thereafter, a series of literature investigated US firms through panel data (Hausman *et al.*, 1984; Hall *et al.*, 1986; Cincera, 1997). They argued that the relations between R&D and patents almost vanish when incorporating the industry or time dimension into the analysis.

Several studies propose the existence of reverse causality between R&D and patent indicators (for example, Nordhaus, 1969; Pakes, 1985). However, empirical evidence from this research does not obtain a consistent result. For example, Pakes (1985) and Hall *et al.* (1986) showed no evidence supporting the reverse causality between these two indicators; Arora *et al.* (2008), Crépon and Duguet (1997), Hall and Ziedonis (2001) found positive reverse links; Sakakibara and Branstetter (2001) show the negative reverse relationship.

In recent years, a growing body of research studying finance and innovation also covers R&D and patents. Most of the researches use R&D investments as a control variable and show significant positive impacts of R&D on patent-based indicators (for example, Chemmanur and Tian, 2018; Fang *et al.*, 2014; Chang *et al.*, 2015; Luong *et al.*, 2017; Zhu and Zhu, 2017). In this chapter, we follow the recent research in the financial area and focus on the impact of R&D investment in the year t on patent-based indicators in the year $t + n$.

R&D and patent-based data represent different steps in the innovation process. While R&D investments measure inputs in the innovation process (Ashwin *et al.*, 2015; Wen *et al.*, 2018), patent-based indicators show the ability to create inventions (Coombs *et al.*, 1996; OECD., 1997; Flor and Oltra, 2004). Compared with patent data, R&D investments do not necessarily lead to new technology or improved processes (Kleinknecht *et al.*, 2002; Flor and Oltra, 2004). They also include the investments of aborted R&D efforts (Becheikh *et al.*, 2006). On the other hand, Gu (2005) demonstrates that patent-based indicators, such as the number of patents and patent citations, contain information about a firm’s technological advantages. Therefore, while a firm’s innovation ability is affected by R&D investments, it is also affected by other indicators.

In this chapter, we investigate the effects of stock liquidity on the R&D-innovation relationship. We assume that stock liquidity directly affects innovation outputs, and indirectly affects on innovation outputs through R&D investments.

4.2.3 Hypothesis

In this subsection, we propose the hypothesis about the effects of stock liquidity on the R&D-patent relationship.

Stock liquidity tends to influence firm innovation outputs through R&D investment. Firms with a higher stock liquidity tend to have less cost to fund R&D projects. According to Brealey *et al.* (2012), firms can raise capital through three ways: internal financing (i.e., retained earnings plus depreciation), debt financing and equity financing. While a public company can finance its investment through an initial public offering (IPO) in the primary market, it cannot obtain cash inflow from the trade of shares in the secondary market (Kim and Weisbach, 2008). This is because the proceeds from trading in the equity markets go to the traders rather than the public company. However, a company with more liquid shares in the equity market can raise capital at a reduced cost (Butler *et al.*, 2005). It will be charged lower fees by the investment banking firms when issuing additional shares after an IPO. This argument, supported by Amihud and Mendelson (1986), posits that buyers are willing to pay a premium for liquidity assets. In addition, as firms with more liquidity shares have a lower cost of equity financing, they are more likely to choose equity financing instead of debt financing when raising capital (Lipson and Mortal, 2009). While firms with a high leverage ratio are less likely to fund long-term projects due to the lack of available capital (Baysinger and Hoskisson, 1989), Lipson and Mortal (2009) show that companies with a higher level of stock liquidity have a lower leverage ratio. Therefore, increased stock liquidity tends to decrease the firm's pressure to make long-term investments, such as R&D investments.

Hypothesis 1a Stock liquidity could indirectly improve innovation outputs through R&D investment.

On the other hand, increased stock liquidity may decrease R&D investments. Corporate innovation is risk-taking behaviour (Holmström, 1989). It is not only a long-term, multi-stage process but also involves a large probability of failure (Holmström, 1989; Chang *et al.*, 2015). For firms allocating funds heavily in R&D, innovation plays a crucial role in their competitive strategies. They have to make a partial disclosure and are subject to a higher degree of information asymmetry (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). In terms of this, they are more prone to be misvalued by investors (Cohen *et al.*, 2013) and can even experience a greater exposure to hostile takeovers (Stein, 1988). When undergoing hostile takeovers, managers tend to cut down long-term investment (for example, R&D investment) and focus on short-term earnings targets in order to stabilise current share prices (Shleifer and Summers, 1988). Chemmanur and Tian (2018) support this view by showing the positive impact of anti-takeover provisions on firm innovation. In particular, this influence is more pronounced when firms are subject to a more significant degree of asymmetric information. Kyle and Vila (1991) show that potential external acquirers can disguise themselves as common traders when stock liquidity is high, which facilities a firm manager's cutting down of long-term R&D projects and concentrating instead on myopic investment.

In addition, firm managers may cut R&D investments because of the presence of short-term institutional investors. The market with higher stock liquidity has lower trading costs. In these markets, short-term institutional investors can easily enter and exit public companies based on news around current earnings. This may cause mis-valuation and under-investment in R&D

investment (Porter, 1992). A firm's managers are more likely to pursue near-term earnings rather than long-term intangible investments (for example, R&D investment) when they are under the pressure from external, short-term institutional investors (Bushee, 1998). In terms of these arguments, we suggest the following hypotheses, outlined below:

Hypothesis 1b Stock liquidity could indirectly impede innovation outputs through R&D investment.

Excepting the above, increased stock liquidity tends to encourage firm managers to engage in innovation by reducing asymmetric information. Although firms which invest in innovation are subject to a higher degree of information asymmetry (Bhattacharya and Ritter, 1983; Anton and Yao, 2002), this tends to be decreased by increasing stock liquidity. According to Chordia *et al.* (2008) and Grossman and Stiglitz (1980), increased stock liquidity improves market efficiency by reducing market frictions and encouraging arbitrage trading (Chordia *et al.*, 2008; Grossman and Stiglitz, 1980). This then decreases the asymmetric information between investors and firms which are pursuing innovative activities. For example, Abdioglu *et al.* (2015) found a higher level of passive and dedicated institutional investment in R&D-intensive firms after a reduction of asymmetric information (enforcement of Sarbanes-Oxley Act, which aims to improve the accuracy of public firms' disclosures). Maug (1998) shows that the rise of stock liquidity offers convenient entry to blockholders, which leads to more monitoring operations within the company. They can collect private information and trade with this information, thereby making the stock price more efficient (Edmans, 2009). This action can discipline managers when managerial compensation is closely tied to stock price (Admati and Pfleiderer, 2009; Edmans, 2009; Edmans and Manso, 2011).

The increase in liquidity could also improve a firm's innovation activities by facilitating the entry of long-term and/or strategic institutional investors (Wen *et al.*, 2018). Zahra (1996) and

Bushee (1998) demonstrate the significant and positive impact of pension fund shareholding on enterprise innovation.[37] In addition, the entry of foreign institutional investors improves the firm's innovation through their actions as active monitors, providing insurance against innovation failures and transmitting foreign technology (Luong *et al.*, 2017).

Hypothesis 2 Stock liquidity could directly affect innovation outputs.

We analyse these two hypotheses in the following sections:

[37] Managers of pension funds tend to enhance long-term value of their protfolios because of the big size and long duration of their investment (Zahra, 1996).

4.3 Sample Selection, Variable Measurement, Descriptive Statistics and Estimation method

4.3.1 Data and sample selection

We collect the patent-based data from the PATSTAT database and firm account information from the Datastream database.[38] Following Hanauer's (2014) steps, we restrict our sample to 1) both active and inactive companies across 23 developed countries/regions and 21 emerging countries/regions (see the selection process in Hanauer (2014)). 2) stocks of type equity, 3) companies located and listed in the domestic country, 4) companies quoted as domestic currency. 5) the primary quotation of security, 6) the security with the biggest market capitalisation and liquidity for companies with more than one equity security. Furthermore, we exclude 1) the corporate applicants if they applied for fewer than 3 applications from 1990 to 2010, 2) securities trade in OTC markets.

In addition, we collect the exchange's HFT start date from Aitken et al. (2015) and only include exchanges that have reported their HFT start date. High-frequency traders mainly focus on the high market value companies (Brogaard *et al.*, 2014). In general, previous papers in this area construct sample based on firms' market capitalization. For example, Brogaard *et al.* (2014) split sample stocks into three market capitalization groups. Malceniece *et al.* (2019) analyse the top 20% of the largest stocks (and 75 stocks) , by market capitalisation in each country. However, HFT is a black box (Narang, 2013). High-frequecny traders are less likely to announce the range in which high-value companies with market capitalization are their trading targets. In this chapter, we mainly focus on the sample which include the top 30 percentile of

[38] We describe the detail of these two databases and the matching procedure in Chapter 3 "Matching PATSTAT applications to Datastream financial data".

the largest public companies, by market capitalisation in each exchange.[39] We exclude companies in finance industries following previous literature in finance and innovation fields. Finally, this sample has 15, 202 firm-year observations, including 796 companies from 10 countries between 1990 and 2010.

4.3.2 Variable measurement

4.3.2.1 Dependent Variables

We represent a firm's innovation outputs using the following four indicators. 1) the number of applications made by the firm and eventually granted in a year, representing the quantity of innovation. 2) the number of citations received by these patents in the year, which shows the quality of the firm's innovative activity. We also define 3) innovation generality index as the extent to which a company's patents are cited by subsequent citations across a wide range of technology fields; 4) innovation originality index as the extent to which a company's patents cite previous patents across a large number of technology fields. We separately explain these indicators in this subsection.

The first measure of innovation, LN_PAT, is the natural logarithm of one plus the number of successful applications in the year $t+1$, $t+2$ and $t+3$ respectively.[40] According to Fang *et al.* (2014), the patent data are right-skewed with the 75th percentile of the number of patents equal to zero. Thus, we use the logarithm of the number of patents. We also add one to the number of patents before taking the logarithm to ensure that we do not have missing values for

[39] We also test the sample which include the top 20 percentile and 40 percentile of the largest public companies in each exchange. The result is similer to the sample which includes the 30% of stocks in each exchange. But we do not report it for brevity.

[40] We describe the detailed procedure of measuring the number of patent applications and citations in Appendix 2, Chapter 3.

firms with zero patents.[41] We examine the influence of a firm's stock liquidity on the number of patents applied in subsequent years. This is because innovative activity is a long-term, multi-stage process and generally takes longer than one year.

The second measure of innovation, *LN_CIT*, shows the quality of a firm's innovative activity. It is the natural logarithm of one plus the number of citations received by these patents in the year $t+1$, $t+2$ and $t+3$ respectively. According to Trajtenberg (1990), it can distinguish breakthrough innovation from incremental technological discovery.

The third measure of innovation, LN_GE*NERAL*, represents the extent to which a company's patents are cited by subsequent citations across a wide range of technology fields (Trajtenberg et al., 1997). This is the natural logarithm of one plus the sum of a firm's generality score in the year $t+1$, $t+2$ and $t+3$ respectively (Zhu and Zhu, 2017). Following Trajtenberg *et al*. (1997), we measure patent m's generality score ($GENERAL_m$) as

$$GENERAL_m = 1 - \sum_{k=1}^{N_m} \left(\frac{NCITING_{mk}}{NCITING_m} \right)^2$$

where m is the mth patent applied for by the corporate applicant in a given year, k is the index of 4-digital IPC patent classes, N_m is the number of different 4-digital IPC patent classes to

[41] For the same reason, we will use the natural logarithm of one plus the number of citations, generality index, and originality index, separately. These correspond to the innovation measurements in this chapter, namely, *LN_CIT*, *LN_GENERAL* and *LN_ORIGINAL*.

which the citations belong.[42][43] $NCITING_m$ is the number of patents citing the patent m, and $NCITING_{mk}$ is the number of patent m's citations that belong to the patent class k. A higher generality value of a patent means the citation to the patent spread over a broader range of technological fields.

The fourth measure of innovation is $LN\_ORIGINAL$. It shows the extent to which a company's patents cites previous patents across a large number of technology fields (Trajtenberg *et al.*, 1997). It is the natural logarithm of one plus the sum of a firm's originality score in the year $t+1$, $t+2$ and $t+3$ respectively (Zhu and Zhu, 2017). Following Trajtenberg *et al.* (1997), we measure patent m's originality score ($ORIGINAL_m$) as

$$ORIGINAL_m = 1 - \sum_{k=1}^{N_m} \left(\frac{NCITED_{mk}}{NCITED_m}\right)^2$$

where $NCITED_m$ is the number of patents cited by patent m, $NCITED_{mk}$ is the number of patents cited by patent m which belong to the patent class k. A higher originality value of a

[42] Following Levine *et al.* (2017), we use the International Patent Classification (IPC) to measure the Herfindahl-Hirschman index of the generality and originality value of each patent. By using IPC classification symbol 'G06K 19/077' as an example, the first character 'G' represent IPC section 'Physics'; the next two characters '06' identifies the IPC class 'Computing; Calculating or Counting'; the next character 'K' shows the IPC subclass 'Recognition of data; Presentation of data; Record carriers; Handling record carriers' (see more detail information in http://www.wipo.int/classifications/ipc/en/). Although the characters "19" and "077" give more information about patent IPC at the main group and subgroup level, we only use the 4-digital IPC patent classes (ie., section, class, subclass) when referring to an IPC. It is because not all patents are provided group and subgroup IPC information (Levine *et al.* 2017).

[43] Following Levine *et al.* (2017), 1) we only cover inventive IPC patent which document discloses a novel subject matter rather than the part to the prior art (see more detail information in https://www.wipo.int/publications/en/details.jsp?id=4490&plang=EN), which is not designated as secondary by a patent authority. 2) we assign equal weight to each IPC subclass of a patent in cases with multiple inventive IPCs (see detail explanation in Levine *et al.* (2017)). 3) To be consistent with the settings in Chapter 3, we set a three-year moving window for counting the generality and originality value.

patent means this patent cites previous patents spread over a broader range of technological fields. We describe the detailed variable information in Table 4.1, Panel A.

*** Table 4.1 ***

4.3.2.2 Independent variable

There is no general definition of liquidity in the financial market. It is not a one-dimensional variable but includes several aspects (Lee *et al.*, 1993). According to Kyle (1985), there is usually five dimensions of liquidity. The first is depth, which is the size of the spread. The second is tightness, which is the ability to buy and sell a certain amount of stocks at the same price and at the same time. The third is immediacy, which is the ability to buy or sell a certain amount of shares immediately at the prevailing price. The fourth is resiliency, which is the ability to trade a certain amount of stocks with litter influence on the current quote. The fifth is the breadth, which is the ability to trade a certain amount of stocks without causing influence on the current quote. In other words, the stock has higher liquidity when it can be bought or sold at a lower cost, narrower spread, higher speed and cause lower influence on current market price.

Stock liquidity is different from funding liquidity and corporate liquidity. According to previous research, funding liquidity refers to a trader/investor's ability to obtain funding (capital or cash) in the short term (Strahan, 2008; Brunnermeier and Pedersen, 2009). It is also defined as banks' ability to settle obligations as they come due (Drehmann and Nikolaou, 2013). Similarly, corporate liquidity represents a firm's ability to meet its short-term financial obligations in terms of the liquid assets available to it. Compared with them, stock liquidity does not directly reflect an entity's funding ability, as public companies have already raised funds through an initial public offering (IPO).

In this chapter, we measure the stock liquidity of the firm, $Liquidity_{i,t}$, as the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming et al., 2020). Fong *et al.* (2017) tested a series of liquidity measures from a global perspective and suggested the Amihud are the best monthly/daily cost-per-dollar-volume proxy. Therefore, we represent stock liquidity based on this indicator. Although Amihud is used in a large number of subsequent studies, it has been first developed in Amihud (2002). The Amihud is computed as follow,

$$A_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d}|}{Dvol_{i,d}}$$

where $A_{i,t}$ is the Amihud measure of firm i in the year t. $r_{i,d}$ and $Dvol_{i,d}$ are the daily return and daily dollar trading volume for stock i on day d. $D_{i,t}$ is the number of days which is available in year t. A stock with a higher Amihud value suffers a lower level of stock liquidity on the equity market. In other words, traders have to pay a higher cost to buy/sell a smaller number of shares in the stock market at a slower speed and this causes a more considerable price impact on the transaction. We use the natural logarithm of the inverse of Amihud as the measure of stock liquidity follows Cumming *et al.* (2020). We describe the detailed variable information in Table 4.1, Panel B.

4.3.2.3 Control variables

In this chapter, we include a series of firm characteristics that may affect a firm's future innovative performance. Brown *et al.* (2009), Brown *et al.* (2012) and Brown *et al.* (2013) find that firms' innovative activities are affected by their size and age. Additionally, Scherer (1986) argues that large firms tend to have higher incentives and are better able to improve innovation. Thus, we introduce firm size, $LN\_TA_{i,t}$, and firm age, $LN\_AGE_{i,t}$, in the regression. Firm size is measured by the natural logarithm of total assets (Wen *et al.* 2018). Firm age is defined as the natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream (Cumming *et al.*, 2020).

It is clear that firms investing more in R&D projects tend to produce more patents and patent citations. Therefore, we control investment in R&D, $RDTA_{i,t}$, measured by research and development expenditures divided by the book value of total assets (Fang *et al.*, 2014).[44] In addition, we control investment in fixed assets, $CAPEXTA_{i,t}$, measured as capital expenditures scaled by the book value of total assets (Cumming *et al.*, 2020); asset tangibility, $PPETA_{i,t}$, defined as the property, plant, and equipment expenditure divided by the book value of total assets, measured at the end of the year t (Fang *et al.*, 2014; Cumming *et al.*, 2020).

Manso (2011) and Atanassov and Liu (2020) show that firms with sufficient cash are more likely to tolerate failure and have greater flexibility. This is the key by which to motivate innovation. In terms of this, we control the ratio of cash, $CASH_{i,t}$, as cash holdings divided by the book value of total assets (Zhu and Zhu, 2017). Baysinger and Hoskisson (1989) argued that firms with higher leverage ratios are less likely to fund long-term projects, such as R&D projects, due to the lack of available capital. Therefore, we control the leverage ratio, $LEV_{i,t}$, as the book value of debt divided by the book value of total assets (Fang et al., 2014).

Booth (1998) shows that firms need investors' confidence in their ability to create and obtain benefits from the intangible assets (i.e., R&D projects) during the long gestation period of the

[44] Following from Wen *et al.* (2018), we do not control $RDTA_{i,t}$ when innovation efficiency is considered as the dependent variable in the estimation.

new patents. Better fundamental performance indicators could help the firm's managers gain confidence from their investors and earn their continuous support to promote innovation (Sriram, 2008). Therefore, following on from previous financial literature, we control growth opportunity, $Q_{i,t}$, defined as firm i's market-to-book ratio, calculated as the market value of equity plus book value of debt divided by book value of assets (Cumming *et al.*, 2020); profitability, $ROA_{i,t}$, defined as the income before extraordinary items divided by book value of total assets, measured at the end of year t (Fang *et al.*, 2014; Cumming *et al.*, 2020).[45] We describe the detailed variable information in Table 4.1, Panel C.

4.3.3 *Descriptive Statistics*

Following Fang *et al.* (2014), we minimise the effect of outliers by winsorising variables at the 1% level in each tail of the distribution. Table 4.2, Panel A provides summary statistics for the firm-level variables used in this study.[46] On average, a firm invests 7% of its total assets in R&D projects as the innovation input per year. In addition, as the innovation output, they submit an average of 74 applications (which are finally granted) per year, and each patent

[45] Although Hall *et al.* (2005) found that Tobin's Q is significantly affected by patent-based indicators, it is widely used in financial literature as control variable to investigate the influence on innovation activities (for example, Fang *et al*., 2014; Xin Chang *et al.*, 2015; Chemmanur and Tian, 2018; Wen *et al.*, 2018; Cumming *et al.*, 2020; He and Hirshleifer, 2020). Therefore, in this thesis, we follow the most recent financial literature and employ Tobin's Q as a control variable.

[46] It should be noted that the number of different variables in Table 4.2, Panel A are different. It is because of the existence of missing value in each firm accounting variables collecting from Datastream. Besides, the number of variables in Table 4.2, Panel A is different from the number of firm-year observations in Table 4.4, 4.5, 4.6 and 4.7. The first reason is still the missing value in firm accounting variables collecting from the Datastream. The second reason is while we produce the descriptive statistics for firm-level variables in the same year, we run the model to analyse the regression of patent-based data in year $t + n$ on independent variables and control variables in year t.

obtains around 22 non-self-citations. Table 4.2, Panel B presents the correlation of firm-level variables in this sample. Among them, there is a 65% correlation coefficient between liquidity and total assets. It might be because the sample in this chapter includes the top 30 percentile of the largest public companies by market capitalisation in each exchange. Companies with larger sizes tend to have higher stock liquidity (Norvaišienė and Stankevičienė, 2014). Following previous research in this area (e.g., Fang et al., 2014; Wen et al., 2018), we control it in regression. Besides, there is a -45% correlation between RDTA and total assets. It is because RDTA is R&D scaled by total assets, and we did not control it in equation (4.1b). The rest of the variables in this table show a low pairwise correlation between each other.

*** Table 4.2 ***

4.3.4 *Estimation method*

We employ a structure model to investigate the effects of stock liquidity on R&D and patent performance. This allows the empirical literature to go beyond the conclusions of the reduced-form causal relationships (Low and Meghir, 2017). In this chapter, our structure model is composed of three equations.

In equation (4.1a), we introduce the HFT start date as an exogenous shock to stock liquidity. HFT is a specific kind of Algorithmic Trading (AT) where orders are entered very quickly, usually in microseconds. There is a debate in the literature with respect to the provision or consumption of liquidity by HFT. On the one hand, some work argues that HFT can improve market liquidity. For example, Hendershott *et al.* (2011) show that AT can increase stock liquidity and decrease adverse selection costs, especially for large stocks. Boehmer *et al.* (2018) find that HFT improves stock liquidity and efficient price discovery. Hasbrouck and Saar (2013) support that HFT contributes to higher market quality, leading to lower spreads, higher depth and lower short-term volatility. On the other hand, some literature shows the negative aspects of HFT and finds it reduces stock liquidity. For instance, Jarnecic and Snape (2014) show that high-frequency traders who always adopt order cancellation and small order technologies increase the trading cost for long-term investors and reduce quote depth. Brogaard *et al.* (2017) show that although high-frequency traders improve stock liquidity through liquidity supplying activities, their liquidity demanding activities cause a larger negative impact on stock liquidity than the positive effect. In conclusion, although there is a debate on whether HFT supplies or consumes stock liquidity, it is clear that HFT causes a direct impact on stock liquidity.

Except for the direct impact of HFT on stock liquidity, it is less likely that HFT directly affects firm innovation inputs and outputs. Besides, it is unlikely that changes in R&D investments and future patent performance affect stock liquidity brought by HFT. Therefore, we use the HFT start date as an exogenous shock of stock liquidity. It avoids the possible simultaneity between stock liquidity and R&D investments. We create a dummy variable that equals zero before the starting date of HFT and equals one after (Aitken *et al.*, 2017). We collect information about HFT start date from Aitken *et al*. (2015) and list them in Table 4.3.

*** Table 4.3 ***

The equation (4.1b) represents the determinants of R&D investments. We employ the Tobit model for this equation to consider the non-negative nature of R&D (Chemmanur and Tian, 2018). Not all firms participate in R&D activities. We could have a selection bias if we only consider firms that invest in R&D projects. Thus, we replace these dependent variables (i.e., R&D) with zero if they have a missing value. In other words, we obtain the dependent variables that are censored at zero. The equation (4.1c) represents the determinants of firm innovation outputs. We also employ the Tobit model to consider the non-negative nature of innovation outputs (Chemmanur and Tian, 2018). Overall, we introduce model (4.1) following Garcia and Mohnen (2010) as below,

(4.1a) $Liquidity_{i,c,t} = \beta_{10} HFT_t + \beta_{11} Z'_{i,c,t} + \epsilon_{1i,c,t}$

,

(4.1b) $R\&D_{i,c,t} =$

$$\begin{cases} 0, & if\ R\&D^*_{i,c,t} = \beta_{20} + \beta_{21} Liquidity_{i,c,t} + \beta_{23} Z'_{i,c,t} + C_c + I_j + Y_t + \epsilon_{2i,c,t} \leq 0 \\ R\&D^*_{i,c,t}, & if\ R\&D^*_{i,c,t} > 0 \end{cases}$$

,

(4.1c)$Innovation\ outputs_{i,c,t+n} =$

$$\begin{cases} 0, & if\ Innovation\ outputs^*_{i,c,t+n} = \beta_{30} + \beta_{31} Liquidity_{i,c,t} + \beta_{32} R\&D_{i,c,t} \\ & \qquad + \beta_{33} Z'_{i,c,t} + C_c + I_j + Y_t + \epsilon_{3i,c,t} \leq 0 \\ Innovation\ outputs^*_{i,c,t+n}, & if\ Innovation\ outputs^*_{i,c,t+n} > 0 \end{cases}$$

where $Innovation\ outputs_{i,c,t+n}$ represents the patent-based innovation outputs of firm i from country c in the year $t+n$. It is separately measured by $LN\_PAT_{i,t+n}$, $LN\_CIT_{i,t+n}$, $LN\_GENERAL_{i,t+n}$ and $LN\_ORIGINAL\ _{i,t+n}$. We describe the definition of these variables in Table 4.1, Panel A. $Liquidity_{i,c,t}$ is the independent variable in this study. It is the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming *et al.*, 2020). We introduce the detailed definition of this variable in Table 4.1, Panel B. $R\&D_{i,c,t+n}$ is the ratio of R&D investment to total assets of firm i from country c in the year t. $Z'_{i,c,t}$ are the firm-level control variables shown in Table 4.1, Panel C (except $R\&D_{i,c,t}$). We control C_c, I_j and Y_t as vectors of country, industry and year fixed effect variables in equations (4.1b) and (4.1c). In addition, we convert the companies into eight unique industry divisions based on Standard

Industry Classifications (SICs). Following Aitken *et al.* (2017), we do not control industry fixed effect in equation (4.1a). We employ maximum-likelihood estimation for the whole system.

4.4 Empirical results

We report the marginal effects of determinates of stock liquidity on firm innovation in this section. We separately represent innovation outputs by the number of patents, citations, patent generality index and patent originality index over the following three years.

4.4.1 Patent quantity

In Table 4.4, we measure a firm's innovation outputs via the number of granted patents in the next three years. In columns (1), (4) and (7), we show that HFT causes a significant positive impact on stock liquidity. More specifically, this positive trend increases over time. It supports Alfaro *et al.*'s (2020) opinion that HFT improves stock liquidity.

*** Table 4.4 ***

In columns (2), (5) and (8), we observe a significant negative impact of stock liquidity on a firm's R&D investments. However, the marginal effect of stock liquidity on R&D investment is only -0.004. Compared with the marginal effect of stock liquidity on patent counts in columns (3), (6) and (9), which are 0.199, 0.189 and 0.211, we suggest that increased stock liquidity causes a slight impact on firms' R&D investment. It might be because our sample only includes the top 30 percentile of the largest public companies by market capitalisation in each exchange. These big companies are more likely to be monitored and trusted by financial analysts and investors. Thus their managers tend to make investment decisions based on long-term targets rather than short-term earnings.

In columns (3), (6) and (9), we observe significant positive impacts of R&D and stock liquidity on firm innovation outputs. In column (3), the marginal effects of patent counts on stock liquidity and R&D are separately 10.704 and 0.199. This means R&D causes larger positive impacts on innovation outputs than stock liquidity. Besides, we show that stock liquidity causes a direct increase of 0.199 in the firm's innovation outputs, while there is a decrease of 0.04 (-0.004 × 10.704) due to the indirect effect through R&D investments. Overall, this table shows that stock liquidity causes a positive impact on firm innovation quantity (0.195 = 0.199 – 0.04). This means that although stock liquidity could indirectly affect firm innovation through R&D, the greatest impact on firm innovation comes from the direct impact of stock liquidity.

In addition, a firm's patent count improves with an increase of the firm size, measured by a higher number of total assets. This finding is consistent with most research in this field (for example, Wen *et al.*, 2018; Chang *et al.*, 2015; Zhu and Zhu, 2017) which finds that a firm's ability to generate patents is affected by its size.

We support the findings from most previous literature that the increased leverage ratio will impede the firm's innovation output (for example, Fang *et al.*, 2014; Wen *et al.*, 2018; Chemmanur and Tian, 2018). This is consistent with Baysinger and Hoskisson's (1989) argument that highly leveraged firms are less likely to be involved in long-term projects (for example, R&D projects) and get an increasing number of patents.

There are controversial opinions about the relationship between asset tangibility and firm innovation.[47] The table in this chapter supports Cumming *et al.* (2020), and Zhu and Zhu (2017)'s finding that firms with a higher ratio of asset tangibility do not cause significant influences on firm innovation outputs in the future. Besides, we show that firms with a higher ratio of asset tangibility invest less in R&D projects. According to Bhattacharya *et al.* (2017),

[47] While Fang *et al.* (2014), Chemmanur and Tian (2018) reported the positive influence of asset tangibility on the number of firm's patent applications, Wen *et al.* (2018) found that firms with a higher ratio of asset tangibility will produce fewer patents.

innovation is regarded as a long-term investment in intangible assets. It is different from regular investments in tangible assets in terms of its long-term and high-risk character. Therefore, a higher ratio of asset tangibility may lead to a lower ratio of asset intangibility (i.e., R&D projects).

We show the positive impacts of capital expenditure on innovation. It is also observed in Chemmanur and Tian (2018), Luong *et al.* (2017) and Zhu and Zhu (2017). Except for this, Cumming *et al.* (2020) find negative relationships.

In this table, we report that firms produce fewer patents the older they get. We should note that we measure the firm's age by the number of years listed on Datastream. As the Datastream only records the public company, the firm age in this chapter is more likely to represent the years since the company went public. However, this does not mean that going public impedes the firm's innovative performance.[48] Bernstein (2015) suggests that going public changes a firm's strategy in pursuing innovation. Bernstein found that IPO companies tend to achieve patents through acquisitions due to the increased access to capital.

We find that better fundamental indicators, such as growth opportunities and cash holding, could encourage firms to invest in R&D investments. This supports the previous argument that managers gain the confidence to participate in innovative activities from their investors through better fundamental indicators (Sriram, 2008). However, this does not mean the firms could produce more patents over the following three years.

In addition, these firm characteristics cause similar impacts on R&D investments and other patent-based indicators in the tables in the following subsections.

[48] If a public company achieves patent through acquisition, it is not recorded in the PATSTAT. Therefore, it is probably that the PATSTAT database underestimate the number of patents held by public companies.

4.4.2 Patent quality

In Table 4.5, we represent the firms' innovation performance by the number of patent citations from the year $t + 1$ to the year $t + 3$. This measures the quality of firms' innovation outputs. In this table, we show a significant positive impact of stock liquidity on firm innovation quality. The marginal effect of stock liquidity for firms' patent counts citations is shown in Table 4.5, Column (3) is 0.184. It is not a low figure as the mean of *LN_CIT* is 1.36.

*** Table 4.5 ***

In addition, we observe a positive but insignificant impact of R&D investments on firm innovation quality. A possible reason is that these large companies tend to invest in incremental innovation projects and obtain disruptive innovation through acquisitions. According to Wu (2012), incremental innovation is an incremental refinement of existing technologies, while disruptive innovation is a process of creating dramatic changes. This is supported by Bernstein's (2015) finding that companies change their innovation strategy after going public. While newly listed firms achieve a large number of high-quality patents through acquisitions, the average citations created by old employees decrease in the five years after an IPO filing. However, PATSTAT does not record patent assignment that public company obtain patents through acquisition. In addition, this might be because our sample does not include self-citations. In terms of this, companies' self-citation during the process of incremental innovation is not recorded in our sample.

Overall, firm innovation quality is not significantly affected by R&D but it is significantly improved by stock liquidity. A possible explanation is the entry of long-term and/or strategic institutional investors following the increased stock liquidity. They lead to extra resources (i.e., advanced technologies), thereby improving the quality of firm innovation.

4.4.3 Patent generality index

In Table 4.6, we represent firms' innovation performance using the patent generality index. The table shows that increased stock liquidity continuously improves a firm's patent generality index from the year $t + 1$ to the year $t + 3$. The greater generality index means the knowledge of this patent is cited by other patents belonging to a broader range of technology areas. This may be one of the results of the increasing quality of the patent. Namely, the patent is cited by other patents in different technological fields because of its high quality.

*** Table 4.6 ***

4.4.4 Patent originality index

In Table 4.7, we represent a firm's innovation performance by the patent originality index. This index increases in the next year after firms experience an increase in stock liquidity. It means the knowledge of this patent is cited by other patents belonging to a broader range of technology areas. It may be one of the results of the increasing quality of the patent. In other words, the patent is cited by other patents in different technological fields because of its high quality.

*** Table 4.7 ***

In summary, we show that although stock liquidity can affect firm innovation through R&D investment, the most impact of stock liquidity on firm innovation comes from the direct impact of stock liquidity itself. While stock liquidity causes a significant negative influence on firm R&D investment, it is much lighter than the impact on firm innovation outputs.

We show that there is a larger impact from R&D investment on firm innovation quantity than stock liquidity. Additionally, while R&D investments do not significantly affect either innovation quality, the generality index, nor the originality index, an increase in stock liquidity tends to improve these indicators in future years.

4.5 Chapter Conclusion

In this chapter, we investigate the effect of stock liquidity on the R&D-innovation relationship. By employing a structure model, we find that although stock liquidity can affect firm innovation through R&D investment, the greatest influence on firm innovation comes from the direct impact of stock liquidity. Although stock liquidity causes a significant negative influence on firm R&D investment, it is much lighter than the impact on firm innovation outputs. In terms of this, we support the argument that increased stock liquidity decreases asymmetric information between investors and innovative firms and encourages the entry of long-term and/or strategic institutional investors. It leads to the monitoring of firm managers and extra resources, thereby improving both the quantity and quality of firm innovation.

In addition, we find that R&D leads to larger impacts on firm innovation outputs than stock liquidity. However, we do not observe a significant improvement of R&D on other patent-based indicators. In addition, we show that there is increased patent quality, the generality index and the originality index following the rise of stock liquidity. Firms with higher stock liquidity are more likely to cite patents in different technology fields and thus more likely to be cited by other patents in different areas. They support our opinion that increased stock liquidity leads to a greater degree of monitoring and extra resources being channelled to the company, thereby encouraging them to produce high-quality patents.

Overall, we contribute to the empirical literature on the relationship between stock liquidity and firm innovation. By employing an international sample, we suggest the opposite opinion to Fang *et al.* (2014) by arguing that growth in stock liquidity could improve firm innovation outputs. We also improve the understanding of the R&D-patents relationship from the perspective of stock liquidity. We explain their relationship through the direct impacts of liquidity on patent-based indicators and the indirect impacts through R&D investments.

However, there are a number of limitations to this conclusion. First, we only included the top 20 percentile of the largest public companies in each exchange. This limits how representative our research is. Besides, we do not include the data of subsidiaries. It is because Datastream only focuses on the current subsidiaries. However, firms may raise funding in their home country while conduction innovation activity in other countries. We do not capture these effects in the current framework of the thesis. In addition, while Fang *et al.* (2014) and Wen *et al.* (2018) are of the opposite opinion regarding whether stock liquidity improves or impedes firm innovation in different countries, we do not consider the impact of country characters in this chapter. Future research can be expected to resolve these limitations.

Table 4.1 Variable definitions

Variable	Definition
Panel A: Dependent variable	
$LN\_PAT_{i,t+n}$	$LN\_PAT_{i,t+n}$ is the natural logarithm of one plus the number of successful applications submitted by firm i in the year $t+1$, $t+2$ and $t+3$ respectively. $$LN\_PAT_{i,t+n} = LN(1 + PAT_{i,t+n})$$
$LN\_CIT_{i,t+n}$	$LN\_CITE_{i,t+n}$ is the natural logarithm of one plus the number of citations made to the firm i's patent in the year $t+1$, $t+2$ and $t+3$ respectively. $$LN\_CIT_{i,t+n} = LN(1 + CITE_{i,t+n})$$
$LN\_GENERAL_{i,t+n}$	$LN\_GENERAL_{i,t+n}$ is the natural logarithm of one plus sum of a firm's generality score (i.e., $GENERAL_{i,t+n}$) in the year $t+1$, $t+2$ and $t+3$ respectively. $GENERAL_{i,t+n}$ is the sum of generality score of patents belonging to the firm i in the year $t+1$, $t+2$ and $t+3$ respectively. A patent m's generality score ($GENERAL_m$) as $$GENERAL_m = 1 - \sum_{k=1}^{N_m}\left(\frac{NCITING_{mk}}{NCITING_m}\right)^2$$ where m is the mth patent applied for by the corporate applicant in a given year, k is the index of 4-digital IPC patent classes, N_m is the number of different 4-digital IPC patent classes to which the citations belong. $NCITING_m$ is the number of patents citing the patent m, and $NCITING_{mk}$ is the number of patent m's citations which belong to the patent class k.
$LN\_ORIGINAL_{i,t+n}$	$LN\_ORIGINAL_{i,t+n}$ is the natural logarithm of one plus the sum of a firm's originality score (i.e., $ORIGINAL_{i,t+n}$) in the year $t+1$, $t+2$ and $t+3$ respectively. The $ORIGINAL_{i,t+n}$ is the sum of originality score of patents belonging to the firm i in the year $t+1$, $t+2$ and $t+3$ respectively. A patent m's originality score ($ORIGINAL_m$) as

	$$ORIGINAL_m = 1 - \sum_{k=1}^{N_m} \left(\frac{NCITED_{mk}}{NCITED_m}\right)^2$$ Where $NCITED_m$ is the number of patents cited by patent m, $NCITED_{mk}$ is the number of patents cited by patent m which belong to the patent class k.
Panel B: Independent Variable	
$LIQUIDITY_{i,t}$	$Liquidity_{i,t}$ is the natural logarithm of the inverse of the Amihud measure of firm i in the year t, $$Liquidity_{i,t} = LN\left(\frac{1}{A_{i,t}}\right) \quad (1)$$ $$A_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{\lvert r_{i,d} \rvert}{Dvol_{i,d}} \quad (2)$$ where $A_{i,t}$ is the Amihud measure of firm i in the year t. $r_{i,d}$ and $Dvol_{i,d}$ are daily return and daily dollar trading volume for stock i on day d. $D_{i,t}$ is the number of days which is available in year t.
Panel C: Firm-level Control Variables	
$LN\_TA_{i,t}$	Firm size, $LN\_TA_{i,t}$, measured by the natural logarithm of total assets (Wen *et al.*, 2018). $$LN\_TA_{i,t} = LN(Book\ Value\ of\ Total\ Assets)$$
$RDTA_{i,t}$	Investment in R&D, $RDTA_{i,t}$, measured by Research and development expenditures divided by the book value of total assets measured at the end of year t. $$RDTA_{i,t} = \frac{R\&D}{Book\ Value\ of\ Total\ Assets}$$
$PPETA_{i,t}$	Asset tangibility, $PPETA_{i,t}$, defined as the property, plant, and equipment expenditure divided by the book value of total assets, measured at the end of the year t. $$PPETA_{i,t} = \frac{Property, Plant, And\ Equipment\ Expenditure}{Book\ Value\ of\ Total\ Assets}$$

$LEV_{i,t}$	Leverage ratio, $LEV_{i,t}$, defined as the book value of debt divided by book value of total assets, measured at the end of year t. $$LEV_{i,t} = \frac{Book\ Value\ of\ Debt}{Book\ Value\ of\ Total\ Assets}$$
$CAPEXTA_{i,t}$	Investment in fixed assets, $CAPEXTA_{i,t}$, measured as capital expenditures scaled by the book value of total assets, measured at the end of year t. $$CAPEXTA_{i,t} = \frac{Capital\ Expenditures}{Book\ Value\ of\ Total\ Assets}$$
$Q_{\ i,t}$	Growth opportunity, $Q_{\ i,t}$, defined as Firm i's market-to-book ratio during calendar year t, calculated as the market value of equity plus book value of debt divided by book value of assets, measured at the end of year t. $$Q_{i,t} = \frac{Market\ Value\ of\ Equity +\ Book\ Value\ of\ Debt}{Book\ Value\ of\ Assets}$$
$LN\_AGE_{\ i,t}$	Firm age, $LN\_AGE_{\ i,t}$, measured as the natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream. $$LN\_AGE_{\ i,t} = LN(1 + Age)$$
$CASH_{\ i,t}$	Cash, $CASH_{\ i,t}$, defined as the ratio of cash holdings to book assets in year t. $$CASH_{\ i,t} = \frac{Cash}{Book\ Value\ of\ Assets}$$
$ROA_{i,t}$	Profitability, $ROA_{i,t}$, defined as the income before extraordinary items divided by book value of total assets, measured at the end of year t.

Table 4.2 Firm-Level Descriptive Statistics

Table 4.2 shows the descriptive statistics for the firm-level variables in our analysis. The sample contains 15,202 firm-year observations, which includes 796 companies from 10 countries during the period between 1990 and 2010. The definition of variables is listed in Table 4.1. All firm-level variables are winsorized at top and bottom 1% of variables' distribution. Panel A shows the summary statistics of firm-level variables. Panel B represents the pairwise correlations between firm variables after removing country-means. ***, **, * represents significance at 1%, 5% and 10%, respectively.

Panel A. Summary Statistics of Firm-Level Variables

Variables	N	Mean	St.Dev	p5	Median	p95
LN_PAT	15,202	1.87	1.77	0.00	1.39	5.18
LN_CIT	15,202	1.36	1.64	0.00	0.69	4.61
LN_GENERAL	15,202	0.74	1.09	0.00	0.00	3.11
LN_ORIGINAL	15,202	0.69	1.05	0.00	0.00	2.99
LIQUIDITY	15,043	9.08	2.46	4.64	9.25	12.89
LN TA	14,588	13.88	2.04	10.42	14.05	17.25
PPETA	14,457	0.57	0.38	0.10	0.49	1.30
LEV	14,578	0.20	0.18	0.00	0.17	0.54
CAPEXTA	13,789	0.05	0.04	0.01	0.04	0.13
RDTA	12,231	0.07	0.09	0.00	0.04	0.24
Q	14,543	2.26	2.09	0.88	1.51	6.22
LN AGE	15,202	2.82	0.68	1.39	3.00	3.64
CASH	12,234	0.13	0.12	0.01	0.09	0.37
ROA	14,301	0.02	0.15	-0.28	0.04	0.18

Table 4.2 (continued)

Firm-level Descriptive Statistics

Panel B. Correlation of Firm-Level Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) LIQUIDITY	1									
(2) LN_TA	0.65***	1								
(3) PPETA	0.01*	0.30***	1							
(4) LEV	0.12***	0.38***	0.29***	1						
(5) CAPEXTA	0.02**	0.02*	0.41***	0.04***	1					
(6) RDTA	-0.13***	-0.45***	-0.29***	-0.23***	-0.04***	1				
(7) Q	0.01	-0.37***	-0.28***	-0.24***	0.04***	0.42***	1			
(8) LN_AGE	0.27***	0.46***	0.31***	0.18***	-0.12***	-0.32***	-0.36***	1		
(9) CASH	-0.11***	-0.30***	-0.33***	-0.26***	-0.17***	0.36***	0.27***	-0.20***	1	
(10) ROA	0.21***	0.25***	0.07***	-0.06***	0.15***	-0.51***	-0.14***	0.13***	-0.20***	1

Table 4.3 HFT starting date

Exchange name	HFT start date
Stockholm Stock Exchange	2005/April
Swiss Stock Exchange	2004/January
Toronto Stock Exchange	2005/May
NASDAQ	2003/January
Tokyo Stock Exchange	2005/May
Australia Stock Exchange	2006/April
XETRA Germany	2003/January
NYSE	2003/May
London Stock Exchange	2006/February
New Zealand Stock Exchange	2004/November
OLSO Norway	2005/April

Data source: Aitken *et al.* (2015).

Table 4.4 Stock Liquidity and Innovation measured by LN_PAT_{t+n}

Dependent variable	LN_PAT_{t+1}			LN_PAT_{t+2}			LN_PAT_{t+3}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$LIQUIDITY_t$	$RDTA_t$	LN_PAT_{t+1}	$LIQUIDITY_t$	$RDTA_t$	LN_PAT_{t+2}	$LIQUIDITY_t$	$RDTA_t$	LN_PAT_{t+3}
HFT	0.959***			0.991***			1.081***		
	[0.036]			[0.039]			[0.044]		
RDTA			10.704***			12.712***			11.863***
			[3.730]			[3.611]			[3.770]
LIQUIDITY		-0.004***	0.199**		-0.004***	0.189**		-0.004***	0.211***
		[0.000]	[0.084]		[0.000]	[0.083]		[0.000]	[0.078]
LN_TA	0.959***		0.487***	0.956***		0.493***	0.955***		0.467***
	[0.010]		[0.082]	[0.010]		[0.080]	[0.011]		[0.075]
PPETA	-0.847***	-0.011***	0.039	-0.847***	-0.010***	0.065	-0.841***	-0.010***	0.069
	[0.053]	[0.002]	[0.105]	[0.056]	[0.002]	[0.105]	[0.058]	[0.002]	[0.103]
LEV	-0.997***	-0.024***	-0.435**	-1.107***	-0.025***	-0.411**	-1.263***	-0.027***	-0.399**
	[0.097]	[0.003]	[0.170]	[0.101]	[0.003]	[0.177]	[0.106]	[0.003]	[0.191]

CAPEXTA	4.326***	0.097***	3.206***	4.383***	0.106***	2.752***	4.675***	0.107***	3.375***
	[0.459]	[0.016]	[0.780]	[0.471]	[0.016]	[0.804]	[0.487]	[0.017]	[0.827]
Q	0.283***	0.008***	-0.056	0.277***	0.008***	-0.059	0.264***	0.007***	-0.043
	[0.009]	[0.000]	[0.046]	[0.009]	[0.000]	[0.043]	[0.009]	[0.000]	[0.041]
LN_AGE	-0.315***	-0.001	-0.155***	-0.301***	0	-0.195***	-0.286***	0	-0.202***
	[0.032]	[0.001]	[0.043]	[0.033]	[0.001]	[0.043]	[0.034]	[0.001]	[0.042]
CASH	-0.237	0.079***	-0.456	-0.253*	0.079***	-0.722*	-0.338**	0.076***	-0.605
	[0.145]	[0.005]	[0.394]	[0.152]	[0.005]	[0.387]	[0.159]	[0.005]	[0.390]
ROA	0.336***	-0.206***	2.315**	0.332***	-0.211***	3.201***	0.319***	-0.210***	3.092***
	[0.113]	[0.004]	[0.969]	[0.117]	[0.004]	[0.958]	[0.122]	[0.004]	[0.994]
No. of observations		9,070			8,450			7,816	
Prob > χ^2		0.0000			0.0000			0.0000	

Note: This table reports the marginal effects of determinants of stock liquidity to firm innovation,

(4.1a) $Liquidity_{i,c,t} = \beta_{10} HFT_t + \beta_{11} Z'_{i,c,t} + \epsilon_{1i,c,t}$,

(4.1b) $R\&D_{i,c,t} = \begin{cases} 0, \ if \ R\&D^*_{i,c,t} = \beta_{20} + \beta_{21} Liquidity_{i,c,t} + \beta_{23} Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{2i,c,t} \leq 0 \\ R\&D^*_{i,c,t}, \ if \ R\&D^*_{i,c,t} > 0 \end{cases}$, (4.1c) $Innovation\ outputs_{i,c,t+n} =$

$$\begin{cases} 0,\ if\ Innovation\ outputs^{*}_{i,c,t+n} = \beta_{30} + \beta_{31}Liquidity_{i,c,t} + \beta_{32}R\&D_{i,c,t} + \beta_{33}Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{1i,c,t} \leq 0 \\ Innovation\ outputs^{*}_{i,c,t+n},\ if\ Innovation\ outputs^{*}_{i,c,t+n} > 0 \end{cases}.$$

$Innovation\ outputs_{i,c,t+n}$ is represented by LN_PAT_{t+1} in column (1), (2) and (3), which is replaced with LN_PAT_{t+2} in column (3), (4) and (5), LN_PAT_{t+3} in column (6), (7) and (8). The marginal effects of equation (4.1a) are recorded in column (1), (4), and (7); the marginal effects of equation (4.1b) are recorded in column (2), (5), and (8); the marginal effects of equation (4.1c) are recorded in column (3), (6), and (9). $Liquidity_{i,c,t}$ is the independent variable in this study. It is the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming *et al.*, 2020). $R\&D_{i,c,t}$ is the research and development investment (R&D) of firm i from country c in the year t. $Z'_{i,c,t}$ are the firm-level control variables shown in Table 4.1, Panel C (except $R\&D_{i,c,t}$). Marginal effects are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. Prob > χ^2 show the significance of the overall model and their corresponding p values. We employ Maximum-likelihood estimation for the whole system.

Table 4.5 Stock Liquidity and Innovation measured by LN_CIT_{t+n}

Dependent variable	LN_CIT_{t+1}			LN_CIT_{t+2}			LN_CIT_{t+3}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$LIQUIDITY_t$	$RDTA_t$	LN_CIT_{t+1}	$LIQUIDITY_t$	$RDTA_t$	LN_CIT_{t+2}	$LIQUIDITY_t$	$RDTA_t$	LN_CIT_{t+3}
HFT	0.959***			0.991***			1.081***		
	[0.036]			[0.039]			[0.044]		
RDTA			6.839			3.786			4.823
			[6.215]			[8.240]			[7.414]
LIQUIDITY		-0.004***	0.184**		-0.004***	0.194**		-0.004***	0.121
		[0.000]	[0.092]		[0.000]	[0.094]		[0.000]	[0.087]
LN_TA	0.959***		0.388***	0.956***		0.359***	0.955***		0.424***
	[0.010]		[0.084]	[0.010]		[0.083]	[0.011]		[0.077]
PPETA	-0.847***	-0.011***	-0.083	-0.847***	-0.010***	-0.077	-0.841***	-0.010***	-0.124
	[0.053]	[0.002]	[0.127]	[0.056]	[0.002]	[0.143]	[0.058]	[0.002]	[0.132]
LEV	-0.997***	-0.024***	-0.620***	-1.107***	-0.025***	-0.709**	-1.263***	-0.027***	-0.723**
	[0.097]	[0.003]	[0.229]	[0.101]	[0.003]	[0.292]	[0.106]	[0.003]	[0.285]
CAPEXTA	4.326***	0.098***	5.315***	4.383***	0.107***	5.348***	4.675***	0.107***	5.570***

	[0.459]	[0.016]	[1.019]	[0.471]	[0.016]	[1.295]	[0.487]	[0.017]	[1.198]
Q	0.283***	0.008***	-0.033	0.277***	0.008***	0.001	0.264***	0.007***	0.021
	[0.009]	[0.000]	[0.069]	[0.009]	[0.000]	[0.085]	[0.009]	[0.000]	[0.072]
LN_AGE	-0.315***	-0.001	-0.065	-0.301***	0	-0.100**	-0.286***	0	-0.123***
	[0.032]	[0.001]	[0.043]	[0.033]	[0.001]	[0.042]	[0.034]	[0.001]	[0.041]
CASH	-0.237	0.079***	0.378	-0.253*	0.079***	0.674	-0.338**	0.076***	0.559
	[0.145]	[0.005]	[0.629]	[0.152]	[0.005]	[0.826]	[0.159]	[0.005]	[0.719]
ROA	0.336***	-0.206***	1.788	0.332***	-0.211***	1.323	0.319***	-0.210***	1.776
	[0.113]	[0.004]	[1.600]	[0.117]	[0.004]	[2.169]	[0.122]	[0.004]	[1.942]
No. of observations		9,070			8,450			7,816	
Prob > χ^2		0.0000			0.0000			0.0000	

Note: This table reports the marginal effects of determinants of stock liquidity to firm innovation,

(4.1a) $Liquidity_{i,c,t} = \beta_{10}HFT_t + \beta_{11}Z'_{i,c,t} + \epsilon_{1i,c,t}$,

(4.1b) $R\&D_{i,c,t} = \begin{cases} 0, \ if\ R\&D^*_{i,c,t} = \beta_{20} + \beta_{21}Liquidity_{i,c,t} + \beta_{23}Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{2i,c,t} \leq 0 \\ R\&D^*_{i,c,t}, \ if\ R\&D^*_{i,c,t} > 0 \end{cases}$,

(4.1c) $Innovation\ outputs_{i,c,t+n} =$

$$\begin{cases} 0, \ if\ Innovation\ outputs^*_{i,c,t+n} = \beta_{30} + \beta_{31}Liquidity_{i,c,t} + \beta_{32}R\&D_{i,c,t} + \beta_{33}Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{1i,c,t} \leq 0 \\ Innovation\ outputs^*_{i,c,t+n}, \ if\ Innovation\ outputs^*_{i,c,t+n} > 0 \end{cases}.$$

$Innovation\ outputs_{i,c,t+n}$ is represented by LN_CIT_{t+1} in column (1), (2) and (3), which is replaced with LN_CIT_{t+2} in column (3), (4) and (5), LN_CIT_{t+3} in column (6), (7) and (8). The marginal effects of equation (4.1a) are recorded in column (1), (4), and (7); the marginal effects of equation (4.1b) are recorded in column (2), (5), and (8); the marginal effects of equation (4.1c) are recorded in column (3), (6), and (9). $Liquidity_{i,c,t}$ is the independent variable in this study. It is the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming et al., 2020). $R\&D_{i,c,t}$ is the research and development investment (R&D) of firm i from country c in the year t. $Z'_{i,c,t}$ are the firm-level control variables shown in Table 4.1, Panel C (except $R\&D_{i,c,t}$). Marginal effects are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. Prob > χ^2show the significance of the overall model and their corresponding p values. We employ Maximum-likelihood estimation for the whole system.

Table 4.6 Stock Liquidity and Innovation measured by $LN\_GENERAL_{t+n}$

Dependent variable	$LN\_GENERAL_{t+1}$			$LN\_GENERAL_{t+2}$			$LN\_GENERAL_{t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$LIQUIDITY_t$	$RDTA_t$	$LN\_GENERAL_{t+1}$	$LIQUIDITY_t$	$RDTA_t$	$LN\_GENERAL_{t+2}$	$LIQUIDITY_t$	$RDTA_t$	$LN\_GENERAL_{t+3}$
HFT	0.959***			0.991***			1.081***		
	[0.036]			[0.039]			[0.044]		
RDTA			-0.969			5.018			1.514
			[5.972]			[5.372]			[7.417]
LIQUIDITY		-0.004***	0.104*		-0.004***	0.137**		-0.004***	0.142**
		[0.000]	[0.063]		[0.000]	[0.061]		[0.000]	[0.064]
LN_TA	0.959***		0.247***	0.956***		0.241***	0.955***		0.213***
	[0.010]		[0.053]	[0.010]		[0.053]	[0.011]		[0.051]
PPETA	-0.847***	-0.011***	-0.121	-0.847***	-0.010***	-0.037	-0.841***	-0.010***	-0.075
	[0.053]	[0.002]	[0.101]	[0.056]	[0.002]	[0.093]	[0.058]	[0.002]	[0.113]
LEV	-0.997***	-0.024***	-0.521***	-1.107***	-0.025***	-0.330*	-1.263***	-0.027***	-0.408
	[0.097]	[0.003]	[0.194]	[0.101]	[0.003]	[0.188]	[0.106]	[0.003]	[0.262]
CAPEXTA	4.326***	0.098***	3.688***	4.383***	0.106***	2.860***	4.675***	0.107***	3.353***

	[0.459]	[0.016]	[0.820]	[0.471]	[0.016]	[0.826]	[0.487]	[0.017]	[1.075]
Q	0.283***	0.008***	0.036	0.277***	0.008***	-0.022	0.264***	0.007***	0.011
	[0.009]	[0.000]	[0.064]	[0.009]	[0.000]	[0.055]	[0.009]	[0.000]	[0.070]
LN_AGE	-0.315***	-0.001	0.02	-0.301***	0	-0.004	-0.286***	0	0.001
	[0.032]	[0.001]	[0.028]	[0.033]	[0.001]	[0.027]	[0.034]	[0.001]	[0.027]
CASH	-0.237	0.079***	0.769	-0.253*	0.079***	0.19	-0.338**	0.076***	0.519
	[0.145]	[0.005]	[0.589]	[0.152]	[0.005]	[0.537]	[0.159]	[0.005]	[0.706]
ROA	0.336***	-0.206***	-0.447	0.332***	-0.211***	1.268	0.319***	-0.210***	0.425
	[0.113]	[0.004]	[1.539]	[0.117]	[0.004]	[1.417]	[0.122]	[0.004]	[1.946]
No. of observations		9,070			8,450			7,816	
Prob > χ^2		0.0000			0.0000			0.0000	

Note: This table reports the marginal effects of determinants of stock liquidity to firm innovation,

(4.1a) $Liquidity_{i,c,t} = \beta_{10} HFT_t + \beta_{11} Z'_{i,c,t} + \epsilon_{1i,c,t}$,

(4.1b) $R\&D_{i,c,t} = \begin{cases} 0, \ if \ R\&D^*_{i,c,t} = \beta_{20} + \beta_{21} Liquidity_{i,c,t} + \beta_{23} Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{2i,c,t} \leq 0 \\ R\&D^*_{i,c,t}, \ if \ R\&D^*_{i,c,t} > 0 \end{cases}$,

(4.1c) $Innovation\ outputs_{i,c,t+n} =$

$$\begin{cases} 0, \ if \ Innovation\ outputs^*_{i,c,t+n} = \beta_{30} + \beta_{31} Liquidity_{i,c,t} + \beta_{32} R\&D_{i,c,t} + \beta_{33} Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{1i,c,t} \leq 0 \\ Innovation\ outputs^*_{i,c,t+n}, \ if \ Innovation\ outputs^*_{i,c,t+n} > 0 \end{cases}.$$

$Innovation\ outputs_{i,c,t+n}$ is represented by $LN_GENERAL_{t+1}$in column (1), (2) and (3), which is replaced with $LN\_GENERAL_{t+2}$ in in column (3), (4) and (5), $LN\_GENERAL_{t+3}$ in in column (6), (7) and (8). The marginal effects of equation (4.1a) are recorded in column (1), (4), and (7); the marginal effects of equation (4.1b) are recorded in column (2), (5), and (8); the marginal effects of equation (4.1c) are recorded in column (3), (6), and (9). $Liquidity_{i,c,t}$ is the independent variable in this study. It is the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming *et al.*, 2020). $R\&D_{i,c,t}$ is the research and development investment (R&D) of firm i from country c in the year t. $Z_{i,c,t}$ are the firm-level control variables shown in Table 4.1, Panel C (except $R\&D_{i,c,t}$). Marginal effects are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. Prob > χ^2show the significance of the overall model and their corresponding p values. We employ Maximum-likelihood estimation for the whole system.

Table 4.7 Stock Liquidity and Innovation measured by $LN\_ORIGINAL_{t+n}$

Dependent variable	$LN\_ORIGINAL_{t+1}$			$LN\_ORIGINAL_{t+2}$			$LN\_ORIGINAL_{t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$LIQUIDITY_t$	$RDTA_t$	$LN\_ORIGINAL_{t+1}$	$LIQUIDITY_t$	$RDTA_t$	$LN\_ORIGINAL_{t+2}$	$LIQUIDITY_t$	$RDTA_t$	$LN\_ORIGINAL_{t+3}$
HFT	0.959***			0.990***			1.081***		
	[0.036]			[0.039]			[0.044]		
RDTA			2.653			-10.18			-8.621
			[6.325]			[6.274]			[6.307]
LIQUIDITY		-0.004***	0.201***		-0.004***	0.104		-0.004***	0.075
		[0.000]	[0.065]		[0.000]	[0.064]		[0.000]	[0.061]
LN_TA	0.959***		0.163***	0.956***		0.188***	0.955***		0.218***
	[0.010]		[0.055]	[0.010]		[0.054]	[0.011]		[0.051]
PPETA	-0.847***	-0.011***	0.025	-0.847***	-0.010***	-0.176*	-0.841***	-0.010***	-0.185*
	[0.053]	[0.002]	[0.105]	[0.056]	[0.002]	[0.107]	[0.058]	[0.002]	[0.105]
LEV	-0.997***	-0.024***	-0.27	-1.107***	-0.025***	-0.695***	-1.263***	-0.027***	-0.716***
	[0.097]	[0.003]	[0.203]	[0.101]	[0.003]	[0.221]	[0.106]	[0.003]	[0.236]
CAPEXTA	4.326***	0.098***	2.725***	4.383***	0.107***	4.647***	4.675***	0.107***	4.697***

	[0.459]	[0.016]	[0.866]	[0.471]	[0.016]	[0.973]	[0.487]	[0.017]	[0.976]
Q	0.283***	0.008***	-0.029	0.277***	0.008***	0.111*	0.264***	0.007***	0.105*
	[0.009]	[0.000]	[0.067]	[0.009]	[0.000]	[0.065]	[0.009]	[0.000]	[0.061]
LN_AGE	-0.315***	-0.001	0.034	-0.301***	0	0.007	-0.286***	0	0.006
	[0.032]	[0.001]	[0.029]	[0.033]	[0.001]	[0.033]	[0.034]	[0.001]	[0.032]
CASH	-0.237	0.079***	0.443	-0.253*	0.079***	1.671***	-0.338**	0.076***	1.450**
	[0.145]	[0.005]	[0.624]	[0.152]	[0.005]	[0.635]	[0.159]	[0.005]	[0.613]
ROA	0.336***	-0.206***	0.516	0.332***	-0.211***	-2.727	0.319***	-0.210***	-2.186
	[0.113]	[0.004]	[1.629]	[0.117]	[0.004]	[1.658]	[0.122]	[0.004]	[1.658]
No. of observations		9,070			8,450			7,816	
Prob > χ^2		0.0000			0.0000			0.0000	

Note: This table reports the marginal effects of determinants of stock liquidity to firm innovation,

(4.1a) $Liquidity_{i,c,t} = \beta_{10}HFT_t + \beta_{11}Z'_{i,c,t} + \epsilon_{1i,c,t}$,

(4.1b) $R\&D_{i,c,t} = \begin{cases} 0, \; if \; R\&D^*_{i,c,t} = \beta_{20} + \beta_{21}Liquidity_{i,c,t} + \beta_{23}Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{2i,c,t} \leq 0 \\ R\&D^*_{i,c,t}, \; if \; R\&D^*_{i,c,t} > 0 \end{cases}$,

(4.1c) $Innovation\ outputs_{i,c,t+n} =$

$\begin{cases} 0, \; if \; Innovation\ outputs^*_{i,c,t+n} = \beta_{30} + \beta_{31}Liquidity_{i,c,t} + \beta_{32}R\&D_{i,c,t} + \beta_{33}Z'_{i,c,t} + C_C + I_j + Y_t + \epsilon_{1i,c,t} \leq 0 \\ Innovation\ outputs^*_{i,c,t+n}, \; if \; Innovation\ outputs^*_{i,c,t+n} > 0 \end{cases}$.

$Innovation\ outputs_{i,c,t+n}$ is represented by $LN\_ORIGINAL_{t+1}$ in column (1), (2) and (3), which is replaced with $LN\_ORIGINAL_{t+2}$ in in column (3), (4) and (5), $LN\_ORIGINAL_{t+3}$ in in column (6), (7) and (8). The marginal effects of equation (4.1a) are recorded in column (1), (4), and (7); the marginal effects of equation (4.1b) are recorded in column (2), (5), and (8); the marginal effects of equation (4.1c) are recorded in column (3), (6), and (9). $Liquidity_{i,c,t}$ is the independent variable in this study. It is the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming *et al.*, 2020). $R\&D_{i,c,t}$ is the research and development investment (R&D) of firm i from country c in the year t. $Z_{i,c,t}$ are the firm-level control variables shown in Table 4.1, Panel C (except $R\&D_{i,c,t}$). Marginal effects are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. Prob > χ^2show the significance of the overall model and their corresponding p values. We employ Maximum-likelihood estimation for the whole system.

Chapter 5 Stock liquidity and firm innovation: international evidence

5.1 Introduction

There is a debate about the relationship between stock market liquidity and firm innovation. While Fang *et al.* (2014) found there exists a negative relationship between stock liquidity and firm innovation in the U.S. market from 1994 to 2005, Dass *et al.* (2017) found no significant relationship, and Wen *et al.* (2018) demonstrated the positive impact of stock liquidity on innovation in the Chinese market. In this chapter, we analyse the relationship between them from a global perspective.

We employ the multilevel model (i.e., the hierarchical linear model or HLM) to separate the within-country and cross-country impacts of firms' stock liquidity on their innovative performance (Greene, 2003; Griffin *et al.*, 2019). To examine a global sample of 71,689 firm-year observations from 5,511 companies across 36 countries between 1990 and 2010, we firstly support our findings in Chapter 4, namely that rising stock liquidity can improve firms' patent quantity, quality, generality index and originality index. In addition, by using this much larger sample, we find that while other firm-level factors, such as firm size, market-to-book ratio and leverage, cause a stable level effect on a firm's innovation performance, the positive influence of stock liquidity on firm innovation increases over the following five years.

To explore estimation results in greater depth, we investigate stock liquidity's impact from the perspective of firm innovation efficiency. We show that firms obtain continuously increased efficiency to produce high-quality patents rather than more patents following a rise in stock liquidity. This is explained by the hypothesis in Chapter 4 wherein increased stock liquidity facilitates the entrance of long-term strategic institutional investors into firms. It brings extra resources (for example, technology in different fields) to the company, thereby improving efficiency to produce high-quality patents. This argument is supported by the growth originality index following stock liquidity. We propose that rising stock liquidity provides opportunities for firms to acquire knowledge from a wider range of technology areas. Moreover, after firms experience an increase in stock liquidity, their patents are more likely to be cited by other patents belonging to a broader range of technology areas. This may be one of the ways in which firms produce high-quality patents.

At country-level, our results show that the development of credit markets and a high degree of economic freedom continuously improve firm innovation performance across a five-year period. In addition, the size of the economy and trade liberalisation leads to a short-term positive influence on firm innovation quantity and quality. Cutting corporate income tax tends to improve firm efficiency to produce high-quality patents. In particular, we show that a firm's innovation performance can be encouraged by the protection of property rights over a five-year period; by the smaller size of government expenditures, enterprises, and tax, or lower and less volatile inflation over the following three years.

We make several potential contributions in this chapter. Firstly, our results contribute to the debate on whether stock liquidity encourages or impedes firm innovation based on a global sample (Fang *et al.*, 2014; Wen *et al.*, 2018). Compared with the latter, our research provides within- and cross-country evidence of the effect of stock liquidity on firm innovation over a more extended period. While we support Wen *et al.* (2018)'s opinion that increased stock liquidity improves firm innovation, our study includes more patent-based measurements by which to analyse in depth the impact of stock liquidity on firm innovation performance.

Additionally, we provide evidence to policymakers on whether they should improve or impede stock liquidity from the perspective of encouraging innovation activities. As technology innovation plays an essential role in improving economic growth (see Solow, 1956; Grossman and Helpman, 1991; Aghion and Howitt, 1992), policymakers in the financial area are expected to encourage innovation outputs through financial systems. Our evidence could help to reduce their confusion on the current debate and support policies to increase stock liquidity. We show that while a growth in stock liquidity encourages firms to produce more patents, it mainly contributes to a firm's efficiency in producing better patents.

Our research provides advice to investors and firm managers regarding how to make investment decisions based on the policy of stock liquidity. Investors tend to invest in firms with better innovation performances, as innovation outputs can be capitalised in their market value and predict a firm's real return in the stock market (Hall *et al.*, 2005; Hsu, 2009). Therefore, our research can encourage investors to allocate more investments in stock exchanges with higher stock liquidity. We would also encourage public companies to continue their R&D activities following policies that increase stock liquidity.

The remainder of this chapter is structured as follows: We review the previous literature and propose a hypothesis about the relationship between stock liquidity and firm innovation in the next section. We describe the sample, variable construction, and estimation method in the third section. In the fourth section, we present our estimation results and provide some analysis. In the fifth section, we provide the results of robustness tests. In the sixth section, we demonstrate our conclusions.

5.2 Literature Review and Hypothesis

This section reviews the literature about firm innovation from the perspective of the macroeconomy, corporate ownership, corporate governance, and financial markets. Although a lot of research has covered this, few focus on the impact of market microstructure. Notably, there is still debate about the relationship between stock liquidity and firm innovation (Fang *et al.*, 2014; Wen *et al.*, 2018).

We will mainly focus on the literature that studies firm innovation from the perspective of innovation output (i.e., patent-based data). A lot of literature has considered firm innovation by R&D investment, but this literature generally considers a firm's innovation input without capturing the innovation outcomes (Fang *et al.*, 2014). In addition, previous research has shown a high correlation between a firm's investment in R&D projects and the number of patents issued by it (Griliches, 1984).

5.2.1 Macro-environment factors

Previous research shows that firms' innovative outcomes tend to be affected by a country's legal system, government policies, culture, taxes and trade liberalisation. A host of literature studies the response of corporate innovation to law and policy, such as Intellectual Property Right (IPR, hereafter) protection rules (Fang *et al.*, 2017; Cohen *et al.*, 2019), Labour laws (Acharya *et al.*, 2013, 2014), Bankruptcy laws (Acharya and Subramanian, 2009; Cerqueiro *et al.*, 2017); Employment Non-Discrimination Acts (Gao and Zhang, 2017), Uncertainty of government policy (Bhattacharya *et al.*, 2017) and government spending and subsidies (Jaffe and Le, 2015; Howell, 2017; Kong, 2020). In addition, Mukherjee *et al.* (2017) and Dechezleprêtre *et al.* (2016) have shown the impacts of tax (i.e., corporate tax or R&D tax) on firms' future patenting activities. Bloom *et al.* (2016) and Coelli *et al.* (2016) investigated the relationship between trade liberalisation and corporate innovation. In addition to this, a group of literature investigates the influence of national culture on innovative activities from the perspective of power distance (Shane, 1992; Kaasa and Vadi, 2010), individualism/collectivism (Jones and Davis, 2000; Kaasa and Vadi, 2010; Desmarchelier and Fang, 2016), masculinity/femininity (Rhyne *et al.*, 2002; Kaasa and Vadi, 2010), Confucian dynamism (Rossberger, 2014), uncertainty avoidance (Allred and Swan, 2004; Bradley *et al.*, 2013), and indulgence (Griffith and Rubera, 2014).

5.2.2 Corporate governance

A series of papers explores the relationship between corporate-level factors and firm innovation. Battaggion and Tajoli (2000) and Lee (2005) studied the influence of ownership concentration on firms' innovative activities. A group of literature investigates how a firm's innovation performance can be affected by the identity of ownership, such as institutional investment (Aghion *et al.*, 2013; Qi, 2015), hedge funds (Brav *et al.*, 2018), foreign ownership (Luong *et al.*, 2017), venture capital (Chemmanur *et al.*, 2014; Tian and Wang, 2014), firm stakeholders (Flammer and Kacperczyk, 2016; Chu *et al.*, 2019), mergers and acquisitions [M&A] (Zhao, 2009; Atanassov, 2013; Bena and Li, 2014; Seru, 2014).

Previous literature also covers the influence of human character on a firm's innovative behaviour. Among them, Galasso and Simcoe (2011), Hirshleifer *et al.* (2012), Custódio *et al.* (2019), Sunder *et al.* (2017), and Baranchuk *et al.* (2014) studied how characteristics and compensations of the chief executive officers (CEOs) affect a firm's innovative performance. Liu *et al.* (2017), Chemmanur *et al.* (2019), Chang *et al.* (2015) and Sauermann and Cohen (2010) investigated the motivation of employees for supporting innovative activities.

In addition to this, researches show that a firm's innovation performance tends to be affected by the adoption of International Financial Reporting Standards (IFRS) (Li *et al.*, 2016); frequency of financial reporting (Fu *et al.*, 2020) and coverage by financial analysts (He and Tian, 2013), 2013).

5.2.3 Financial market structure

A series of literature studies a firm's innovation performance before and after going public (Wu, 2012; Aggarwal and Hsu, 2014; Bernstein, 2015; Acharya and Xu, 2017). Other studies investigate the effect of equity markets on firm innovation and compare it with other financing methods (Giudici and Paleari, 2000; Hsu *et al.*, 2014; Moshirian *et al.*, 2015). In addition to this, Blanco and Wehrheim (2017) and Chang *et al.* (2015) analysed how trading in the derivatives market, which consists of derivative exchanges and over the counter (OTC) markets, influences firm innovation.

5.2.4 Market microstructure in the equity market

Few papers involved studies about the relationship between market microstructure and firm innovation. [49] To the best of our knowledge, the literature in this field has involved research from the perspective of market manipulation (i.e., insider trading, end-of-day dislocation; Aboody and Lev, 2000; Levine *et al.*, 2017; Cumming *et al.*, 2020), takeover (Atanassov, 2013; Chemmanur and Tian, 2018), trading by institutional investors (Bushee, 1998; Abdioglu *et al.*,

[49] According to Harris (2003), market microstructure is a branch of financial economics that researches trading and the organisation of markets.

2015) and stock liquidity (Tadesse, 2006; Fang *et al.*, 2014; Wen *et al.*, 2018; Cumming *et al.*, 2020).

5.2.5 Previous empirical research about the impacts of stock liquidity on firm innovation and hypothesis

There is a debate about the relationship between stock liquidity and firm innovation. While Fang *et al.* (2014) demonstrate the negative influence of stock liquidity on firm innovation, Wen *et al.* (2018), Tadesse (2006), and Cumming *et al.* (2020) support that there is a positive relationship between stock liquidity and firm innovation.

Fang *et al.* (2014) analysed selected firms which traded on NYSE, Amex, or NASDAQ from 1994 to 2005. They employed the large movements of minimum tick size as exogenous shocks to stock liquidity and found that firms experiencing a larger increase in stock liquidity produced fewer patents and patent citations. They also argued that a larger exogenous increase in stock liquidity following decimalisation leads to a higher probability of facing hostile takeover and the increased participation of nondedicated institutional investors. They found that firm managers under pressure tended to abandon long-term investment in innovation in order to improve current profits.

However, the reliability of this result is weakened by Dass *et al.* (2017) via an extended data set. While Fang *et al.* (2014) correct the truncation problems by estimating the patent counts in the last six years of the sample, Dass *et al.* (2017) employ the same approach to analyse the real data set, which includes the actual data of the last six years of Fang *et al's.* (2014) sample.[50] However, they found no significant relationship between stock liquidity and innovation.

Following Fang *et al.* (2014)'s method, Wen *et al.* (2018) found a positive relationship between stock liquidity and innovation in the Chinese stock markets (i.e., Shanghai Stock Exchange and Shenzhen Stock Exchange). They applied two different exogenous variations to avoid inter-relationship, namely, split-share structure policy and the adjustment of stamp duty rate. The research posits that liquidity improves the valuation of privatised State-Owned Enterprises (SOEs) and also the participation of dedicated institutional investors, thereby decreasing agency problems and increasing innovation amongst SOEs. In addition to this literature, Tadesse (2006) shows that stock market liquidity is positively related to technological innovation. Cumming *et al.* (2020) found the positive impact of stock liquidity on innovation can be mitigated by the presence of end-of-day manipulation.

In summary, these two papers analyse the relationship between stock liquidity and firm innovation in different countries using the same approach but finding opposite conclusions. This may be due to the different institutional approaches within the US and China, such as industry background, economic regulation, and the policy environment. For example, Jiang and Kim (2020) demonstrate that ownership in Chinese companies is highly concentrated compared to the US and other developed countries' companies. It is also true that the sample of Fang *et al*. (2014) is less relevant to the actual data.

[50] Fang *et al.* (2014) follow the method of Hall *et al.* (2001, 2005) to correct the truncation problems associated with the NBER patent database (which is the database collect the patent-based data). The truncation problem arises as the patent can be seen in the NBER database only after it is granted, however, there is a lag between patent application date and granted date. Therefore, many patent applications filed during the later year of the sample do not appear in the sample as they are still under review and have not been granted by 2006.

In addition to this, many researchers have shown that a smaller tick improves the price discovery process (Beaulieu *et al.*, 2003; Chou and Chung, 2006; Chen and Gau, 2009). Moreover, innovative companies may be encouraged to invest more in R&D in a market with a low level of informational asymmetry. For example, Abdioglu *et al.* (2015) found a higher level of passive and dedicated institutional investment in R&D-intensive firms after a reduction of asymmetric information (brought about by the enforcement of Sarbanes-Oxley Act, which aims to improve the accuracy of public firms' disclosures). In terms of this, it is possible that a decrease in the minimum tick size could affect firm innovation by influencing the price discovery process. This argument is opposite to that of Fang *et al.* (2014) which utilises the decimalisation and movements of minimum tick size as exogenous variations to overcome the interplay between stock liquidity and innovation.

Therefore, there is still a debate around the impact of stock liquidity on firm innovation. To the best of knowledge, we do not find any research investigate the effect of stock liquidity on firm innovation activities considering both firm-level and country-level control factors. However, as we described in subsection 5.2.1 and 5.3.2.3, firm innovation performance is affected by country-level factors. It is necessary to include the country-level control factors.

In this chapter, we aim to employ the multilevel model to analyse within and cross-country effects of liquidity on innovation. To investigate the impact of stock liquidity on firm innovation based on an international multi-level sample, we propose a hypothesis:

Hypothesis An increase in stock liquidity improves firm innovation performance.

In the following sections, we analyse the relationship between stock liquidity and firm innovation from a global market perspective.

5.3 Sample Selection, Variable Measurement, Descriptive Statistics and Estimation method

5.3.1 Data and sample selection

In addition to patent-based data and firm account data employed in Chapter 4, we collected national accounts data (for example, GDP, inflation rate) and worldwide governance indicators (WGI) from the World Bank database; the Corporate income tax rate from Tax Foundation; Education rate from Barro and Lee (2013); Economic freedom of the world (EFW) index from The Fraser Institute; and secrecy indicators from Hope *et al.* (2008).

5.3.2 Variable measurement

5.3.2.1 Dependent Variables

We consider firm innovation performance by following six indicators. Including the four indicators employed in Chapter 4, we include two additional indicators in this chapter to represent innovation efficiency.

Innovation efficiency (IE) reflects a firm's ability to produce patents and obtain patent citations for every one percent increase in R&D expenditures in year t, $t+1$, $t+2$, $t+3$ and $t+5$, respectively.[51] Following Wen *et al.* (2018), we represent it as the ratio of patents to the natural logarithm of R&D investment. According to Hirshleifer *et al's.* (2013) suggestion that the number of citations made to a patent can better reflect the patent's technological or economic

[51] In this chapter, we also run the regression on year $t+4$ and get similar results with regressions on other years. However, we do not report it for brevity. We are able to run the model to analyse the regression on year $t+4$ and $t+5$ because we include more firm-year observations in this chapter than in chapter 4.

significance, we also represent the IE as the ratio of patent citations to the natural logarithm of R&D investment. We describe the detailed variable information in Table 5.1, Panel A. We also provide summary statistics of these two variables in Table 4.2, Panel A.

*** Table 5.1 ***

5.3.2.2 Independent variable

In this chapter, we use the same liquidity variable as in Chapter 4. As we describe in subsection 4.3.2.2 Independent variable in Chapter 4, the Amihud ratio is the best monthly/daily cost-per-dollar-volume proxy to measure stock liquidity in international research (Fong *et al.*, 2017). Therefore, in this chapter, we still measure the stock liquidity of the firm, $Liquidity_{i,t}$, as the natural logarithm of the inverse of the Amihud measure of illiquidity (Cumming et al., 2020).

5.3.2.3 Control variables

In this chapter, we employ the same firm-level control variables as in Chapter 4. We also follow the previous literature and measure these variables for firm i at the end of each calendar year. We describe the detailed variable information in Table 4.1, Panel C.

Except for this, we control investment in R&D, $RDTA_{i,t}$, measured by research and development expenditures divided by the book value of total assets (Fang *et al.*, 2014). Following from Wen *et al.* (2018), we do not control $RDTA_{i,t}$ when innovation efficiency is considered as the dependent variable in the estimation. We describe the detailed variable information in Table 4.1, Panel A.

For country characteristics, we follow Levine *et al.* (2017) and control for the size of the economy, Gross Domestic Product ($GDP_{c,t}$) (according to Levine *et al.*, 2017, in natural logarithm). It is likely to shape innovation and influence the degree to which firms file patents with the patent office in more developed countries (Acharya and Subramanian, 2009; Levine *et al.*, 2017).

We control the level of domestic stock market capitalisation, $Equity_{c,t}$ (Titman *et al.*, 2013), and domestic credit market capitalisation, $Credit_{c,t}$ (Tadesse, 2006; Hsu *et al.*, 2014). This is because firms' innovative activity is more likely to be encouraged by a well-developed stock market and discouraged by the development of the credit market (Hsu *et al.*, 2014). $Equity_{c,t}$ is the trading value of shares traded in country c scaled by country c's GDP in year t. The trading value of shares is equal to the total number of domestic and foreign shares traded in country c, multiplied by their respective matching prices. Only one side of the transaction is considered in the calculation. Besides, $Credit_{c,t}$, is the ratio of domestic credit provided by financial sectors in country c to country c's GDP in year t. Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis as well as the net credit to the central government. The ratio shows development of financial sector and depth of banking sector in terms of size.

We control the intensity of international trade, $Trade_{c,t}$, computed as the import and export of goods and services as a fraction of country c's GDP in year t (Levine *et al.*, 2017), as trade liberalisation tends to improve firm innovation (Gorodnichenko *et al.*, 2015; Coelli *et al.*, 2016). Bloom *et al.* (2016) argue that import competition from Chinese companies motivates European companies to upgrade their technology. Coelli *et al.* (2016) find that trade liberalisation improves corporate innovation via improved market access and more import competition.

We also control the country's inflation rate, $Inflation_{c,t}$, as it is a kind of hidden tax (McMullen *et al.*, 2008). It is found by Zhu and Zhu (2017), which shows that inflation plays an essential role in impeding firms' innovative activities. We collect these country-level control variables from the World Development Indicators (WDI) database and the Financial Development and Structure (FDS) database through the World Bank.

We control the economic freedom index, $EFW_{c,t}$. This shows the degree to which a country's institutions and policies are consistent with economic freedom. Gwartney and Lawson (2003) measure the EFW index from the following five major areas and argue that a country will have a higher rating on the EFW index when it has 1) smaller size of government expenditures, enterprises, and tax; 2) better structure and security of property rights; 3) an easier way to access sound money; 4) A higher degree of freedom to exchange with foreigners; 5) a better regulation of credit, labour, and business. Using the EFW index, Zhu and Zhu (2017) found firms are willing to participate in innovative activities when they are in countries with a limited government, sound and efficient regulatory systems, and open markets. We collected the EFW index from Gwartney and Lawson (2003), which covers 162 countries from 1970 to 2017 (broken down into five-year intervals between 1970 and 2000). Following Picci (2010), the observation for the year will be used for four adjacent years. For example, the observation for the year 1990 is used for the year 1991, 1992; the year 1993, 1994, 1996 and 1997 are set equal to the observation for the year 1995. A country with a higher level of this index represents a higher economic freedom level.

We control the corporate income tax rate in line with Atanassov and Liu (2020)'s finding that the corporate tax impedes firms' innovation by reducing their pledgeable income. Brown *et al.* (2009) showed that innovative firms prefer to invest in R&D projects using after-tax internal funds rather than tapping external markets. In addition, Mukherjee *et al.* (2017) found that firms respond to an increase in corporate tax by reducing future patenting activities. They empirically document that an increase in corporate income taxes reduces not only the quantity and quality of firms' innovation but also the number of new product announcements.[52] In terms of this, following Atanassov and Liu (2020), we controlled for corporate income tax, $CTR_{c,t}$, as the tax rate in country c in the year t. We collected the corporate income tax rate around the world from the Tax Foundation dataset.[53] It provides the corporate tax rate for countries over the total sample period.

Varsakelis (2006) shows that society will produce more innovative outcomes when it invests highly in the quality of education. In terms of this, we use $EDU_{c,t}$ to represent the level of country c's educational attainment, it is the ratio of the population (age 15 and over) that have completed at least tertiary education in the year t. Barro and Lee constructed the dataset in 2013 (Barro and Lee, 2013). It covers 146 countries/regions from 1950 to 2010 (broken down into five year intervals).

Hope et al. (2008) constructed a secrecy indicator, SEC_c, based on Hofstede's (1980) national culture indicators. It is measured as below,

$$SEC_c = UA_c + PD_c - IND_c$$

Where UA_c represents the uncertainty avoidance score of country c, PD_c represents power distance score of country c and IND_c represents individualism score of country c (Hofstede, 1980). According to Hofsted *et al.* (2010), a country with a higher UA_c is more concerned with threats from ambiguous or unknown situations. To avoid conflict and competition and preserve

[52] The database of major new product introductions is hand-constructed by Mukherjee *et al.* (2017) through a textual search of the LexisNexis News database for company press releases.

[53] The dataset covers around 250 countries from 1980 to 2019. See more detail information about Tax Foundation in https://www.wipo.int/publications/en/details.jsp?id=4490&plang=EN.

security, the country prefers to restrict information disclosure, which increases the SEC_c (Gray, 1988). A higher PD_c means people in the country are more accepting of a hierarchical order and less likely to break down power barriers (Hofsted et al., 2010). This kind of country is more likely to restrict information disclosure to preserve power inequalities (Gray, 1988). In addition to this, a country with high scores of IND_c means people in this country are focussed only on the individual needs of themselves and their family (Hofsted et al., 2010). This contrasts with collectivism and secrecy because people in an individualistic culture are less likely to concern themselves with the well-being of their firms and more willing to share information with external parties (Gray, 1988). In summary, countries with a higher score of SEC_c have a lower level of information disclosures. Hope et al. (2008) showed that firms in these countries are less likely to hire high-quality audits and more likely to receive low-quality financial reporting. It increases information asymmetries and agency conflicts between a firm's management team and their stockholders or potential investors (for example, Francis and Wilson, 1988; Craswell et al., 1995). Firms tend to be sensitive to this impact when they are processing innovative activities. Therefore, we collect data from Hofstede (1980) and control for this variable. The detailed variable information is described in Table 5.1, Panel B.

5.3.3 Descriptive Statistics

In this chapter, we collect firm-level data following Chapter 4. However, we construct a larger sample in this chapter. Therefore, we report the firm-level descriptive statistics in this chapter again. Table 5.2, Panel A provides summary statistics for the firm-level variables used in this study. In this table, the number of different variables is different. It is because of the existence of missing value in each firm accounting variables collecting from Datastream. On average, a firm invests 6.4% of its total asset in R&D projects as the innovation input per year. Besides, as the innovation output, they submit an average of 13.8 applications (which is finally granted) per year, and each patent obtains around 7.1 non-self-citations. Table 5.2, Panel B presents the correlation of firm-level variables in this sample. Although there is a 0.58 correlation between stock liquidity and total assets, following previous research in this area (e.g., Fang *et al.*, 2014; Wen *et al.*, 2018), we still control total assets in regression. The rest of the variables in this table show a low pairwise correlation between each other.

*** Table 5.2 ***

While we report the firm-level descriptive statistics in Table 5.2, we report the country-level descriptive statistics in Table 5.3. In Table 5.3, Panel A, we report the mean value of the country/region variables used in this study. On average, the US produces the highest GDP (10.589 trillion dollars per year), financial sectors in Japan provides the highest domestic credit (229% of GDP per year), the value of stock traded is largest in Hong Kong (517% of GDP per year). Table 5.2, Panel B shows the correlation of country-level variables in the sample.

*** Table 5.3 ***

5.3.4 Estimation method

This sample contains multilevel data (i.e., firm-level variables and country-level variables). It includes 71,689 firm-year observations of 5,511 firms from 36 countries between 1990 and 2010. According to the literature review, it is also clear that firms' innovative outcomes are affected by both country-level and firm-level factors. Therefore, we follow Greene (2003) and Griffin *et al.* (2019) and employ the HLM approach to separate the firm-level (i.e., within-country) and country-level (i.e., cross-country) impacts of firms' stock liquidity on their innovative performance.

HLM is a complex form of ordinary least squares (OLS) regression (Woltman *et al.*, 2012). We employ this approach in order to distinguish between within-country and cross-country effects (Bryk and Raudenbush, 1992; Goldstein, 2011; Li *et al.*, 2013). While OLS regression equally weights each firm-level observation, the HLM framework weights country-level regression based on the precision of firm-level data rather than the sample size across countries. It adjusts the standard errors to reflect the cross-correlations between firm-level data due to within-country clustering.

Using the HLM approach, variables at the lowest hierarchical level (i.e., level 1) are nested within a higher hierarchical level (i.e., level-2) groups and have in common the impact of level-2 variables (Woltman *et al.*, 2012). In this chapter, following Griffin *et al.* (2019), we employ firm-level variables as the level 1 variables and country-level variables as the level 2 variables. In other words, in our sample, firms (level 1) are situated within countries (level 2). Notably, we measure the patent-based variables at level 1 as the dependent variable is always situated at the lowest hierarchical level in HLM (Castro, 2002).

We estimate the intraclass correlation coefficient (ICC) through a null (or unconditional) model (using $LN\_PAT_{i,t+1}$ as dependent variable) to investigate whether there is a significant variation in the intercept across countries (i.e., whether this research should employ the multilevel model). The ICC ranges from 0 to 1 and represents the proportion of the total variance at level 1 (i.e., firm-level in this research) caused by group membership at level 2 (i.e., country-level in this research) (Anderson, 2012). It is unnecessary to use the HLM if the ICC is lower than 0.055 (Bliese, 2000). In this research, ICC is 0.065, which is larger than 0.055; therefore, we employ the HLM model as a baseline test.

According to Griffin *et al.* (2019), we use the following HLM model,

(5.1a) $$y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t},$$

(5.1b) $$\alpha_c = W_c'\gamma + v_c$$

where $y_{i,c,t+n}$ is the patent-based innovation outcomes of firm i from country c in the year $t + n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t. W_c represents the vector of country-level characteristics of country c shown in Table 5.2. To obtain the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), we remove the country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c.

We employ two information-theoretic indices: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), to access the model fit in this chapter (Schwarz, 1978; Akaike, 1987). They are widely used to decide whether adding predictors represent improvements. A reduction of AIC or BIC tends to represent a more favourable result for the new model (Glaser and Hastings, 2011). The AIC and BIC of our null model separately equal 235,060 and 235,087. We will report these two indicators in the following tables to determine whether new models provide a better fit for the data.

In addition to the HLM approach, we employ the Tobit model as a robustness test in subsection 5.5.1 to consider the non-negative nature of patent counts (Chemmanur and Tian, 2018). As we describe in subsection 4.3.4, not all firms have innovation outputs. Therefore, we employ the Tobit model to obtain the dependent variables that are censored at zero.

5.4 Empirical results

5.4.1 Patent-based measurement

This subsection evaluates the relationship between stock liquidity and firm innovative performance using the HLM approach. We separately examine the impact of stock liquidity on firms' patent quantity, quality, generality index, originality index and efficiency from year $t+1$ to year $t+5$.

5.4.1.1 Patent quantity

In Table 5.4, we investigate the impact of stock liquidity on firms' innovation outputs, which we measure by the number of granted patents over a five year period. We report a positive and significant relationship between the stock liquidity and the number of granted patents from the first to fifth year. Notably, the regression coefficient on stock liquidity grows over time (i.e., there is an increase from 0.04 and 0.06 in year $t+1$ to 0.10 and 0.11 in year $t+5$). This means the improvement of stock liquidity causes a continuously increased positive influence on a firm's innovative activities.

*** Table 5.4 ***

We also find that a firm with an increasing innovation input, measured by a higher R&D-to-assets ratio in year t, will experience a larger innovation output over the coming year. It is reported by other literature in this area (e.g., Fang *et al.*, 2014; Chang *et al.*, 2015; Luong *et al.*, 2017; Zhu and Zhu, 2017; Chemmanur and Tian, 2018). This result means the investment in R&D could improve a firm's ability to produce more patents over the following five year period.

For other firm-level variables in this table, similar to Chapter 4, we show that a firm's innovation outputs are improved by a growth in capital expenditure, growth opportunity and firm size. Moreover, they are impeded by increased leverage ratio and firm age.

Except for this, we show a positive impact of asset tangibility on the number of granted patents. As described above, there are controversial opinions about the relationship between asset tangibility and firm innovation. In this table, our results support Fang *et al.* (2014) and Chemmanur and Tian (2018), who also report this same positive influence. One possible explanation is that tangible assets, such as property, plant and equipment, are more suitable for collateral (Lim *et al.*, 2020) and thereby making it easier to secure funding in order to support the firm's innovative activities.

At country level, we show that firms are encouraged to produce more patents when they are in countries with more developed credit markets. As this chapter only covers public companies, it means that a developed credit market is a powerful tool with which to promote corporate innovation even for listed companies.

We also show that patent quantity is not associated with equity market development. However, this does not necessarily mean the development of the equity market is less associated with the firm's innovative performance. For example, Black and Gilson (1998) suggested that a well-developed equity market (but not a credit market) can indirectly improve innovation by providing a lucrative exit opportunity for venture capital investors. The insignificant relationship maybe because that the PATSTAT database underestimates the number of patents held by public companies. Bernstein (2015) suggests that going public changes a firm's strategy in pursuing innovation. IPO companies tend to achieve patents through acquisitions due to the increased access to capital. However, if a public company achieves patent through acquisition, it is not been recorded in the PATSTAT. Besides, while public companies tend to invest in incremental innovation projects and obtain disruptive innovation through acquisitions, our sample does not include the self-citations (See detailed reason why we not include the self-citations in Step 7 in Appendix 3.2 Measuring the number of applications and number of citations).

Additionally, we report that the quantity of firm innovation increases in countries with a higher level of economic freedom. Similarly, Zhu and Zhu (2017) find that firms are willing to participate in innovative activities when they are in a country with a limited government, a sound and efficient regulatory system, and open markets. We analyse the impact of each of these economic freedom indicators in a later subsection.

In addition, we find that firms in countries with a higher level of economic development and international trading tend to produce more patents in the short term. Larger economies are more likely to provide a better environment for firms to participate in innovation activities. These results support Gorodnichenko *et al.* (2015) and Coelli *et al.* (2016) arguing that trade liberalisation encourages corporate innovation outputs. The first possible explanation is that rising import competition pushes domestic companies to engage in innovation activities and produce more patents (Bloom *et al.*, 2016). The second explanation is that the entry of foreign institutional investors tends to improve a firm's innovation as active monitors provide insurance against innovation failures and transmit foreign technology (Luong *et al.*, 2017). We do not find continuously and/or significant impacts of other country-level indicators on firm innovation outputs in this table.

Overall, the coefficients of stock liquidity in year $t + 1$ are larger in cross-country regression than within-country regression. However, this difference decreased over time (from 0.02 in the year $t + 1$ to 0.01 in the year $t + 5$). Therefore, we argue that while country-level indicators affect firm innovation outputs, they only cause small influences on the relationship between stock liquidity and firm innovation in the long term.

5.4.1.2 Patent quality

In Table 5.5, we report that a firm's stock liquidity improves its quality of innovation output measured by the number of citations made to its patents across a five year period. We show that a firm experiences a higher level of stock liquidity in the year t and produces better quality patents from the year $t + 1$ to $t + 5$. Besides, in comparison to Table 5.4, stock liquidity causes larger impacts on a firm's innovation quality rather than on its quantity in the year $t + 1$ but has a similar impact in the year $t + 5$.

*** Table 5.5 ***

We demonstrate that companies holding more cash can continuously produce higher quality patents over the following five years. This is consistent with the estimation results of Zhu and Zhu (2017). Sufficient cash holding implies that firm can access more easily internal fundings and/or external fundings. Managers in these kind of companies tend to be more confident when facing innovation failures and more willing to participate in innovation activities. This increases the probability that firms will produce high-quality patents.

Similar to Table 5.4, firm innovation quality is improved by the country's credit development level and economic freedom indexes across the following five years, and economy size and international trading level in the short term.

5.4.1.3 Patent generality index

In Table 5.6, we show that a firm's patent generality index will increase following the improvement of its stock liquidity. The patent generality index represents the breadth of applicability of an invention across different technology fields. The greater the index, the more this patent is cited by other patents belonging to a broader range of technology areas. It may be one of the results which increases the quality of the patent. Namely, the patent is cited by other patents in different technological fields because of its high quality.

*** Table 5.6 ***

5.4.1.4 Patent originality index

In Table 5.7, we report the positive relationship between a firm's stock liquidity and its patent originality index. An increasing originality index means the knowledge of its patent comes from a broader range of technology fields. It shows a possible reason why the patent has a higher quality (i.e., is cited by more patents) following the increase of stock liquidity. The knowledge coming from different technology areas improves the quality of the patent and thereby is cited by more parties.

*** Table 5.7 ***

In Tables 5.6 and 5.7, both the patent generality index and the originality index are improved by increased GDP, credit markets and economic freedom indexes. Compared with Table 5.4 and 5.5, these two indicators are not significantly affected by the international trading level. Thus, we argue that the invention breadth embodied in patents is less likely to be affected by the import and export of goods and services into the country.

5.4.1.5 Innovation efficiency

We investigate the relationship between a firm's stock liquidity and its innovative efficiency in Table 5.8 and 5.9. In Table 5.8, we observe the negative impact of stock liquidity on $IE\_PAT_{i,t+n}$ in the year $t+1$ and insignificant impact from the year $t+2$ to the year $t+5$. We observe the significant positive influence of stock liquidity on firm innovation in Table 5.4, which implies that while the firm's R&D investment increases, the number of patent applications does not increase dramatically.

*** Table 5.8 ***

In Table 5.9, we show a continuous positive relationship between stock liquidity and $IE\_CIT_{i,t+n}$ between the year $t+1$ and the year $t+5$. It is important to note that the coefficients of $IE\_CIT_{i,t+n}$ are significantly higher than other patent-based measurements in previous tables. This means that firms become more efficient at producing high-quality patents *after* experiencing a growth of stock liquidity.

*** Table 5.9 ***

According to observations in Tables 5.4, 5.5, 5.8 and 5.9, while stock liquidity increases both LN_PAT_{t+n} and LN_CIT_{t+n}, it only improves $IE\_CIT_{i,t+n}$. In other words, although stock liquidity improves the patent quantity, its main contribution is to the efficient production of high-quality innovations.

We also report that the innovation efficiency would increase from the year *t*+1 and the year *t*+3 after the country cuts the corporate income tax rate. This complements Atanassov and Liu's

(2020) finding and suggests that cutting the corporate tax improve a firm's efficiency to produce high-quality patents.

Overall, stock liquidity improves a firm's innovation ability presented by the patent-based measurements. Most notably, this positive influence grows over time from the year $t + 1$ to the year $t + 5$. To investigate these tables, we argue that while stock liquidity increases the patent quantity, it mainly contributes to efficiency in the production of high-quality patents. One of the possible reasons for the growth in innovation quality is that this firm cite patents in different technology fields. In terms of increasing quality, the firm's patents are also cited on other patents in different fields.

In these six tables, we show that a firm's innovation performance is improved by growth in total assets, R&D investments, capital expenditure, growth opportunity and cash holding. Moreover, they are impeded by an increased leverage ratio. It is different from Chapter 4 that we do not observe significant impacts of growth opportunity and cash holding on innovation outputs in Chapter 4. It may be because we use different samples which cover the different number of companies.

In addition, country-level characters in these six tables cause similar impacts on patent-based indicators. We argue that the development of credit markets and a level of high economic freedom would continuously improve a firm's innovation performance over the following five years. In addition, the size of the economy and trade liberalisation leads to a short term positive influence on firm innovation quantity and quality. Cutting corporate income tax tends to improve firm efficiency to produce high-quality patents. We do not find continuously and/or significant impacts of other country-level indicators on firm innovation outputs.

5.4.2 Economic Freedom

In this subsection, we analyse the impact of economic freedom on corporate innovation from different perspectives. According to Gwartney and Lawson (2003), the EFW index shows the degree to which a country's institutions and policies are consistent with economic freedom. There is an average of around 45 indicators from 5 areas. Each area represents one perspective of a country's economic freedom. In subsection 5.4.1, we observe significantly positive relationships between the EFW index and firm innovation performance through the HLM frameworks. However, we do not know which part of the EFW indexes improves firm innovation. In this subsection, we specifically test the impact of economic freedom.

In Table 5.10, we observe that $EFW\_LSPR_{c,t}$ could continuously improve firm innovation outputs from year $t+1$ to year $t+5$. This means that firms are continuously encouraged to produce more patents when they are in a country with better protection of persons and their rightfully acquired property. As we described in Chapter 4, innovative firms feel they have to make only a partial disclosure because information about their invention(s) may benefit their competitors (Cumming *et al.*, 2020). In terms of this, they are more prone to be misvalued by investors (Cohen *et al.*, 2013) and face the potential threats of short-term institutional investors and hostile takeovers (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). Countries with better protection of property rights could overcome this problem and encourage firms to disclose detailed information about their innovation activities. Under such conditions, increased stock liquidity could facilitate the entry of long-term and/or strategic institutional investors (Wen *et al.*, 2018), thereby improving firm innovation performance.

*** Table 5.10 ***

In addition, we find countries with smaller government expenditures, enterprises, and tax ($EFW\_SG_{c,t}$) or lower and less volatile inflation ($EFW\_SM_{c,t}$) could encourage firms to produce more patents from year $t + 1$ to year $t + 3$.

Countries with a higher degree of freedom to exchange with foreigners (i.e., $EFW\_FTI_{c,t}$); or fewer restrictions on exchange in credit, labour, and product markets (i.e., $EFW\_R_{c,t}$) could also improve firms' innovation quantity. However, these influences only exist in the following years.

In summary, we support Zhu and Zhu (2017) that more economic freedom enhances firm innovation. In addition, while all EFW indicators could lead to positive impacts on firm innovation outputs, we have specifically emphasised the importance of protection of property rights and access to sound money, as they could cause positive influences over a longer period than other indicators.

5.5 Robustness results

In this section, we take alternative models and variables to ensure the robustness of our empirical result. Overall, we make firm the result of our analysis in Section 4.

5.5.1 Tobit model

Following Fang *et al.* (2014), we employ a Tobit model as a robustness test on the relationship between stock liquidity and the number of patents. In Table 5.11, we find that the stock liquidity would significantly improve the firm's patent counts from year $t+1$ to year $t+5$. These influences increase over the years, which is similar to the resultgained using HLM in Table 5.4.

*** Table 5.11 ***

For country characters, we find that GDP and international trading have longer-term impacts on patent counts in this table than in Table 5.4. The increased economic freedom index still leads to positive impacts on firm innovation outputs. In this Table, however, this positive impact only exists across the following three years. We do not observe the continuous impacts of credit markets on firm innovation.

Except for these, we observe longer-term significant relationships between country-level variables and firm's patent quantity in this table than in Table 5.4. For example, while we find a negative but insignificant relationship between stock market development and patent quantity in Table 5.4, we show a negative and significant relationship between them in Table 5.11.

Besides, while we observe a positive impact of corporate tax on a firm's patent quantity in the next year in Table 5.4, there is a continuous positive relationship between them from year $t+1$ to year $t+3$ in Table 5.11. A possible explanation is companies devote more money to R&D

activities in countries with higher corporate tax rates due to the R&D tax relief. It improves a firm's ability to produce more patents but impedes its ability to produce higher-quality patents.[54]

In addition, while the coefficient of secrecy indicator on patent counts is close to 0 but insignificant in Table 5.4, it is close to 0 and significant in this table. Therefore, we argue that this table supports our estimation results of secrecy indicators using the HLM approach in subsection 5.4.1.

Overall, the Tobit model supports our analysis results obtaining from the HLM framework in subsection 5.4.1. We show the increased positive impacts of stock liquidity on firm innovation performance. In addition, we support that firms could produce more patents in larger economies where this is a higher level of international trading and economic freedom.

5.5.2 R&D expenditure

This subsection uses R&D expenditure as an alternative variable of the firm's patent-based measurement. It displays the input of the innovative process. In Table 5.12, we represent the R&D expenditure as the natural logarithm of the firm's R&D investment in the year t, $t+1$, $t+2$, $t+3$ and $t+5$, respectively. In this table, we observe that firms increase R&D investments following a rise in their stock liquidity. Moreover, this influence gradually expands with the year.

*** Table 5.12 ***

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[54] There is a negative relationship between increased corporate income tax and firms' efficiency to produce high-quality patents in Table 5.9.

5.6 Chapter Conclusion

In this chapter, we employ the HLM method to investigate a global sample of 71,689 firm-year observations from 5,511 companies across 36 countries from 1990 to 2010. Compared with the latter, our research provides within- and cross-country evidence of the effect of stock liquidity on firm innovation over a more extended period. These evidences support the positive relationship between stock liquidity and firm innovation performance. This enhances our arguments in Chapter 4 wherein there is an increased positive influence of stock liquidity on firm patents' quality, quantity, generality index and originality index. In addition, by using this much larger sample, we find that while other firm-level factors, such as firm size, market-to-book ratio and leverage, cause a stable level effect on a firm's innovation performance, the positive influence of stock liquidity on firm innovation increases over the following five years.

Our main findings in this chapter come from the perspective of innovation efficiency. We find that while increased stock liquidity improves a firm's innovation performance, and it mainly contributes to firms' efficiency of producing high-quality patents rather than more patents. One of the explanations for this is the increased patent originality index following improved stock liquidity. Firms produce high-quality patents by acquiring knowledge from a wider range of technology areas. And as a result, their patents tend to be cited by other patents belonging to a broader range of technology areas.

In addition, from the country character's perspective, we successfully argue that firms could produce more patents in larger economies with a higher level of international trading and economic freedom. For economic freedom levels across five different areas, we find that countries with better protection of persons and their rightfully acquired property would improve firm innovation performance over a longer period than other areas.

According to these results, we contribute to the debate on whether stock liquidity improves or impedes firm innovation. While we support Wen *et al.* (2018)'s opinion that increased stock liquidity improves firm innovation, our study includes more patent-based measurements to deeply analyse the impact of stock liquidity on firm innovation performance. Moreover, we provide evidence that policymakers could encourage innovation performance through increased stock liquidity. Innovation could benefit the development of the economy as it plays an essential role in improving economic growth. In addition to this, we suggest that investors could allocate more investments to stock exchanges with higher liquidity, and public companies should be encouraged to continue their R&D activities following policies that increase stock liquidity.

Table 5.1 Variable definitions

Variable	Definition
Panel A: Dependent variable	
$IE_{i,t+n}$	$IE_{i,t+n}$ is represented as 1) the ratio of patents scaled by the natural logarithm of R&D investment in the year $t+1$, $t+2$, $t+3$ and $t+5$ respectively. $$IE\_PAT_{i,t+n} = \frac{PAT_{i,t+n}}{LN(R\&D_{i,t+n})}$$ 2) the ratio of citation scaled by the natural logarithm of R&D investment in the year $t+1$, $t+2$, $t+3$ and $t+5$ respectively. $$IE\_CIT_{i,t+n} = \frac{CIT_{i,t+n}}{LN(R\&D_{i,t+n})}$$
Panel B: Country-level control variables	
$LN\_GDP_{c,t}$	The size of the economy, Gross Domestic Product ($GDP_{c,t}$), defined as the natural logarithm of the GPD of country c, measured at the end of year t. (Data source: World Development Indicators (WDI))
$Equity_{c,t}$	Domestic stock market capitalisation, $Equity_{c,t}$, is the trading value of shares traded in country c scaled by country c's GDP in year t. The trading value of shares is equal to the total number of domestic and foreign shares traded in country c, multiplied by their respective matching prices. Only one side of the transaction is considered in the calculation. (Data source: World Development Indicators (WDI))
$Credit_{c,t}$	Domestic credit market capitalisation, $Credit_{c,t}$, is the ratio of domestic credit provided by financial sectors in country c to country c's GDP in year t. Domestic credit provided by the financial sector include all credit to various sectors on a gross basis as well as the net credit to the central government (see more detail information in https://data.worldbank.org/indicator/FS.AST.DOMS.GD.ZS). The ratio shows development of financial sector and depth of banking sector in terms of size. (Data source: World Development Indicators (WDI))
$Trade_{c,t}$	The intensity of international trade, $Trade_{c,t}$, computed as the import and export of goods and services as a fraction of country c's GDP in year t. (Data source: World Development Indicators (WDI))

$Inflation_{c,t}$	Inflation rate, $Inflation_{c,t}$, computed as the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. (Data source: World Development Indicators (WDI)).
$CTR_{c,t}$	The corporate income tax rate, $CTR_{c,t}$, as the corporate income tax rate in country c in the year t. Following Atanassov and Liu (2020), this chapter represents the corporate income tax rate via the actual change in it in the year (Data source: Tax Foundation).
$EDU_{c,t}$	Education rate, $EDU_{c,t}$, represents the level of country c's educational attainment in the year t. It is the ratio of the population (age 15 and over) that have at least completed tertiary education in the year t (Data source: Barro and Lee, 2013).
$EFW_{c,t}$	Economic freedom of the world index, $EFW_{c,t}$, refers to the degree to which a country's institutions and policies are consistent with economic freedom. The higher score represents a higher level of economic freedom in the country. It is the summary of five indicators, which are 'Size of Government' (i.e., $EFW\_SG_{c,t}$), 'Legal System and Property Rights' (i.e., $EFW\_LSPR_{c,t}$), 'Sound Money' (i.e.,$EFW\_SM_{c,t}$), 'Freedom to Trade Internationally' (i.e.,$EFW\_FTI_{c,t}$) and 'Regulation' (i.e.,$EFW\_R_{c,t}$). These five indicators separately represent countries' economic freedom level in one area. According to Gwartney (2017), for 'Size of Government', countries with low levels of government spending as a share of the total, a smaller government enterprise sector, and lower marginal tax rates earn the higher ratings in this area. For 'Legal System and Property Rights', countries with better protection of persons and their rightfully acquired property earn the higher ratings in this area. For 'Sound Money', countries can easier access the sound money earn higher ratings in this area. It is because inflation erodes the value of rightfully earned wages and savings. Sound money is thus essential to protect property rights. When inflation is not only high but also volatile, it becomes difficult for individuals to plan for the future and thus use economic freedom effectively. For 'Freedom to Trade Internationally', countries have fewer restrictions for their businesses and individuals to freedom exchange (e.g., buying, selling, making contracts) with businesses and individuals in other nations earn higher ratings in this

	area. For 'Regulation', countries with fewer restriction on exchange in credit, labour, and product markets earn higher ratings in this area.
$SEC_{c,t}$	Secrecy indicator, SEC_c, based on Hofstede's (1980) national culture indicators. It is measured as below, $$SEC_c = UA_c + PD_c - IND_c$$ Where UA_c represents the uncertainty avoidance score of country c, PD_c represents power distance score of country c and IND_c represents individualism score of country c (Hofstede, 1980). According to Hofsted et al. (2010), a country with a higher UA_c is more concerned with threats from ambiguous or unknown situations, with a higher PD_c means people in the country are more acceptable to follow a hierarchical order and less likely to break down power barriers; with a high scores of IND_c means people in this country only care about themselves and their own family.

Table 5.2 Firm-Level Descriptive Statistics

Table 5.2 shows the descriptive statistics for the firm-level variables in our analysis. The sample contains 71,689 observations, which includes 5,511 companies from 36 countries during the period between 1990 and 2010. The definition of variables is listed in Table 4.1 and Table 5.1, Panel A. All firm-level variables are winsorised at top and bottom 1% of variables' distribution. Panel A shows the summary statistics of firm-level variables. Panel B represents the pairwise correlations between firm variables after removing country-means. ***, **, * represents significance at 1%, 5% and 10%, respectively.

Panel A. Summary Statistics of Firm-Level Variables

Variables	N	Mean	St.Dev	p5	Median	p95
LN_PAT	71,689	1.17	1.44	0.00	0.69	4.29
LN_CIT	71,689	0.73	1.26	0.00	0.00	3.58
LN_GENERAL	71,689	0.36	0.77	0.00	0.00	2.13
LN_ORIGINAL	71,689	0.35	0.75	0.00	0.00	2.07
IE_PAT	69,264	7.84	3.02	2.74	7.90	12.69
IE_CIT	65,097	13.00	2.01	9.89	12.85	16.67
LIQUIDITY	63,343	0.57	0.37	0.09	0.51	1.27
LN_TA	65,032	0.21	0.18	0.00	0.19	0.54
PPETA	60,475	0.05	0.05	0.01	0.04	0.15
LEV	47,496	0.06	0.10	0.00	0.03	0.24
CAPEXTA	64,229	1.95	1.73	0.74	1.37	5.21
RDTA	71,689	2.43	0.79	1.10	2.49	3.56
Q	47,502	0.12	0.13	0.01	0.08	0.37
LN_AGE	62,951	0.01	0.17	-0.33	0.04	0.17
CASH	47,502	0.12	0.13	0.01	0.08	0.37
ROA	62,951	0.01	0.17	-0.33	0.04	0.17

Table 5.2 (continued)

Firm-level Descriptive Statistics

Panel B. Correlation of Firm-Level Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) LIQUIDITY	1									
(2) LN_TA	0.58***	1								
(3) PPETA	-0.03***	0.24***	1							
(4) LEV	0.06***	0.27***	0.25***	1						
(5) CAPEXTA	0.10***	0.06***	0.37***	0.09***	1					
(6) RDTA	-0.14***	-0.38***	-0.26***	-0.21***	-0.08***	1				
(7) Q	0.10***	-0.23***	-0.27***	-0.21***	0.04***	0.42***	1			
(8) LN_AGE	0.17***	0.44***	0.29***	0.14***	-0.11***	-0.23***	-0.24***	1		
(9) CASH	-0.07***	-0.26***	-0.31***	-0.28***	-0.18***	0.36***	0.28***	-0.18***	1	
(10) ROA	0.24***	0.33***	0.12***	0	0.14***	-0.62***	-0.20***	0.14***	-0.28***	1

Table 5.3 Country-Level Descriptive Statistics

Table 5.2 presents the descriptive statistics for country-characteristics variables in this sample; the definition of these variables is shown in Table 5.1, Panel B. Panel A shows the summary statistics of country-level variables. Panel B represents the pairwise correlations between firm variables after removing country-means.***,**,* represents significance at 1%, 5% and 10%, respectively.

Panel A. Summary Statistics of Country-Level Variables

Country_Name	GDP	Credit	Equity	Trade	Inflation	EFW	CTR	EDU	SEC	no_obs
AUSTRALIA	27.05	1.11	1.04	0.40	0.03	8.16	0.32	0.16	-1.00	905
AUSTRIA	26.29	1.25	0.23	0.84	0.02	7.73	0.31	0.07	26.00	271
BELGIUM	26.51	1.10	0.59	1.36	0.02	7.61	0.37	0.16	84.00	271
BRAZIL	27.39	0.83	0.53	0.22	3.51	5.61	0.31	0.04	107.00	232
CANADA	27.50	1.21	1.21	0.69	0.02	8.19	0.39	0.16	7.00	2,006
CHINA	28.56	1.30	0.56	0.51	0.04	6.02	0.30	0.03	90.00	3,096
CZECH REPUBLIC	24.95	0.54	0.16	0.90	0.07	6.72	0.35	0.05	73.00	107
DENMARK	26.10	1.43	0.46	0.83	0.02	7.93	0.30	0.13	-33.00	361
FINLAND	25.88	0.99	1.19	0.72	0.02	7.92	0.28	0.11	29.00	401
FRANCE	28.21	1.21	0.66	0.50	0.02	7.41	0.36	0.08	83.00	2,715

GERMANY	28.53	1.35	0.40	0.60	0.01	7.84	0.46	0.10	33.00	3,211
GREECE	26.04	1.09	0.51	0.50	0.04	7.04	0.33	0.17	125.00	59
HONG KONG	25.84	1.42	5.17	2.91	0.01	8.93	0.17	0.13	72.00	104
HUNGARY	25.06	0.66	0.24	1.23	0.10	7.09	0.19	0.11	48.00	33
INDIA	27.16	0.56	0.83	0.33	0.07	6.26	0.37	0.04	69.00	726
IRELAND	25.92	1.80	0.53	1.60	0.02	8.06	0.16	0.21	-7.00	16
ITALY	28.08	1.18	0.45	0.47	0.03	7.32	0.40	0.05	49.00	899
JAPAN	29.14	2.29	0.71	0.22	0.00	7.84	0.44	0.16	100.00	17,948
MALAYSIA	25.81	1.24	1.38	1.89	0.05	6.60	0.27	0.05	110.00	9
MEXICO	27.10	0.36	0.26	0.48	0.15	6.54	0.33	0.07	133.00	28
NETHERLANDS	27.02	1.72	0.88	1.17	0.02	7.88	0.32	0.13	11.00	194
NEW ZEALAND	25.27	1.25	0.35	0.60	0.03	8.46	0.32	0.17	-8.00	82
NORWAY	26.13	0.84	0.45	0.71	0.04	7.58	0.29	0.10	12.00	251
PHILIPPINES	25.18	0.50	0.47	0.86	0.08	6.83	0.34	0.06	106.00	21
POLAND	26.46	0.47	0.28	0.71	0.04	6.88	0.23	0.09	101.00	71

RUSSIAN FEDERATION	27.47	0.28	0.62	0.55	0.17	6.12	0.24	0.22	149.00	158
SINGAPORE	25.44	0.72	1.82	3.69	0.02	8.63	0.23	0.15	62.00	163
SOUTH AFRICA	25.84	0.68	1.74	0.49	0.09	6.40	0.40	0.00	.	175
SOUTH KOREA	27.26	1.11	0.58	0.71	0.03	7.19	0.28	0.21	127.00	5,486
SPAIN	27.42	1.76	0.63	0.50	0.04	7.46	0.34	0.11	92.00	426
SWEDEN	26.54	0.96	0.84	0.78	0.02	7.64	0.29	0.14	-11.00	759
SWITZERLAND	26.61	1.62	1.93	0.95	0.01	8.49	0.25	0.12	24.00	768
TAIWAN	.	.	.	.	.	7.43	0.24	0.07	110.00	3,878
THAILAND	25.96	1.20	0.55	1.20	0.03	6.76	0.30	0.08	108.00	26
UNITED KINGDOM	28.22	1.33	1.17	0.51	0.03	8.36	0.31	0.13	-19.00	2,083
UNITED STATES	29.94	0.85	1.13	0.24	0.02	8.47	0.39	0.23	-5.00	23,750
Mean (firm-year level)	28.84	1.37	0.89	0.39	0.03	7.87	0.38	0.16	51.18	
Mean (country-level)	26.78	1.04	0.89	0.84	0.17	7.42	0.32	0.11	56.61	

Table 5.3 (continued)

Country-Level Descriptive Statistics

Panel B. Correlation of Country-Level Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) LN_GDP	1								
(2) Credit	0.02***	1							
(3) Equity	0.23***	-0.26***	1						
(4) Trade	-0.66***	-0.14***	0.14***	1					
(5) Inflation	-0.05***	-0.03***	-0.01**	-0.01**	1				
(6) EFW	0.49***	-0.15***	0.54***	-0.20***	-0.13***	1			
(7) CTR	0.43***	0.39***	-0.18***	-0.57***	-0.05***	0.26***	1		
(8) EDU	0.54***	-0.19***	0.36***	-0.20***	-0.06***	0.65***	0.13***	1	
(9) SEC	-0.36***	0.64***	-0.46***	0.11***	0.02***	-0.66***	-0.08***	-0.40***	1

Table 5.4 Stock Liquidity and Innovation measured by LN_PAT_{t+n}: HLM

Dependent variable	LN_PAT_{t+1}			LN_PAT_{t+2}			LN_PAT_{t+3}			LN_PAT_{t+5}		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		0.04***	0.06***		0.05***	0.07***		0.06***	0.08***		0.10***	0.11***
		[0.00]	[0.00]		[0.00]	[0.01]		[0.01]	[0.01]		[0.01]	[0.01]
LN_TA		0.57***	0.55***		0.56***	0.53***		0.55***	0.52***		0.52***	0.51***
		[0.01]	[0.01]		[0.01]	[0.01]		[0.01]	[0.01]		[0.01]	[0.01]
PPETA		0.13***	0.15***		0.16***	0.18***		0.17***	0.19***		0.18***	0.20***
		[0.03]	[0.03]		[0.03]	[0.03]		[0.03]	[0.04]		[0.04]	[0.04]
LEV		-0.40***	-0.34***		-0.41***	-0.37***		-0.39***	-0.34***		-0.36***	-0.28***
		[0.05]	[0.05]		[0.05]	[0.05]		[0.05]	[0.06]		[0.06]	[0.07]
CAPEXTA		2.19***	2.20***		2.11***	2.07***		2.33***	2.35***		2.42***	2.45***
		[0.19]	[0.21]		[0.20]	[0.23]		[0.22]	[0.24]		[0.25]	[0.28]
RDTA		3.16***	2.89***		3.14***	2.85***		3.32***	3.03***		3.84***	3.54***

	[0.11]	[0.11]	[0.12]	[0.12]	[0.14]	[0.14]	[0.17]	[0.17]
Q	0.08***	0.07***	0.08***	0.07***	0.08***	0.07***	0.07***	0.06***
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
LN_AGE	-0.10***	-0.06***	-0.11***	-0.07***	-0.10***	-0.06***	-0.10***	-0.07***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
CASH	0.28***	0.30***	0.33***	0.33***	0.31***	0.31***	0.18	0.17
	[0.06]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.09]	[0.09]
ROA	0.35***	0.21***	0.48***	0.33***	0.56***	0.39***	0.63***	0.42***
	[0.06]	[0.06]	[0.06]	[0.06]	[0.07]	[0.07]	[0.08]	[0.08]
Country Characteristics								
LN_GDP		0.31***		0.16*		0.05		0.11
		[0.07]		[0.07]		[0.08]		[0.09]
Credit		0.27***		0.45***		0.63***		0.62***
		[0.07]		[0.07]		[0.08]		[0.10]
Equity		-0.02		-0.04		-0.04		-0.09
		[0.04]		[0.04]		[0.04]		[0.06]

Trade			0.41**			0.34*			0.17			0.22
			[0.14]			[0.13]			[0.14]			[0.15]
Inflation			-0.64			1.29			2.02*			-2.05
			[0.80]			[0.91]			[1.00]			[1.18]
EFW			0.34***			0.28***			0.27***			0.22*
			[0.06]			[0.07]			[0.07]			[0.09]
CTR			1.07*			0.9			0.65			0.79
			[0.45]			[0.48]			[0.57]			[0.66]
EDU			0.26			0.97			-0.58			-4.51***
			[0.69]			[0.80]			[1.06]			[1.18]
SEC			0			0			0			0
			[0.00]			[0.00]			[0.00]			[0.00]
Country Fixed effects		Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	66,178	29,921	26,087	60,831	26,998	23,622	55,592	24,068	21,017	45,647	18,552	16,146

AIC	235,060	96,390	82,858	217,116	87,491	75,478	199,511	78,493	67,527	165,657	61,344	52,577
BIC	235,087	97,486	83,724	217,143	88,566	76,325	199,538	79,528	68,338	165,683	62,315	53,331

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately LN_PAT_{t+1}, LN_PAT_{t+2}, LN_PAT_{t+3} and LN_PAT_{t+5} of firm i from country c in the year $t + n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on LN_PAT_{t+4} and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.5 Stock Liquidity and Innovation measured by LN_CIT_{t+n}: HLM

Dependent variable	LN_CIT_{t+1}			LN_CIT_{t+2}			LN_CIT_{t+3}			LN_CIT_{t+5}		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		0.06***	0.07***		0.07***	0.08***		0.08***	0.09***		0.10***	0.11***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.01]		[0.01]	[0.01]
LN_TA		0.42***	0.42***		0.41***	0.41***		0.40***	0.40***		0.38***	0.38***
		[0.01]	[0.01]		[0.01]	[0.01]		[0.01]	[0.01]		[0.01]	[0.01]
PPETA		0.05	0.04		0.07*	0.06*		0.05	0.05		0.04	0.05
		[0.03]	[0.03]		[0.03]	[0.03]		[0.03]	[0.03]		[0.03]	[0.04]
LEV		-0.40***	-0.34***		-0.40***	-0.34***		-0.39***	-0.34***		-0.33***	-0.28***
		[0.04]	[0.04]		[0.04]	[0.05]		[0.05]	[0.05]		[0.06]	[0.06]
CAPEXTA		2.22***	2.35***		2.22***	2.36***		2.45***	2.53***		2.59***	2.73***
		[0.17]	[0.19]		[0.18]	[0.21]		[0.19]	[0.22]		[0.22]	[0.25]
RDTA		2.54***	2.45***		2.55***	2.43***		2.69***	2.57***		3.12***	2.96***

	[0.10]	[0.10]	[0.11]	[0.11]	[0.12]	[0.12]	[0.15]	[0.15]
Q	0.07***	0.06***	0.07***	0.06***	0.06***	0.06***	0.06***	0.05***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
LN_AGE	-0.06***	-0.04***	-0.07***	-0.04***	-0.06***	-0.04**	-0.07***	-0.05**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
CASH	0.30***	0.36***	0.34***	0.38***	0.31***	0.34***	0.21*	0.23**
	[0.06]	[0.06]	[0.06]	[0.06]	[0.07]	[0.07]	[0.08]	[0.08]
ROA	0.32***	0.21***	0.43***	0.30***	0.47***	0.32***	0.56***	0.38***
	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.06]	[0.07]	[0.07]
Country Characteristics								
LN_GDP		0.18**		0.08		0.06		0.07
		[0.06]		[0.07]		[0.07]		[0.08]
Credit		0.41***		0.54***		0.53***		0.46***
		[0.06]		[0.07]		[0.07]		[0.09]
Equity		-0.05		-0.04		-0.09*		-0.15**
		[0.04]		[0.04]		[0.04]		[0.06]

Trade			0.27*			0.25*			0.23			0.29*
			[0.12]			[0.13]			[0.13]			[0.14]
Inflation			0.88			1.3			0.56			-1.96
			[0.72]			[0.83]			[0.91]			[1.06]
EFW			0.28***			0.20**			0.22***			0.23**
			[0.06]			[0.06]			[0.07]			[0.08]
CTR			-0.73			-0.87*			-0.51			0.47
			[0.40]			[0.44]			[0.52]			[0.59]
EDU			0.81			0.66			-0.37			-2.29*
			[0.63]			[0.74]			[0.97]			[1.06]
SEC			0			0			0			0
			[0.00]			[0.00]			[0.00]			[0.00]
Country Fixed effects		Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	66,178	29,921	26,087	60,831	26,998	23,622	55,592	24,068	21,017	45,647	18,552	16,146

AIC	214,101	89,727	78,024	197,757	81,340	70,990	181,557	72,797	63,464	150,273	56,590	49,210
BIC	214,128	90,823	78,890	197,784	82,414	71,837	181,584	73,832	64,275	150,299	57,560	49,964

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately LN_CIT_{t+1}, LN_CIT_{t+2}, LN_CIT_{t+3} and LN_CIT_{t+5} of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on LN_CIT_{t+4} and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.6 Stock Liquidity and Innovation measured by $LN\_GENERAL_{t+n}$: HLM

Dependent variable	$LN\_GENERAL_{t+1}$			$LN\_GENERAL_{t+2}$			$LN\_GENERAL_{t+3}$			$LN\_GENERAL_{t+5}$		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		0.04***	0.04***		0.04***	0.04***		0.05***	0.05***		0.06***	0.06***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]
LN_TA		0.26***	0.27***		0.26***	0.26***		0.25***	0.26***		0.24***	0.25***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.01]	[0.01]
PPETA		0.02	0.02		0.03	0.02		0.01	0.01		0	0
		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.03]
LEV		-0.25***	-0.23***		-0.25***	-0.23***		-0.26***	-0.23***		-0.24***	-0.21***
		[0.03]	[0.03]		[0.03]	[0.03]		[0.03]	[0.03]		[0.04]	[0.04]
CAPEXTA		1.13***	1.22***		1.17***	1.29***		1.37***	1.52***		1.38***	1.54***
		[0.11]	[0.13]		[0.12]	[0.14]		[0.13]	[0.15]		[0.15]	[0.17]
RDTA		1.53***	1.52***		1.53***	1.51***		1.61***	1.58***		1.87***	1.82***

	[0.06]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.10]	[0.10]
Q	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LN_AGE	-0.01	0	-0.01	0	-0.01	0	-0.02	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
CASH	0.15***	0.16***	0.17***	0.18***	0.14**	0.15**	0.08	0.09
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.06]
ROA	0.10**	0.05	0.15***	0.09*	0.17***	0.10*	0.21***	0.12*
	[0.03]	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]
Country Characteristics								
LN_GDP		0.08*		0.06		0.02		0.02
		[0.04]		[0.04]		[0.04]		[0.05]
Credit		0.35***		0.40***		0.40***		0.33***
		[0.04]		[0.04]		[0.05]		[0.06]
Equity		-0.04		-0.04		-0.04		-0.04
		[0.02]		[0.03]		[0.03]		[0.04]

Trade			0.11			0.12			0.06			0.07
			[0.08]			[0.08]			[0.08]			[0.09]
Inflation			1.02*			1.03			0.28			-0.6
			[0.48]			[0.55]			[0.60]			[0.71]
EFW			0.21***			0.16***			0.15***			0.14**
			[0.04]			[0.04]			[0.04]			[0.05]
CTR			-0.14			-0.17			0.17			0.42
			[0.27]			[0.29]			[0.34]			[0.39]
EDU			0.63			0.49			0.18			-0.65
			[0.41]			[0.48]			[0.63]			[0.69]
SEC			0			0			0			0
			[0.00]			[0.00]			[0.00]			[0.00]
Country Fixed effects		Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	66,178	29,921	26,087	60,831	26,998	23,622	55,592	24,068	21,017	45,647	18,552	16,146

AIC	150,928	64,098	56,173	140,111	58,450	51,394	129,273	52,589	46,195	107,942	41,503	36,434
BIC	150,955	65,195	57,039	140,138	59,525	52,241	129,299	53,624	47,006	107,968	42,474	37,187

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately $LN\_GENERAL_{t+1}$, $LN\_GENERAL_{t+2}$, $LN\_GENERAL_{t+3}$ and $LN\_GENERAL_{t+5}$ of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on $LN\_GENERAL_{t+4}$ and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.7 Stock Liquidity and Innovation measured by $LN\_ORIGINAL_{t+n}$: HLM

Dependent variable	$LN\_ORIGINAL_{t+1}$			$LN\_ORIGINAL_{t+2}$			$LN\_ORIGINAL_{t+3}$			$LN\_ORIGINAL_{t+5}$		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		0.03***	0.03***		0.04***	0.04***		0.04***	0.04***		0.06***	0.05***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]
LN_TA		0.28***	0.28***		0.28***	0.28***		0.27***	0.27***		0.26***	0.27***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.01]	[0.01]
PPETA		0.04*	0.04*		0.04*	0.04*		0.04	0.03		0.02	0.01
		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.03]
LEV		-0.27***	-0.24***		-0.28***	-0.24***		-0.27***	-0.23***		-0.26***	-0.22***
		[0.03]	[0.03]		[0.03]	[0.03]		[0.03]	[0.03]		[0.04]	[0.04]
CAPEXTA		1.08***	1.13***		1.15***	1.27***		1.26***	1.42***		1.42***	1.57***
		[0.11]	[0.13]		[0.12]	[0.14]		[0.13]	[0.15]		[0.15]	[0.17]
RDTA		1.52***	1.49***		1.53***	1.49***		1.63***	1.59***		1.94***	1.90***

	[0.07]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.10]	[0.10]
Q	0.04***	0.03***	0.04***	0.04***	0.04***	0.03***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LN_AGE	-0.02**	-0.01	-0.03***	-0.01	-0.03***	-0.01	-0.03**	-0.02*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
CASH	0.15***	0.18***	0.18***	0.20***	0.16***	0.18***	0.07	0.08
	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.06]	[0.06]
ROA	0.08*	0.03	0.12***	0.06	0.16***	0.09*	0.20***	0.12*
	[0.03]	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]
Country Characteristics								
LN_GDP		0.12**		0.03		-0.01		-0.02
		[0.04]		[0.04]		[0.04]		[0.05]
Credit		0.30***		0.36***		0.40***		0.39***
		[0.04]		[0.04]		[0.05]		[0.06]
Equity		-0.05*		-0.04		-0.05		-0.02
		[0.02]		[0.03]		[0.03]		[0.04]

Trade			0.1			0.02			0.01			0.02
			[0.08]			[0.07]			[0.08]			[0.09]
Inflation			-0.29			1.02			1.54*			-0.59
			[0.48]			[0.55]			[0.60]			[0.71]
EFW			0.25***			0.18***			0.15***			0.07
			[0.04]			[0.04]			[0.04]			[0.05]
CTR			0.23			0.2			0.44			0.45
			[0.27]			[0.28]			[0.34]			[0.39]
EDU			0.68			1.04*			1.16			-1.08
			[0.41]			[0.47]			[0.61]			[0.70]
SEC			0			0			0			0
			[0.00]			[0.00]			[0.00]			[0.00]
Country Fixed effects		Yes		Yes					Yes			
Industry Fixed effects		Yes	Yes	Yes	Yes		Yes		Yes			
Year Fixed effects		Yes	Yes	Yes	Yes		Yes		Yes			
No. of observations	66,178	29,921	26,087	60,831	26,998	23,622	55,592	24,068	21,017	45,647	18,552	16,146

AIC	150,558	64,472	56,050	140,724	59,023	51,438	130,194	53,265	46,340	109,130	42,033	36,505
BIC	150,586	65,568	56,916	140,751	60,098	52,285	130,221	54,300	47,151	109,156	43,004	37,259

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately $LN\_ORIGINAL_{t+1}$, $LN\_ORIGINAL_{t+2}$, $LN\_ORIGINAL_{t+3}$ and $LN\_ORIGINAL_{t+5}$ of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on $LN\_ORIGINAL_{t+4}$ and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.8 Stock Liquidity and Innovation measured by IE_PAT_{t+n}: HLM

Dependent variable	IE_PAT_{t+1}			IE_PAT_{t+2}			IE_PAT_{t+3}			IE_PAT_{t+5}		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		-0.10***	-0.08**		-0.07**	-0.04		-0.03	-0.01		0.04	0.05
		[0.02]	[0.02]		[0.02]	[0.03]		[0.03]	[0.03]		[0.03]	[0.03]
LN_TA		2.25***	2.19***		2.27***	2.19***		2.30***	2.24***		2.32***	2.30***
		[0.03]	[0.04]		[0.04]	[0.04]		[0.04]	[0.04]		[0.05]	[0.05]
PPETA		-0.05	-0.09		-0.01	0		-0.06	-0.01		-0.21	-0.03
		[0.14]	[0.15]		[0.16]	[0.17]		[0.17]	[0.18]		[0.20]	[0.22]
LEV		-2.34***	-2.22***		-2.49***	-2.43***		-2.57***	-2.58***		-2.93***	-2.91***
		[0.23]	[0.24]		[0.25]	[0.26]		[0.28]	[0.28]		[0.33]	[0.34]
CAPEXTA		11.12***	9.74***		10.88***	9.62***		12.20***	11.00***		13.85***	12.07***
		[0.97]	[1.07]		[1.03]	[1.14]		[1.13]	[1.24]		[1.32]	[1.47]
Q		0.33***	0.28***		0.34***	0.29***		0.35***	0.30***		0.33***	0.29***

	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
LN_AGE	0.03	0.12	-0.04	0.08	-0.08	0.05	-0.14	-0.03
	[0.07]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.09]	[0.09]
CASH	1.07**	0.73*	1.03**	0.71*	0.78*	0.51	0.47	0.21
	[0.33]	[0.33]	[0.36]	[0.36]	[0.40]	[0.40]	[0.49]	[0.49]
ROA	-3.86***	-4.10***	-3.80***	-4.09***	-3.89***	-4.29***	-3.85***	-4.50***
	[0.24]	[0.25]	[0.26]	[0.26]	[0.29]	[0.29]	[0.36]	[0.36]
Country Characteristics								
LN_GDP		-0.23		-0.49		-0.67		-0.43
		[0.30]		[0.31]		[0.35]		[0.41]
Credit		1.49***		1.83***		2.14***		1.70***
		[0.34]		[0.35]		[0.40]		[0.51]
Equity		0.29		0.3		0.27		0.05
		[0.20]		[0.21]		[0.23]		[0.33]
Trade		-0.38		-0.55		-0.9		-0.7
		[0.56]		[0.58]		[0.64]		[0.74]

Inflation			0.51			0.93			2.46			-9.31
			[4.01]			[4.68]			[5.22]			[6.31]
EFW			0.92**			0.62			0.52			0.69
			[0.31]			[0.33]			[0.36]			[0.45]
CTR			2.13			-0.17			-4.2			-3.62
			[2.17]			[2.32]			[2.80]			[3.30]
EDU			0.47			2.64			-3.8			-12.82*
			[3.28]			[3.84]			[5.20]			[5.94]
SEC			0.01			0.01			0.01			0.01
			[0.01]			[0.01]			[0.01]			[0.01]
Country Fixed effects		Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	43,396	28,795	25,034	40,655	26,153	22,827	37,819	23,595	20,546	32,042	18,747	16,276
AIC	282,441	184,620	159,407	265,517	168,764	146,080	248,600	153,831	132,644	212,666	124,091	106,718
BIC	282,467	185,695	160,228	265,543	169,810	146,883	248,626	154,848	133,413	212,691	125,040	107,442

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W'_c\gamma + v_c$. where $y_{i,c,t+n}$ are separately IE_PAT_{t+1}, IE_PAT_{t+2}, IE_PAT_{t+3} and IE_PAT_{t+5} of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on IE_PAT_{t+4} and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.9 Stock Liquidity and Innovation measured by IE_CIT_{t+n}: HLM

Dependent variable	IE_CIT_{t+1}			IE_CIT_{t+2}			IE_CIT_{t+3}			IE_CIT_{t+5}		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics												
LIQUIDITY		0.10***	0.09***		0.13***	0.11***		0.16***	0.14***		0.20***	0.18***
		[0.01]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]
LN_TA		1.01***	1.07***		0.99***	1.04***		0.97***	1.04***		0.93***	1.01***
		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.03]		[0.03]	[0.03]
PPETA		-0.07	-0.12		-0.09	-0.12		-0.13	-0.17		-0.23	-0.25
		[0.09]	[0.10]		[0.10]	[0.11]		[0.11]	[0.12]		[0.12]	[0.14]
LEV		-1.40***	-1.37***		-1.41***	-1.42***		-1.45***	-1.44***		-1.49***	-1.46***
		[0.15]	[0.16]		[0.16]	[0.17]		[0.17]	[0.18]		[0.20]	[0.21]
CAPEXTA		7.29***	7.12***		7.60***	7.59***		8.31***	8.50***		9.11***	9.23***
		[0.61]	[0.70]		[0.65]	[0.74]		[0.70]	[0.81]		[0.80]	[0.94]
Q		0.19***	0.17***		0.19***	0.17***		0.18***	0.17***		0.16***	0.16***

	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
LN_AGE	0.07	0.07	0.04	0.04	0.01	0	-0.05	-0.07
	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]
CASH	0.49*	0.44*	0.56*	0.49*	0.4	0.31	0.34	0.25
	[0.21]	[0.22]	[0.22]	[0.23]	[0.25]	[0.26]	[0.30]	[0.31]
ROA	-1.53***	-1.87***	-1.45***	-1.83***	-1.45***	-1.89***	-1.23***	-1.75***
	[0.15]	[0.16]	[0.17]	[0.17]	[0.18]	[0.19]	[0.22]	[0.23]
Country Characteristics								
LN_GDP		0		-0.01		0.01		-0.04
		[0.17]		[0.18]		[0.19]		[0.19]
Credit		1.02***		1.06***		0.87***		0.58*
		[0.21]		[0.22]		[0.24]		[0.29]
Equity		-0.2		-0.14		-0.19		-0.50**
		[0.12]		[0.13]		[0.14]		[0.19]
Trade		-0.09		-0.14		-0.16		-0.13
		[0.32]		[0.32]		[0.34]		[0.36]

Inflation			3.1			1.86			-0.41			-5.23
			[2.58]			[3.00]			[3.33]			[3.91]
EFW			0.78***			0.53*			0.45*			0.63*
			[0.20]			[0.21]			[0.23]			[0.27]
CTR			-4.48**			-5.78***			-5.90***			-3.4
			[1.38]			[1.46]			[1.72]			[1.93]
EDU			2.31			2.91			2.74			2.04
			[2.02]			[2.34]			[2.98]			[3.16]
SEC			0			0			0			0.01
			[0.00]			[0.00]			[0.00]			[0.00]
Country Fixed effects		Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	43,396	28,795	25,034	40,655	26,153	22,827	37,819	23,595	20,546	32,042	18,747	16,276
AIC	240,515	157,895	137,860	225,768	144,213	126,372	211,172	131,277	114,808	179,671	105,559	92,174
BIC	240,541	158,970	138,681	225,794	145,259	127,176	211,198	132,294	115,577	179,696	106,508	92,897

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W'_c\gamma + v_c$. where $y_{i,c,t+n}$ are separately IE_CIT_{t+1}, IE_CIT_{t+2}, IE_CIT_{t+3} and IE_CIT_{t+5} of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We also run the regression on IE_CIT_{t+4} and get similar results with regressions on other years. We do not report it for brevity. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Table 5.10 The impact of Economic Freedom on LN_PAT_{n+t}: HLM

Dependent variable			LN_PAT_{t+1}					LN_PAT_{t+2}					LN_PAT_{t+3}					LN_PAT_{t+5}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Firm Characteristics																				
LIQUIDITY	0.05***	0.06***	0.06***	0.06***	0.06***	0.07***	0.07***	0.07***	0.07***	0.07***	0.08***	0.08***	0.08***	0.08***	0.08***	0.11***	0.11***	0.11***	0.11***	0.11***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Country Characteristics																				
EFW_SG	0.16***					0.12**					0.12**					-0.01				
	[0.04]					[0.04]					[0.04]					[0.05]				
EFW_LSPR		0.06*					0.07*					0.09**					0.10*			
		[0.03]					[0.03]					[0.03]					[0.04]			
EFW_SM			0.27***					0.31***					0.28***					0.11		
			[0.05]					[0.05]					[0.06]					[0.07]		
EFW_FTI				0.10**					0.04					0.02					0.02	
				[0.03]					[0.03]					[0.04]					[0.04]	
EFW_R					0.17***					0.09					0.07					0.15*
					[0.05]					[0.05]					[0.05]					[0.07]
LN_GDP	0.31***	0.29***	0.34***	0.22***	0.37***	0.12	0.15*	0.18*	0.08	0.19**	-0.08	0.06	0.05	0	0.07	0	0.12	0.13	0.04	0.13
	[0.07]	[0.07]	[0.07]	[0.06]	[0.07]	[0.07]	[0.07]	[0.07]	[0.06]	[0.07]	[0.07]	[0.07]	[0.08]	[0.07]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]	[0.09]
Credit	0.21**	0.34***	0.22**	0.30***	0.36***	0.41***	0.49***	0.39***	0.51***	0.52***	0.69***	0.67***	0.57***	0.70***	0.70***	0.88***	0.64***	0.59***	0.70***	0.68***
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.08]	[0.07]	[0.07]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]	[0.09]	[0.10]	[0.10]	[0.10]	[0.10]
Equity	0.07	0.02	0	0.10**	0.01	0.06	-0.02	-0.04	0.07	0	0.08	-0.03	-0.02	0.04	0	-0.01	-0.08	-0.06	0	-0.08
	[0.04]	[0.04]	[0.04]	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]
Trade	0.25	0.44***	0.48***		0.48***	0.16	0.37**	0.41**		0.38**	-0.05	0.22	0.2		0.22	0.18	0.26	0.25		0.24
	[0.14]	[0.12]	[0.13]		[0.14]	[0.13]	[0.12]	[0.13]		[0.13]	[0.15]	[0.13]	[0.14]		[0.14]	[0.16]	[0.15]	[0.15]		[0.15]
Inflation	0.61	-0.46		-0.62	-0.73	3.15***	1.34		1.18	1.23	3.15***	2.11*		1.79	1.95	-2.47*	-1.8		-2.05	-1.84
	[0.75]	[0.80]		[0.79]	[0.80]	[0.84]	[0.91]		[0.91]	[0.92]	[0.93]	[1.00]		[1.00]	[1.00]	[1.07]	[1.18]		[1.18]	[1.18]
CTR		0.34	0.11	0.43	0.81		0.5	0.41	0.35	0.51		0.14	0.18	0.13	0.21		0.28	-0.07	0.39	0.78
		[0.42]	[0.40]	[0.42]	[0.46]		[0.46]	[0.43]	[0.47]	[0.48]		[0.54]	[0.52]	[0.58]	[0.56]		[0.62]	[0.58]	[0.67]	[0.66]
EDU	-0.22	0.49	0.18	1.28	0.5	0.37	0.98	0.48	2.14**	1.43	-0.88	-1.11	-1.7	0.53	0.04	-4.84***	-5.06***	-3.94***	-3.68**	-4.45***
	[0.65]	[0.68]	[0.69]	[0.66]	[0.70]	[0.74]	[0.80]	[0.80]	[0.76]	[0.79]	[0.95]	[1.12]	[1.07]	[1.04]	[1.06]	[1.08]	[1.27]	[1.14]	[1.15]	[1.18]

SEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed effects																				
Industry Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	26,371	26,087	26,087	26,087	26,087	23,905	23,622	23,622	23,622	23,622	21,299	21,017	21,017	21,017	21,017	16,417	16,146	16,146	16,146	16,146
AIC	84,036	82,882	82,856	82,886	82,874	76,618	75,488	75,461	75,500	75,492	68,635	67,533	67,519	67,542	67,540	53,573	52,579	52,581	52,584	52,579
BIC	84,895	83,748	83,714	83,744	83,740	77,459	76,336	76,300	76,339	76,339	69,448	68,345	68,322	68,345	68,351	54,328	53,332	53,327	53,330	53,332

Note: This table reports the estimation result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately LN_PAT_{t+1}, LN_PAT_{t+2}, LN_PAT_{t+3} and LN_PAT_{t+5} of firm i from country c in the year $t + n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Panel B and C of Table 1, Chapter 4. W_c represents the vector of country-level characteristics of country c shown in Panel D of Table 1, Chapter 4. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level.

Table 5.11 Stock Liquidity and Innovation measured by LN_PAT_{t+n}: Tobit Model

Dependent variable	LN_PAT_{t+1}		LN_PAT_{t+2}		LN_PAT_{t+3}		LN_PAT_{t+5}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LIQUIDITY	0.04***	0.05***	0.05***	0.06***	0.06***	0.07***	0.10***	0.10***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
LN_TA	0.50***	0.49***	0.49***	0.47***	0.48***	0.46***	0.45***	0.45***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
PPETA	0.08***	0.06*	0.11***	0.10***	0.13***	0.11***	0.15***	0.14***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.04]	[0.04]	[0.04]
LEV	-0.35***	-0.29***	-0.37***	-0.33***	-0.34***	-0.29***	-0.31***	-0.22***
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.07]
CAPEXTA	2.15***	2.45***	1.99***	2.21***	2.17***	2.48***	2.08***	2.33***
	[0.19]	[0.21]	[0.20]	[0.23]	[0.22]	[0.24]	[0.25]	[0.28]
RDTA	3.03***	2.76***	3.02***	2.75***	3.21***	2.98***	3.76***	3.54***
	[0.11]	[0.11]	[0.12]	[0.12]	[0.14]	[0.14]	[0.17]	[0.17]

Q	0.07***	0.06***	0.07***	0.06***	0.07***	0.06***	0.05***	0.05***
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
LN_AGE	-0.13***	-0.11***	-0.14***	-0.12***	-0.13***	-0.11***	-0.12***	-0.12***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
CASH	0.19***	0.12*	0.21***	0.12*	0.23***	0.14*	0.13	0.04
	[0.07]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.09]	[0.10]
ROA	0.48***	0.33***	0.64***	0.48***	0.75***	0.60***	0.86***	0.71***
	[0.06]	[0.06]	[0.06]	[0.06]	[0.07]	[0.07]	[0.08]	[0.08]
LN_GDP		0.11***		0.11***		0.13***		0.15***
		[0.02]		[0.02]		[0.02]		[0.03]
Credit		0.02		0.07**		0.05		-0.11**
		[0.03]		[0.03]		[0.04]		[0.05]
Equity		-0.11***		-0.14***		-0.13***		-0.15***
		[0.03]		[0.03]		[0.03]		[0.04]
Trade		0.31***		0.35***		0.36***		0.35***

		[0.05]		[0.05]		[0.06]		[0.07]
Inflation		0.98		2.87***		3.69***		0.99
		[0.68]		[0.76]		[0.84]		[0.97]
EFW		0.18***		0.17***		0.17***		0.1
		[0.05]		[0.05]		[0.06]		[0.07]
CTR		0.91***		1.01***		1.01***		1.15***
		[0.28]		[0.31]		[0.34]		[0.40]
EDU		0.14		0.36		0.05		-0.76*
		[0.26]		[0.30]		[0.36]		[0.44]
SEC		0.00***		0.00***		0.00***		0.00***
		[0.00]		[0.00]		[0.00]		[0.00]
Country Fixed Effects	Yes		Yes		Yes		Yes	
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	29,921	26,087	26,998	23,622	24,068	21,017	18,552	16,146

Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: This table reports the marginal effects of the Tobit model: $LN\_PAT_{t+n} = \alpha + \beta_1 Liquidity_{i,t} + \beta_2 Firm$ control $variables_{i,t} + C_c + I_j + Y_t + \epsilon_{i,t}$. The dependent variable is LN_PAT_{t+1} in column (1), which is replaced with LN_PAT_{t+2}, LN_PAT_{t+3} and LN_PAT_{t+5} in column (3), (5) and (7), respectively. Variable definitions are provided in Panel B and C of Table 1, Chapter 4. Country fixed effects, C_c, industry fixed effects, I_j, year fixed effects, Y_t, are included in all regressions. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. This table also reports the marginal effects of the Tobit model $LN\_PAT_{t+n} = \alpha + \beta_1 Liquidity_{i,t} + \beta_2 Firm$ control $variables_{i,t} + \beta_3 Country_{c,t} + I_j + Y_t + \epsilon_{i,t}$. The dependent variable is LN_PAT_{t+1} in column (2), which is replaced with LN_PAT_{t+2}, LN_PAT_{t+3} and LN_PAT_{t+5} in column (4), (6) and (8), respectively. Variable definitions are provided in Panel B and C of Table 1, Chapter 4. Industry fixed effects, I_j, year fixed effects, Y_t, are included in all regressions. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. Prob > χ^2show the significance of the overall model and their corresponding p values. In this case, the model is statistically significant because the p-value is less than .000. We do not report $\mathrm{Pseudo} - \mathrm{R}^2$because it is meaningless on a Tobit regression (Sribney, 1997).

Table 5.12 Stock Liquidity and Innovation measured by LN_RD_{t+n}: HLM

Dependent variable	LN_RD_{t+0}			LN_RD_{t+1}			LN_RD_{t+2}			LN_RD_{t+3}			LN_RD_{t+5}		
	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country	null model	Within -Country	Cross -Country
Firm Characteristics															
LIQUIDITY		0.07***	0.08***		0.08***	0.09***		0.09***	0.10***		0.10***	0.11***		0.12***	0.14***
		[0.0037]	[0.0040]		[0.0039]	[0.0041]		[0.0041]	[0.0044]		[0.0044]	[0.0047]		[0.0050]	[0.0054]
LN_TA		0.87***	0.86***		0.86***	0.86***		0.85***	0.85***		0.84***	0.83***		0.82***	0.80***
		[0.0054]	[0.0058]		[0.0057]	[0.0061]		[0.0060]	[0.0065]		[0.0064]	[0.0069]		[0.0075]	[0.0081]
PPETA		-0.17***	-0.10***		-0.23***	-0.18***		-0.26***	-0.20***		-0.28***	-0.19***		-0.25***	-0.16***
		[0.0229]	[0.0247]		[0.0242]	[0.0259]		[0.0261]	[0.0278]		[0.0281]	[0.0299]		[0.0330]	[0.0352]
LEV		-0.87***	-0.77***		-0.87***	-0.77***		-0.87***	-0.77***		-0.86***	-0.78***		-0.82***	-0.74***
		[0.0375]	[0.0392]		[0.0393]	[0.0408]		[0.0421]	[0.0436]		[0.0452]	[0.0468]		[0.0527]	[0.0543]
CAPEXTA		0.92***	1.18***		1.21***	1.43***		1.34***	1.41***		1.43***	1.43***		1.47***	1.41***
		[0.1579]	[0.1758]		[0.1628]	[0.1810]		[0.1723]	[0.1914]		[0.1846]	[0.2057]		[0.2130]	[0.2383]
Q		0.07***	0.06***		0.10***	0.09***		0.12***	0.11***		0.13***	0.12***		0.13***	0.13***

	[0.0039]	[0.0040]	[0.0040]	[0.0041]	[0.0042]	[0.0043]	[0.0043]	[0.0044]	[0.0050]	[0.0051]
LN_AGE	-0.08***	-0.07***	-0.11***	-0.10***	-0.14***	-0.12***	-0.15***	-0.13***	-0.17***	-0.16***
	[0.0105]	[0.0110]	[0.0110]	[0.0115]	[0.0117]	[0.0122]	[0.0125]	[0.0130]	[0.0147]	[0.0154]
CASH	0.54***	0.56***	0.56***	0.60***	0.56***	0.62***	0.51***	0.58***	0.51***	0.56***
	[0.0522]	[0.0537]	[0.0550]	[0.0562]	[0.0596]	[0.0604]	[0.0648]	[0.0655]	[0.0791]	[0.0798]
ROA	-1.59***	-1.60***	-1.24***	-1.28***	-1.02***	-1.08***	-0.90***	-0.99***	-0.82***	-0.96***
	[0.0385]	[0.0393]	[0.0408]	[0.0414]	[0.0441]	[0.0445]	[0.0483]	[0.0487]	[0.0583]	[0.0585]
Country Characteristics										
LN_GDP		0.09		-0.12		-0.19**		-0.28***		-0.19*
		[0.0610]		[0.0628]		[0.0673]		[0.0778]		[0.0956]
Credit		0.16**		0.19**		0.15*		0.12		0.06
		[0.0601]		[0.0626]		[0.0656]		[0.0741]		[0.0907]
Equity		-0.03		-0.05		-0.10**		-0.10*		-0.23***
		[0.0341]		[0.0359]		[0.0381]		[0.0406]		[0.0568]
Trade		0.06		-0.03		0.03		-0.18		-0.22
		[0.1297]		[0.1297]		[0.1392]		[0.1589]		[0.1836]
Inflation		-2.02**		-1.35*		0.41		0.16		-4.10***

			[0.6611]			[0.6867]			[0.7995]			[0.8767]			[1.0483]
EFW			0.27***			0.38***			0.39***			0.43***			0.38***
			[0.0513]			[0.0542]			[0.0582]			[0.0623]			[0.0767]
CTR			0.17			0.65			0.19			0.28			0.42
			[0.3644]			[0.3810]			[0.4079]			[0.4937]			[0.5830]
EDU			1.59**			1.63**			1.17			-0.54			0.36
			[0.5601]			[0.6072]			[0.7145]			[0.9777]			[1.1148]
SEC			-0.01***			-0.01***			-0.01**			-0.01**			-0.01*
			[0.0023]			[0.0023]			[0.0026]			[0.0027]			[0.0029]
Country Fixed effects		Yes			Yes			Yes			Yes			Yes	
Industry Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year Fixed effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
No. of observations	45,898	31,475	27,258	43,408	28,802	25,040	40,665	26,159	22,833	37,828	23,600	20,551	32,051	18,752	16,281
AIC	190,037	89,811	76,719	179,970	82,056	70,309	169,028	75,187	64,675	157,582	68,506	58,708	134,259	55,729	47,513
BIC	190,064	90,898	77,565	179,996	83,131	71,130	169,054	76,233	65,478	157,608	69,523	59,478	134,284	56,678	48,236

Note: This table reports the regression result of the HLM model in equations (5.1a) $y_{i,c,t+n} = \alpha_c + X'_{i,c,t}\beta + u_{i,c,t}$, (5.1b) $\alpha_c = W_c'\gamma + v_c$. where $y_{i,c,t+n}$ are separately LN_RD_t, LN_RD_{t+1}, LN_RD_{t+2}, LN_RD_{t+3} and LN_RD_{t+5} of firm i from country c in the year $t+n$; α_c represents a country-level intercept term; $X_{i,c,t}$ shows a vector of firm-level characteristics of firm i from country c in the year t in Table 4.1, Panel B and C. W_c represents the vector of country-level characteristics of country c shown in Table 5.1, Panel B. To obtains the pure firm-level impact of $X_{i,c,t}$ on $y_{i,c,t+n}$ in equation (5.1a), this chapter removes country-year mean from all firm-level observations in $X_{i,c,t}$, in other words, we include the country and year fixed effects in the within-country model of equation (5.1a). Besides, to capture the pure country-level relationship between W_c and α_c in equation (5.1b), we include both country-level variables and country-year means of firm-level factors in W_c. All regressions include 2-digit SIC industry fixed effect and year fixed effects. Estimation results are shown, and their standard errors are displayed in the brackets below. *** (**) (*) Significance at the 1% (5%) (10%) two-tailed level. We report the AIC and BIC of null model and equation (5.1) to determine whether equations (5.1) provide a better fit for the data.

Appendix to Chapter 5

Although previous literature finds that firm innovation could be affected by other country/international indicators, we do not use them as control variables in the regression. This is because these indicators are highly correlated with each other. This section lists these indicators below.

Clò *et al.* (2020) showed that a country with a high-quality government (i.e., low corruption, high government effectiveness, high rule of law, good regulatory quality, good voice and accountability) improves the firm's innovation. Therefore, we plan to control for a list of indicators that represent the quality of the government from the perspective of 1) control of corruption (i.e., $WGI\_CC_{c,t}$), 2) government effectiveness (i.e., $WGI\_GE_{c,t}$), 3) regulatory quality (i.e., $WGI\_RQ_{c,t}$), 4) the rule of law (i.e., $WGI\_RL_{c,t}$) and 5) voice and accountability (i.e., $WGI\_VA_{c,t}$).[55] These data are collected from the World Bank's Worldwide Governance Indicators (WGI) from the years 1996, 1998, 2000, and 2002-2010.

Another alternative measurement is the freedom in the world (FIW) indicators, $FIW_{c,t}$, which contains political rights (PR) indicators and civil liberties (CL) indicators.[56] It was constructed by Messick and Kimura (1996) for Freedom House and currently covers around 200 countries from 1972 to 2019. The FIW indicators are ranged from one to seven, where one represents the country with the highest degree of freedom, seven the lowest.

[55] The detailed variable information is described in Panel D of Table 4.1, Chapter 4. It also notes that these indicators are highly correlated with each other (the correlation coefficients range between 0.7 and 0.9) (Clò *et al.*, 2020).

[56] Gwartney and Lawson (2003) demonstrated that while EFW index and FIW index covers the different sphere of human interaction, the foundation of economic freedom is as same as that of political and civil liberty. In addition, they support the notion that economic freedom tends to be improved by political freedom and civil liberty.

The enforcement of patent rights is shown to play a significant role in improving innovative activities (Panda and Sharma, 2020). Therefore we plan to control the index of patent protection, $IPP_{c,t}$, as the patent protection index for country c in the year t. The index of patent protection (i.e., index of patent rights) is created by Ginarte and Park (1997) and then updated by Park (2008). They designed this index to describe the strength of patent protection rather than the quality of the patent system in each country.[57] Currently, this index is produced for 123 countries/regions from 1960 to 2015 (broken down into five year intervals). Following Picci (2010), the observation for the year will be used for the four adjacent years. For example, the observation for the year 1990 is used for the year 1991, 1992; the year 1993, 1994, 1996 and 1997 are set equal to the observation for the year 1995. A country with a higher level of this index represents a stronger level of protection.

An alternative indicator of $IPP_{c,t}$ is the patent enforcement index, $PEI_{c,t}$, which was produced by Papageorgiadis and Sofka (2020). They argued that Ginarte and Park (1997) and Park (2008) only considered information about intellectual property book laws across the country. However, the agencies, courts, police and customs organisations are less likely to apply a specific patent law immediately and uniformly after it is adopted by the country. $PEI_{c,t}$ incorporates information about an individual's experience and local knowledge source of patent lawyers and managers during the enforcement process. The dataset covers 51 countries from 1998 to 2017. A country with a higher level of $PEI_{c,t}$ indicates a higher degree of patent enforcement.

We list their correlation in Appendix Table 5.1.

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[57] According to Park (2008), it measures as "the unweighted sum of five separate scores for coverage (inventions that are patentable); membership in international treaties; duration of protection; enforcement mechanisms; and restrictions (for example, compulsory licensing in the event that a patented invention is not sufficiently exploited)."

Table A5.1 Correlation of high correlated Country-Level Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) EFW	1									
(2) WGI_CC	0.839***	1								
(3) WGI_GE	0.864***	0.941***	1							
(4) WGI_RL	0.859***	0.935***	0.926***	1						
(5) WGI_RQ	0.882***	0.891***	0.923***	0.880***	1					
(6) WGI_VA	0.791***	0.839***	0.814***	0.917***	0.814***	1				
(7) FIW_PR	-0.691***	-0.699***	-0.701***	-0.841***	-0.688***	-0.950***	1			
(8) FIW_CL	-0.784***	-0.766***	-0.787***	-0.876***	-0.830***	-0.948***	0.892***	1		
(9) IPP	0.712***	0.648***	0.691***	0.682***	0.633***	0.563***	-0.487***	-0.545***	1	
(10) PEI	0.879***	0.952***	0.931***	0.894***	0.872***	0.749***	-0.622***	-0.696***	0.721***	1

Chapter 6 The Road to Economic Recovery: Pandemics and Innovation

6.1 Introduction

"At such difficult times, the importance of innovation comes to the fore. When we emerge from this challenging time, we will need the UK's entrepreneurial spirit to be stronger than ever."

Tej Parikh (Institute of Directors) responding to the announcement of the Future Fund

On 20 April 2020, in response to the COVID-19 pandemic, the UK government announced the Future Fund, a billion pound support package for innovative firms.[58] The objective of this policy is very clear: to support the road to economic recovery by increasing the intensity of innovation. The link between innovation and GDP growth is undisputed: Kogan *et al.* (2017) demonstrate that innovation waves are followed by an acceleration in per capita GDP and productivity. Hasan and Tucci (2010) show that countries hosting more innovative firms also have higher economic growth. Importantly, Kogan *et al.* (2017) and Acemoglu *et al.* (2018) show that increases in aggregate innovation dominate creative destruction, leading to real increases in output. Acemoglu *et al.* (2018) demonstrate that such increases can be achieved more efficiently via a targeted policy response to encourage innovation within the more innovative firms.

This chapter reviews the literature about the economic consequence of pandemics from the perspective of the macroeconomy, consumption, financial markets, supply-side, and socioeconomy. We mainly focus on the economic impacts of COVID-19 and supplement it by

[58] Along similar lines, on 27 March 2020, the US President, Donald Trump, signed into law the Coronavirus Aid, Relief, and Economic Security Act with an aim to support individuals and businesses affected by the impact of COVID-19.

research about previous pandemics. They generally focus on the short-term influence and represent economic indicators by GDP or consumption. To the best of knowledge, we do not find any paper to test the impacts of pandemics on innovation even the technology innovation is widely regarded as a vital driver of a nation's long-term economic growth (Solow, 1956; Grossman and Helpman, 1991; Aghion and Howitt, 1992).

According to the literature review and economic theory, we assume the pandemics cause negative impacts on innovation through both labour and financial mechanisms. While innovation requires long-term, labour-intensive teamwork (Holmström, 1989; X Chang *et al.*, 2015), pandemics (i.e., increased infection and/or death toll) destroy innovation by increasing labour costs, reducing working hours and teamwork's productivity. Besides, firms tend to cut plan of new projects in terms of financial constraints and increased willingness of precautionary savings.

In this chapter, we investigate the effect of past pandemics on innovation output. To the best of our knowledge, this is the first attempt to provide evidence regarding the long-term effects of pandemics on research productivity, thereby shedding light on the ways in which pandemic episodes impact economic growth.

We use patent data from the European Patent Office's PATSTAT database and select data from 1900 to 2012.[59] We focus on the set of G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) and pandemic episodes with at least reported

[59] This chapter does not use R&D expenditure to measure innovation activity. Although R&D can represent innovative input during the normal period, it may not efficiently measure innovation performance during and after the pandemic. The R&D spending includes wage and salary of researchers. However, the pandemic (increased infection and death toll) rise real wage for suriviors in the long run (Jordà *et al.*, 2020) but is less likely to improve their research producvitiy. Therefore, the increased R&D investment may not be able to represent an increased innovative ability during and after the period of pandemic.

100,000 deaths. Our measure of innovation output is the number of successful applications per country per year. We use a set of model-free or local projection estimators that allows us to estimate local projections sequentially *h* steps ahead into the future.

We show that following a pandemic, innovation output is disrupted for a period of approximately seven years, probably because of a drop in research productivity. This result is striking as it shows a much more long-term effect in innovation output that the one anticipated. Our model provides more reliable forecasts of the long-run rather than the short-run effects of pandemics on innovation output. We show that the main result of the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in innovative activity in the Information and Communication technology sector. Furthermore, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. Pandemic shocks lead to a short-term drop in the number of patent applications. Finally, pandemic duration is strongly associated with a drop in patent applications. The results are robust to a number of robustness tests.

Our results have important policy implications. The chapter supports the policies designed to reduce the effect of the "Great lockdown" on research productivity. Given the non-rival nature of innovation, the response to COVID19 needs therefore to have a global character as this will support economic growth. To this end, governments need to be prepared to support innovators in the immediate aftermath of the pandemic, and patent offices may have to speed up the process of approving new patents. Finally, we recommend adopting policies that target the more innovative firms as this is expected to help reduce the time it will take for innovation to recover from the effects of COVID19.

In Section 6.2, we review the literature about the economic impacts of pandemics. In Section 6.3, we outline the Schumpeterian theory of economic growth and develop the hypothesis. In

Section 6.4, we discuss our innovation data and develop our empirical strategy. In Section 6.5, we present the results of the empirical analysis and discuss policy implications. In Section 6.6, we present the results from our robustness checks. In Section 6.7, we demonstrate the limitation of this chapter and in Section 6.8 we conclude the chapter.

6.2 Literature Review

This section reviews literature about the economic impact of the pandemic around the world. We mainly focus on the economic implications of COVID-19 and supplement it by research about the previous pandemic. In the following subsections, we firstly review the literature investigating this impact based on the macroeconomic indicators, and the trade-off between the severity of the pandemic and the size of the recession caused by the pandemic. And then, we describe three channels in which the pandemic affect the economy, namely, consumption, financial market and supply chain. In the end, we summary the impacts of COVID-19 and governments' response policies on socioeconomy from the perspective of labour markets, human health and well-being, gender and racial inequality, and the environment.

6.2.1 Macroeconomic impact

COVID-19 pandemic has been regarded by World Trade Organisation (WTO) and OECD as the largest threat to the global economy since the 2007-08 financial crisis. It is shown to increase economic uncertainty, geopolitical risk and implied volatility of oil price (OECD, 2020; Sharif *et al.*, 2020). As an example of economic uncertainty, this pandemic has caused depression of multiple industries (e.g., tourism, transportation) and temperately closure of educational, commercial, sports and spiritual institutions (Boone, 2020). In addition to this, Baker *et al.* (2020) argue that COVID-induced uncertainty causes more than half of the contraction in US real GDP.

A number of studies investigate economic losses from the outbreak of pandemics. 1918 Pandemic (i.e., Spanish flu) spreads worldwide from 1918 to 1919. According to the Centers for Disease Control and Prevention (CDC) estimation, it infected about one-third of the world's population and killed at least 50 million people among them.[60] Barro *et al.* (2020) analyse this pandemic by using cross-country panel regressions and demonstrate that the real per capita GDP and real capita consumption are estimated to be decreased by 6 and 8 percent separately. Correia *et al.* (1918) focus on the US market and show this pandemic decreased manufacturing activity by about 20%. Jordà *et al.* (2020) focus on the economic impact of pandemics in the long-term. They show that pandemics do not destroy the physical capital (compared to war); instead, it decreases the labour supply and increases the real wage for each survivor.

In addition to these, a set of papers use the 1918 Pandemic as a severe flu pandemic sample and estimate its economic cost in the modern era. Burns *et al.* (2006) estimate that the cost of a 1918-type pandemic is close to 3.1 pecent of global GDP. Among them, 0.4 pecent comes from mortality, 0.9 percent is due to illness and absenteeism, and 1.9 percent is because of the effort to avoid infection. Besides, Arnold *et al.* (2006) estimate that this kind of pandemic could cause around 4.25 pecent loss in annual GDP in the US. While the supply side causes a 2.25 percent loss of economy, the demand side causes the rest.

Grais *et al.* (2003) set up a scenario that 1968 Hong Kong flu returns in 2000. They describe that the flu will do not follow the seasonal pattern and spread concurrently around the world. Besides, It will leave a shorter time for public health intervention than before.

There are a number of literature analysing the trade-off between the severity of the pandemic and the size of the recession caused by COVID-19 (e.g., Correia *et al.*, 1918; Alvarez *et al.*, 2020; Barro *et al.*, 2020; Eichenbaum *et al.*, 2020; Glover *et al.*, 2020). According to Eichenbaum *et al.* (2020), with more restrictive containment policies being applied, people tend to decrease their consumption and working hours due to the increasing cost of

[60] See more detail information in https://www.cdc.gov/flu/pandemic-resources/1918-pandemic-h1n1.html.

consumption. It would reduce the death toll but increase the severity of the economic downturn. Alvarez *et al.* (2020) aim to find an optimal lockdown policy to balance this trade-off. They argue that the government should start a severe lockdown two weeks after the outbreak and keep it tight for a full month. It is followed by a gradual withdrawal, which releases 40% of the population at the beginning and 80% after three months.

The analysis of trade-off is also included in previous research. Adda (2016) tests a group of viral diseases from France via an across-region dataset. It shows that while school closures and restriction on public transportation reduce the spread of viral diseases, they are not cost-effective in the economy. Besides, the pandemic-related death rate is higher in developing countries than in industrialised countries due to worse health care systems, living conditions and individuals' health status (Patterson and Pyle, 1991; Johnson and Mueller, 2002; Murray *et al.*, 2006; Oshitani, Kamigaki and Suzuki, 2008).

Carlsson-Szlezak *et al.* (2020a) and Carlsson-Szlezak *et al.* (2020b) suggest three main transmission channels through which the COVID-19 negatively affects the economy. The first pathway, which directly affects the economy, is the decreased consumption of goods and services. The second is the indirect influence working through the shock of financial markets. The third is the impact of the supply-side, which consists of supply chains, labour demand and employment. The following subsection describes the impact of COVID-19 on these three channels.

6.2.2 Direct channel: Consumption

Baker *et al.* (2020) show that household consumption dramatically increases at the beginning of the COVID-19 outbreak and mainly concentrates on retail, credit card spending, and food items. It is followed by a sharp decline in the overall spending when the virus spread and a growing number of people stay at home. A higher social distancing level decreases household spending, particularly in restaurants, retail, and public transport.

Goolsbee and Syverson (2020) find that while consumer traffic is reduced by 60 percent following the COVID-19 outbreak, only 7 percent of them is explained by the legal restrictions. The rest is mainly relevant to the individual choices, which due to the fears of infection. Besides, this pandemic changes consumers' spending habits that increase (decreases) the visit to 'essential' ('non-essential') business and food sellers (restaurants and bars). Sheridan *et al.* (2020) suggest a similar result by comparing the average daily spending in Denmark and Sweden during the COVID-19. While both are similarly exposed to this pandemic, Denmark imposes a more stringent social-distancing law than Sweden. The authors find that the restriction law causes only few drops in consumption, and the most reduction is due to the pandemic itself. This restriction decreases the aggregate spending of low-health-risk individuals but also decrease the spending of high-health-risk individuals in personal health service.

The impact of HIV/ASID on consumption is different from that of influenza pandemics. According to Bollinger *et al.* (1999), household spending for medical care, drugs, and funeral expenses substantially increase after one of the household members is infected by HIV/ASID virus.

6.2.3 Indirect channel: Financial markets

According to Jordà *et al.* (2020), the countries experience a low natural interest rate in the next decades of the pandemic. It is explained by the increased precautionary savings and depressed investment opportunities. Barro *et al.* (2020) find a dramatically short-term decrease in realised real returns on stocks and short-term government bills following the growth of flu death rates. Besides, Altig *et al.* (2020) find a considerable rise in implied stock market volatility in reaction to the COVID-19 outbreak. The volatility peaked in mid-March, which is earlier than other uncertainty indicators, shows the different opinions between Wall Street and Main Street on the pandemic.[61]

A set of literature anlysis the firm characteristics that transfer the impact of COVID-19 on their abnormal return in the financial market. Ramelli and Wagner (2020) argue that the financial market investors expect the financial channels to amplify the non-financial effect of COVID-19. The corporate value is driven by the firms' exposure to international trade in the outbreak period and driven by liquidity (i.e., cash holding) and refinancing risk (i.e., leverage) in the fever period. Besides, Albuquerque *et al.* (2020) show that stocks with high Environmental and Social (ES) rating have better performance than others during the first quarter of 2020.

Ding *et al.* (2020) supplement that the stock prices decrease less by the COVID-19 when the firm has stronger financial performance before 2020; more corporate social responsibility activities; less entrenched executives; controlled more by non-financial companies rather than hedge funds. Fahlenbrach *et al.* (2020) find that financial flexibility protects firms from the COVID-19.

Alfaro *et al.* (2020) analyse the impact of the COVID-19 pandemic on firm-level daily returns in the US market. They find that unanticipated changes in predicted infections could forecast

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[61] Other economic uncertainty indicators included in Altig *et al.* (2020) are newspaper-based policy uncertainty, Twitter chatter about economic uncertainty, subjective uncertainty about business growth, forecaster disagreement about future GDP growth, and a model-based measure of macro uncertainty.

aggregate stock market returns in the next day.[62] Besides, firms in labour-intensive (versus highly leveraged, more capital-intensive) industries experience a slighter decrease in stock prices, but a larger proportional shedding of workers. It reflects that workers (versus property, plant and equipment) are easier to be shed during the period of extreme economic instability.

Gormsen and Koijen (2020) test the reaction of stock price and future dividend to COVID-19. They find compared with the beginning of 2020, the growth expectation in dividends and GDP in June have fallen in the US and EU. Besides, they observe a 10% increase in stock price around the announcement of the fiscal stimulus bill on 26 March, while a slight decline in the short-term dividends during the same period. It represents that the stock market is improved by the value of dividends in the distant future rather than the near-term.

Baker *et al.* (2020) display that the news reports of COVID-19 cause large daily movements in the US stock market, which has never happened during any previous infectious disease outbreak. They explain the reason by the sensitivity of a service-oriented economy to the government restrictions on commercial activity and voluntary social distancing.

6.2.4 Impact of supply-side

Gourinchas (2020) argue that the modern economy is supported by the complex interconnections between different parties (e.g., suppliers, firms, employees, consumers). Therefore, a sudden stop in supply chains and circular flows tend to cause a cascading influence

[62] Alfaro *et al.* (2020) find that doubling (halving) of projected infections predicted infections could forecast a decrease (increase) in aggregate stock market value from 4 to 10 percent in the next day. A similer patten is also found in Hong Kong during the 2013 SARS outbreak. They show the value decrease (increase) from 8 to 11 percent under the same condition. In this case, they suggest that stock prices may begin to rally, and become less sensitive to the pandemic, if the growth of new case does not exceed initially anticipated.

on the economy. Because of the spillover effects throughout supply chains, this negative effect is more severe for countries highly dependent on international trade (Fernandes, 2020). Bonadio *et al.* (2020) show that COVID-19 is expected to decrease the average real GDP by 29.6%, with one-quarter of the decline is explained by disruptions in global supply chains.

Gourinchas (2020) suggests a more considerable impact of COVID-19 on the economy than the financial crisis. It is because while the unemployment rate in the US financial crisis peaked at 'just' 10%, at least 50% of people cannot work during the short-term because of COVID-19. Previous researches also demonstrate that influenza and HIV/AIDS pandemic are responsible for the loss of adults' productivity and health (e.g., Quinn, 1996; Kumpulainen and Mäkelä, 1997; Keech *et al.*, 1998; Dixon *et al.*, 2002; Szucs, 2004; Robson *et al.*, 2006; Xue *et al.*, 2010).[63]

6.2.5 Socioeconomic consequence

A growing literature investigates the socioeconomic consequence of COVID-19 and governments' response policies. The studies mainly concern impacts on labour markets, human health and well-being, gender and racial inequality, and the environment.

A large body of literature studies the negative impact of COVID-19 on labour markets (e.g., Bartik *et al.*, 2020; Boneva *et al.*, 2020; Coibion *et al.*, 2020; Dingel and Neiman, 2020; Kahn *et al.*, 2020). According to Boneva *et al.* (2020), individuals who have to work remotely from home are more likely to lose their job. Besides, younger adults and workers without a university education tend to experience reductions in their income. Coibion *et al.* (2020) find drops in the

[63] An example is 1918 Pandemic, around 50% pandemic-related death reports in the worlds occurred in adults aged between 20 and 40 (Gasparini *et al.*, 2012).

labour participation rate in the long-term and explain it via the disproportionate influence on the older population. [64] Barrero *et al.* (2020) argue that the COVID-19 outbreak induces a major job reallocation in the US and find 42 percent of layoffs caused by the pandemic finally become permanent job loss.

For research relevant to health outcomes, a set of literature document the impact of COVID-19 on physical health and mortality (e.g., Goldstein and Lee, 2020; Lin and Meissner, 2020; Maringe *et al.*, 2020). Other research such as Tubadji *et al.* (2020), Brodeur *et al.* (2020), Davillas and Jones (2020), Xiong *et al.* (2020) study the influence on mental health and well-being. In addition to this, a growing literature shows the negative impact of lockdown policy on public mental health (e.g., (Armbruster and Klotzbücher, 2020; Brodeur *et al.*, 2020).

A set of literature demonstrates the unequal impact of COVID-19 on different genders and different ethnic groups. Studies provide evidence that this pandemic causes negative influences on women by increasing childcare needs (Alon *et al.*, 2020) and domestic violence (Beland et al., 2020a). Besides, service sectors, which has a high share of female employment, suffer more from COVID-19 than others (Alon *et al.*, 2020).

COVID-19 leads to a higher mortality rate for minority groups in the US than for other groups (Tai *et al.*, 2020). Besides, Latino groups and immigrants experience higher unemployment than others during the COVID-19 in the US (Borjas and Cassidy, 2020; Fairlie *et al.*, 2020). The authors explain that Latino workers concentrate on non-essential service sectors or/and have lower skills, while the immigrants' jobs are generally remotely from home. In addition to this, the COVID-19 pandemic induces a rise of Sinophobia across the web and magnifies the hostility against foreigners (Bartos *et al.*, 2020; Schild *et al.*, 2020).

[64] Labour participation rate decreases when more unemployed workers stop searching for work actively.

The environment becomes better following the global lockdown and slowdown in economic activities (Bao and Zhang, 2020; Cicala *et al.*, 2020; He *et al.*, 2020). It is reflected in the reduction of air quality index and air pollutions (such as $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO).

To summarise, while much research studies the economic impacts of pandemics, they generally focus on the short-term influence and represent economic indicators by GDP or consumption. Alougth Jordà et al. (2020) investigate pandemics' economic impacts in the long-term; they mainly compare the difference between pandemic and wars. Besides, to the best of knowledge, we do not find any paper test on how pandemic affects innovation even the technology innovation is widely regarded as a vital driver of a nation's long-term economic growth (Solow, 1956; Grossman and Helpman, 1991; Aghion and Howitt, 1992).

6.3 The Schumpeterian theory of economic growth, shocks to innovation output and hypothesis

In this section, we discuss innovation as a mediating factor in achieving economic growth. Schumpeterian growth theory relies on the assumption that aggregate innovation dominates creative destruction. The economic consequences of pandemic shocks are felt for long into the future and macroeconomic and firm-specific shocks lead to smaller innovation output. In the following paragraphs, considering the link between pandemic shocks, economic growth and innovation, we suggest that pandemic shocks are likely to lead to a reduction in aggregate innovation output.

6.3.1 The Schumpeterian growth theory

Undoubtedly, Schumpeter's biggest contribution to economic thinking is the notion of "creative destruction" that characterises economic systems. According to Schumpeter, the process by which economies grow is a mostly evolutionary process, during which new innovations replace old innovations. This evolutionary process is endogenous, that is, it comes from within the economic system itself, it occurs discontinuously, at irregular intervals and with varying magnitudes, and brings fundamental changes, replacing old conditions with new equilibria (see Elliott, 1980).

Schumpeterian growth theory is effectively the "operational arm" of Schumpeter's idea of creative destruction.[65] Schumpeterian growth models assume that (i) firm and personal innovations (the innovators) affect the entire economy, (ii) innovators are motivated by the

[65] For a detailed presentation of Schumpeterian growth theory, see Aghion *et al.* (2014).

prospects of private wealth that come in the form of monopoly rents and (iii) new innovators have the capacity to eventually replace old innovators (creative destruction). The amount of research conducted by the innovators is a function of the prospects of monopoly rents and increases in higher wages for skilled workers over the next period (see Aghion and Howitt, 1992). In its basic form, therefore, the value of a new innovation is a positive function of the expected profit from this innovation minus the cost of creative destruction, that is the loss of monopoly rents from new innovations that replace old innovations (Aghion et al., 2014).

On aggregate, the effect of innovation on economic growth is positive when the increases in productivity achieved by new innovations are greater than the loss of monopoly rents of the previous innovator. Aghion and Howitt (1992) called the former effect "knowledge spillover effect" and the latter "business-stealing effect". Empirically, Acemoglu *et al.* (2018) have identified that holding other things constant, increases in aggregate innovation dominate creative destruction, leading to real increases in output. Kogan *et al.* (2017) show that, as suggested by theory, innovation comes in waves that are followed by acceleration in per capita GDP and productivity. Finally, Hasan and Tucci (2010) show that countries hosting more innovative firms also have higher economic growth.

6.3.2 Economic consequences of pandemic shocks and the role of innovation

The above demonstrates that according to the Schumpeterian growth theory, growth is primarily determined by the ability of people to create new ideas. How though, do pandemics affect economic growth?

In a neoclassical growth model, pandemic shocks threaten economic growth by disrupting both supply and demand in an economy. On the supply side, the effect of a pandemic shock is mostly felt by a loss in the number of hours worked. On the demand side, the loss relates to a fall in consumption. Empirical research on the effect of pandemic shocks to economic growth is limited but clearly growing. For the US, Meltzer *et al.* (1999) show that the estimated economic impact of another influenza pandemic would be between US$71.3 to $166.5 billion. However, the study assumes a closed economy and therefore ignores the costs related to disruptions in commerce. Jonung and Roeger (2006) show that under "reasonable scenarios", a pandemic shock is expected to lead to a loss in European Union GDP of between two and four percent. However, the latest growth forecast for the EU economy is that it is expected to contract by over seven percent in 2020 (see European Commission, 2020). More recently, Jordà *et al.* (2020) show that following a pandemic shock, the natural rate of interest declines for approximately two decades, therefore demonstrating the very long-term effects of pandemics on economic growth.[66]

In an idea-based theory of economic growth, the ability of an economy to grow is the product of research productivity and the numbers of researchers:

Economic growth = number of researchers × research productivity

To this end, Bloom *et al.* (2020) show that research productivity in the US halves every 13 years. Therefore maintaining constant growth requires a constant increase in the number of researchers (see also Kogan *et al.*, 2017). Pandemic shocks can first of all lead to a reduction in the number of researchers. This may be the outcome of a very high death toll, a shift of a large number of researchers to other activities, a large number of researchers losing their jobs or a combination of all three. Research productivity is also expected to fall as the social

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[66] A number of recent studies have attempted to quantify the effect of the COVID19 pandemic on economic growth (see Baker *et al.*, 2020; Leduc and Liu, 2020).

environment that affects the intensity of creativity is affected (see Amabile *et al.*, 1996). In other words, innovation requires a stimulating and supporting environment and pandemics threaten the nature of creativity that is essential for research productivity.

6.3.3 Labour and financial mechanisms

According to the literature review and above economic theories, we assume the pandemic impedes innovation performance from both labour and financial perspective. Innovation is a labour-intensive activity (Holmström, 1989). However, the spread of pandemic disease tends to cause the rise of infection and death toll, thereby reducing innovative productivity. For example, 1918 Pandemic is estimated to infect about one-third of the world's population and killed at least 50 million people among them. These pandemics reduce the labour supply and increase the real wage for each survivor in the long run (Jordà *et al.*, 2020). It means that while pandemics are highly likely to decrease working hours are innovative activities, the innovators' productivity is less likely to be increased. Besides, innovators' productivity may be reduced by the infection of relatives. For instance, when one of the household members is infected by HIV/AIDS, the other members have to sacrifice working hours to take care of him/her (Bollinger *et al.*, 1999).

Innovation also requires long-term, multiple stage teamwork (Holmström, 1989; Xin Chang *et al.*, 2015). However, pandemic outbreaks tend to impede teamwork by decreasing face-to-face communication and usage of laboratories. Especially, infection (or even death) of critical members in the team may cause large negative impacts on innovation activities in the long-term.

The pandemic tends to cause negative impacts on innovation performance through financial channels. The overall consumption decreases following the pandemic outbreak (Goolsbee and Syverson, 2020). It will lead to a drop in firms' income. The firms' managers are myopic and willing to reduce long-term projects (i.e., R&D) to meet short-term earning target (Bushee, 1998; Graham *et al.*, 2005). Therefore, pandemics are highly likely to reduce firms' innovative activities because of reduced internal funding.

Besides, Jordà et al. (2020) show that the countries experience a low natural interest rate in the next decades of the pandemic. They explain it through the increased precautionary savings and depressed investment opportunities. It implies that firms experience financial constraints and work poorly in producing new projects or new products. Even firms could lend money in a loose credit environment; they are more likely to use this fund to improve risk prevention ability and resume productivity rather than invest in long-term projects.

The other explanation is that investors are less willing to invest in new projects during the pandemic due to adverse selection and moral hazard. Innovation is a risk-taking behaviour and leads to informational asymmetric between investors and innovators (Holmström, 1989; Levine *et al.*, 2017). Innovators with higher risk projects are more willing to attract investment (Stiglitz and Weiss, 1981). Besides, they are possible to substitute high-risk for low-risk projects after obtaining investment. Therefore, when pandemics interpret communication between investors and innovators and increase the informational asymmetric between them, the investors may become more careful to treat new projects.

To summarise, in light of the above, we hypothesise that pandemic shocks pose a threat to research and funding productivity, thereby reducing innovation output. In the main analysis below, we attempt to examine magnitude and the duration of the pandemic shock to aggregate innovation output.

6.4 Data, variables and methods

In this section we explain our data sources, variable measurements and estimation methods.

6.4.1 Data and variables

The World Health Organisation (WHO) defines a pandemic as "the worldwide spread of a new disease" (WHO, 2020). However, it makes no mention of a minimum number of cases/deaths that have to be reported in order to call an outbreak a pandemic. As such, we follow the recent paper by Jordà *et al.* (2020) and select pandemic episodes with at least 100,000 deaths reported (see also Cirillo and Taleb, 2020). The list of pandemics is reported in Table 6.1. On 15 May 2020, the death toll due to the COVID-19 pandemic was 307,000, a figure much higher than the minimum threshold used in this study.

Table 6.1

We use patent data from the European Patent Office's PATSTAT database (2016 Autumn Edition). We select data from 1900 to 2012 (approximately 21.5 million successful patent applications) as we drop the final four years to ensure that the data is relatively free of truncation bias (Dass *et al.*, 2017). We focus on the set of G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States). The bulk of global innovative activity is concentrated in those seven countries (see also Section 6.5 and Guloglu *et al.*, 2012). We measure innovation as the number of successful patent applications per country.[67] As a robustness test, we also reproduce the results using a sample of the top ten most

[67] In line with studies in the innovation literature (see Levine *et al.*, 2017), we (i) identify the first time an invention is patented and call it the "original patent", (ii) date patents using the application year of the original patent as the

innovative countries over the sample period (France, Germany, Korea, Japan, the United Kingdom, the United States, China, Switzerland, Austria, and Russia, hereafter T10).

In Figure 6.1, Panel 1, we present the time series of the average number of applications granted for the G7 countries and the applications granted for the G7 as a proportion of total patenting activity. Equally, in Figure 6.1, Panel 2, we estimate the same time series for the T10 countries. Innovation output is rather volatile but remained at relatively similar levels until the beginning of the 1970s when Japan and China increased their innovation output. Interestingly, the slump in innovation activity in the 1970s and 1980s is related to innovation activity conducted by the former Soviet Union.

Figure 6.1

6.4.2 Estimation methods

We use a local projection estimator model introduced by Jordà (2005) to estimate the impulse response functions of pandemic shocks to innovation output. Local projection estimators are shown to produce more reliable forecasts over Vector Autoregression (VAR) models at medium to longer forecast horizons.

In particular, Pope (1990) shows that the bias in the estimation of the autoregressive parameters increases as impulses are at longer forecast horizons. Additionally, VAR estimators require large lag length to produce reliable impulse responses (Kapetanios *et al.*, 2007). Local

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application date is closer to the actual date of innovation and (iii) focus on utility patents only. We record the country of the invention using the Patent Authority that accepts the application of the original patent, See also the Robustness tests section.

projection estimators are more robust to misspecification errors introduced by the data generation process by regressing the dependent variable vector at $t+h$ on the information set at time *t*. Hence, a new forecast is created by each impulse horizon as compared to the use of iterant forecasting based on the same coefficient estimates from one VAR estimation. The loss of efficiency from estimating local projection impulse responses as opposed to using correctly-estimated VARs, is low at medium to long-term forecast horizons (Haug and Smith, 2012). Furthermore, unlike VAR estimators, the nonlinear transformations of the estimated slope parameter are not required by impulse responses based on local projections. As a result, this approach can be better approximated by Gaussian distributions and thereby increase the coverage accuracy of impulse response confidence intervals.

Our objective is to estimate the impulse response functions for innovation following a pandemic episode. We use a model-free or local projection estimator that allows us to estimate local projections sequentially h steps ahead (see Jordà, 2005; Jordà and Taylor, 2016) as follows:

$$\Delta Innov_{i,t+h} = \alpha_i^h + \beta^h P_t + \sum_{l=1}^{L} \beta_l^h \, Innov_{i,t-l} + C_i^h + e_{i,t+h}^h; \qquad (6.1)$$

for $h = 1, \dots, 15,$ and $L = 3$

Where $Innov_{i,t-l}$ is the natural logarithm of one plus the number of successful patent applications per year and for each country i. $\Delta Innov_{i,t+h}$ denotes the innovation's growth rate and is the difference of the natural logarithm of the innovation variable from time *t* to $t+h$; P_t denotes the dummy variable that is 1 if there is a pandemic start, 0 otherwise; *Ci* denotes country fixed-effects. Three lags of innovation indicator are adopted as control variables.[68]

Furthermore, we access the effect of pandemic shocks by sector of economic activity by estimating the following set of regressions:

$$\Delta Innov_{i,t+h,z} = \alpha_i^h + \beta_z^h P_t + \sum_{l=1}^{L} \beta_l^h \, Innov_{i,t-l} + \; C_i^h + e_{i,t+h,z} \quad (6.2)$$

In Equation (6.2) we estimate separate regressions by sector of economic activity, z. To this end, we use the existing statistical classification of economic activities for the European Union, NACE Rev.2, in order to categorise patents into three sectors: (1) manufacturing, (2) construction and (3) information and communication. NACE Rev. 2 is developed on the basis of the United Nations' International Standard Industrial Classification of All Economic Activities (ISIC Rev. 4). The first application recorded with NACE Rev.2 in the PATSTAT was submitted in 1845. It shows the weight of the association between an application and different technical fields. By using this, we are able to classify patents to one or more sectors based on their degree of association. Approximately, only 6.7% of patent applications (1.46 million applications) do not have a sector classification.

Finally, we investigate the effect of pandemic shocks to the number of patent applications. In particular, on PATSTAT, (i) we identify the first application of each invention, (ii) record the country of residence of its primary assignee (i.e., owner) as the country of the invention and (iii) focus on utility patents only.

[68] We choose the pandemic start date as we expect that the pandemic period is the most disruptive period for innovation. The choice of number of lags does not affect the results. See also the Robustness tests section.

We examine (1) the next year effect of the end of a pandemic to the number of submitted applications and (2) the effect of the pandemic duration on next year's number of submitted applications. To this end, we estimate the following regressions:

$$Innov_{i,t+1} = \alpha_i \ + \beta P_t^{End/Dur} + C_i \ + e_{i,t+1} \tag{6.3}$$

where $Innov_{i,t+1}$ denotes the natural logarithm of 1 plus the number of submitted patent applications at year *t+1* for each country *i*. $P_t^{End/Dur}$ refers to the dummy variables of pandemic (P^{End} and P^{Dur}) at time *t*. P^{End} is 1 if there is a pandemic end, 0 otherwise. P^{Dur} is 1 if there is a pandemic, 0 otherwise. *Ci* denotes country fixed-effects.

6.5 Empirical Results

In this section, we provide the main results of this study and discuss policy implications. We start by investigating the effect of pandemic shocks on aggregate innovation output. Next, we classify patents by sector of economic activity and show the effect of pandemics separately for the manufacturing, construction and information and communication sectors. In the third subsection, we show the effect of pandemic shocks by country of award and in the final section, we demonstrate the effect of pandemic shocks on patent applications. Finally, given the ongoing COVID19 pandemic, we discuss some very important policy implications that stem from our research.

6.5.1 Pandemic shocks and aggregate innovation

In Table 6.2, we present our main results. The dependent variable is the change in innovation output. Each row refers to a separate local projection model with country-fixed effects. Three lags of innovation output are included in each regression (not reproduced here).

The results presented in Table 6.2 show that pandemic shocks disrupt research productivity with effects being felt long into the future. Innovation remains relatively stable for approximately four years after the pandemic start. This result however is not surprising. R&D investments take several years to materialise, so the relatively stable trend of applications four years after the pandemic start most likely reflects R&D investments that started before the pandemic had any effect on R&D projects. Subsequent innovation output is reduced for three years and, overall, it takes approximately seven years for innovation output to return to pre-pandemic levels. Clearly, the model provides more reliable forecasts of the long-run rather than the short-run effects of pandemics on innovation output.

Table 6.2

In Figure 6.2, we produce the impulse responses of innovation output to a pandemic. The solid line refers to the pandemic coefficient value for h = 1,...,15 and the light and dark shaded areas refer to 70% and 95% error bands, respectively.

The impulse response plots are striking. In a recent interview, Professor Bloom, Senior Fellow at Stanford's Institute for Economic Policy Research, summarised the fears for a "slump in innovation" as follows: *"The new ideas we are losing today could show up as fewer new products in 2021 and beyond, lowering long-run growth"* (Gorlick, 2020). In line with this prediction, Figure 6.2 demonstrates that the effects of past pandemics on research productivity – and therefore on innovation output – are felt for approximately seven years from the onset of the pandemic. This result, whilst in line with the current expectations of the impact of COVID19 on economic growth, they show a much longer-term effect on innovation output that the one anticipated.

Figure 6.2

6.5.2 Pandemic shocks by Sector of Economic Activity

In this subsection, we present the results of the effect of pandemic shocks to innovation output by sector of economic activity (NACE Rev.2).[69] We present the impulse response results in Figure 6.3.

[69] We do not report the regression results of the set of local projection estimator models by country in order to conserve space. The results are available upon request. We provide an interpretation of the impulse response plots with respect to the pandemic coefficient values in Section 6.5.1.

Figure 6.3

In line with the main result, following a pandemic shock, innovation output remains unchanged for approximately four years, probably due to the lag between R&D investments and patent applications. Overall, the manufacturing and the construction sectors are immune to the pandemic shock. Importantly, our main result regarding the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in the Information and Communication technology sector, a sector that depends more on research productivity than the construction and manufacturing sectors do.

Overall, the results by sector of economic activity demonstrate that one-size-fits-all government policies that support innovation output may be inefficient as more research-intensive sectors receive a disproportionately large pandemic shock. An allocation of resources to sectors that historically have a greater exposure to pandemics is likely to lead to a faster economic recovery.

6.5.3 Results by country of award

In this subsection we investigate the effect of pandemic shocks on innovation output by country of award. In the first part of the analysis, we establish that following a pandemic shock, global innovation outlook takes approximately seven years to recover. We present the results by country in Figure 6.4.

Figure 6.4

There are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. The magnitude of the pandemic shock is small for Italy and for Japan considerably larger than the remaining G7 countries. Notably, innovation output in Canada is relatively more volatile than in the rest of G7. Whilst for the five of seven countries, the duration of the pandemic shock ie the time to recovery, is approximately seven years, for Italy, recovery is achieved after four years. On the other hand, innovation output in the UK remains at below pre-pandemic level for several years. Overall, the results by country underline the need for government initiatives that remedy the effect of the pandemic shock, especially with respect to the idiosyncrasies of the innovative sectors across countries.

6.5.4 Effect of pandemic shocks on patent applications

Finally, we investigate the effect of pandemic shocks and duration on patent applications. Even though the number of patent applications is likely to be affected by the applicant's ability to submit patent applications rather than just the ability to develop new ideas, this measure ultimately reflects the short-term effect of pandemic shocks to innovation. We focus on the pandemic end rather than the pandemic start as the first year of the pandemic will most likely reflect the research productivity of the previous year. Also, as the HIV/AIDS pandemic has a very long duration, we drop HIV/AIDS from the measurement of the pandemic duration dummy.

We present the results of the effect of pandemic shocks and duration on patent applications in Table 6.3. For robustness, we report the regression results for both the G7 and the T10 samples. Furthermore, we report the results with and without country-fixed effects.

As anticipated, pandemic shocks lead to a short-term drop in the number of patent applications. This result is statistically significant at 1% for the G7 countries. For the T10 countries, the effect of pandemic shocks to patent applications is negative but not significant. We conjecture that the insignificant result for the T10 countries reflects the fact that (i) the most significant pandemic episodes happened at the start of the twentieth century and (ii) the G7 (T10) countries have tended to capture an even smaller (larger) proportion of the total patenting activity since the 1990s. Figure 6.1, Panels 1 and 2 demonstrate that T10 traces more accurately global patenting activity towards the end rather than the start of the sample period. Equally, pandemic duration is strongly associated with a drop in patent applications. In contrast to the regression results for the P^{end} dummy, P^{dur} is negative and statistically significant at 1% level for both the G7 and T10 samples.

6.5.5 Policy implications

The results presented in this section have very important policy implications. First, given that the pandemic poses a clear threat to research productivity in the long-run, policies that may reduce the effect of the "Great Lockdown" on research productivity are needed. Second, whilst the pandemic shock has an effect on global innovation output, the results vary by country and sectors of economic activity. The response to COVID19 needs therefore to have a global character[70] but countries also need to introduce support schemes for the sectors that are more exposed to the pandemic shock. Overall, policies which target the more innovative firms are expected to remedy the effect of COV19 on future growth. Third, the pandemic shock is expected to have a strongly negative effect on patent applications. Governments, need to be prepared to support innovators in the immediate aftermath of the pandemic. Patent offices may have to speedup the process of approving new patents. Bloom *et al.* (2020) show that "ideas

[70] The "Next Generation EU" support fund with a total value of €750B is such an example. The fact that the European Commission has also recommended changes to the long-term European Union budget for 2021-2027 is in-line with the policy recommendation relating to the duration of the pandemic.

are non-rival", meaning that "they can be used simultaneously by any number of people". Supporting inventors and expediting the patent application process is therefore key in supporting economic growth. Finally, innovation output is significantly and negatively affected by the duration of the pandemic and it is therefore important to implement support policies for the duration of the pandemic rather than as one-off expenditures only.

6.6 Robustness tests

To further support our main finding that pandemic shocks disrupt innovation output for long into the future, in this section we check the robustness of our results. Overall, we obtain qualitatively similar results that are robust to the model specifications. In each subsection below, we outline the specifications of each robustness test. We present all robustness test results in Table 6.4 and the corresponding impulse response functions in Figure 6.5.

Table 6.4

Figure 6.5

6.6.1 Using the pandemic end date

We first examine whether the effect of pandemic shocks on innovation output is robust to alternative pandemic date specifications. To this end, we re-run the baseline set of regressions and define P_t as the dummy variable that is 1 if there is a pandemic end, 0 otherwise. The results are presented in Table 6.4, Panel 1. In Figure 6.5, Panel 1, we present the impulse response function of the effect of pandemic shocks to innovation output.

6.6.2 Using the ten most innovative countries

One criticism may be that the G7 countries are not representative of global innovative activity. To respond to this criticism, we estimate Equation 1 using the top ten most innovative countries over the sample period (T10). Figure 6.1, Panel 2, shows the average number of successful patents per country and the percentage of global innovation activity that is awarded to the top ten most innovative countries over the sample period. We report the results of this set of regression models in Table 6.4, Panel 2. In Figure 6.5, Panel 2, we present the corresponding impulse response function.

6.6.3 Dropping the HIV pandemic

With the exception of HIV, most pandemics are short-lived. For robustness we drop HIV from the list of pandemics as it did not have a distinctive outbreak and estimate Equation 1 again. We present the re-estimation results in Table 6.4, Panel 3 and in Figure 6.5, Panel 3.

6.6.4 Use the patent owner's country of residence

Finally, approximately 31% of the successful patent applications do not mention the nationality of their applicants. In the main analysis, we used the country of the patenting office that is the first to accept the application of the original patent in order to classify patent applications per country. As a robustness test, in Table 6.4, Panel 4 and in Figure 6.5, Panel 4, we use the patent owner's residential country as the country of the invention.

Overall, the results in this section show that qualitatively the established relationship between pandemic shocks and innovation output remains the same, albeit statistical significance is not always consistent across samples and robustness tests. Nevertheless, the impulse response functions show that the main result still holds: following a pandemic, innovation output is disrupted for approximately seven years.

6.7 Limitation

A limitation of this chapter is that we do not distinguish between pandemic shocks and policy response shock caused by the pandemic. However, the government containment policies, such as social-distancing policy, are only imposed during the pandemic. Besides, they tend to cause less damage to the economy. For example, Goolsbee and Syverson (2020) find that while consumer traffic is reduced by 60 percent following the COVID-19 outbreak, only 7 percent of them is explained by the legal restrictions. The rest is mainly relevant to the individual choices, which due to the fears of infection. Besiedes, Sheridan *et al.* (2020) suggest that restriction law causes only a few drops in consumption, and the most reduction is due to the pandemic itself. However, it is true that these researches only focus on short-term impacts. Therefore, it might be a limitation of our chapter.

6.8 Chapter Conclusion

In this chapter, we employ an idea-based theory of economic growth in which growth is a function of both research productivity and the number of researchers. Given that pandemics pose a threat to research productivity, we use a local projection estimator to model the effect of pandemic shocks on innovation output.

We show that following a pandemic, innovation output is disrupted for a period of approximately seven years, probably because of a drop in research productivity. Given that COVID19 is expected to be a major obstacle to research productivity, especially during the lockdown, the effects of the pandemic on future innovation output and subsequently on growth are expected to be felt for long into the future. The main result in the effect of pandemic shocks on aggregate innovation output is driven primarily by a significant reduction in innovative activity in the Information and Communication technology sector. In addition, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. Pandemic shocks lead to a short-term drop in the number of patent applications. Finally, pandemic duration is strongly associated with a drop in patent applications.

This chapter contributes to the recent debate on the economic consequences of COVID19. It supports policies designed to reduce the effect of the "Great Lockdown" on research productivity. We recommend policies that have a global character, support innovators, speed up the process of approving new patents and target the more innovative firms. However, further research should delve deeper into the exact effects of COVID19 and the "Great Lockdown" on research productivity.

Table 6.1 Pandemic episodes since 1900 with at least 100,000 deaths

Event	**Death toll**	**Location**	**Start /End date**
Encephalitis lethargica pandemic	1.5 million	Worldwide	1915-26
Spanish flu	17-100 million	Worldwide	1918-20
Asian flu	1-4 million	Worldwide	1957–58
Hong Kong flu	1-4 million	Worldwide	1968–69
HIV/AIDS	32 million+	Worldwide	1981– present
H1N1/09 virus	203,000	Worldwide	2009-10

Note: source: https://en.wikipedia.org/wiki/List_of_epidemics

Table 6.2 Effect of a pandemic episode on innovation output

Dependent variable: *ΔInnovi, t+h*					
h	*P*	*L*	*C*	*N*	R^2
1	0.05	3	Yes	625	0.07
	(0.06)				
2	0.12**	3	Yes	622	0.11
	(0.04)				
3	0.06	3	Yes	620	0.12
	(0.15)				
4	0.28	3	Yes	615	0.13
	(0.16)				
5	0.15	3	Yes	608	0.18
	(0.19)				
6	-0.32	3	Yes	602	0.22
	(0.26)				
7	-0.6	3	Yes	594	0.26
	(0.4)				
8	0.42**	3	Yes	586	0.27
	(0.15)				
9	0.42*	3	Yes	578	0.29
	(0.18)				
10	0.18	3	Yes	570	0.32
	(0.41)				

11	0.50**	3	Yes	562	0.38
	(0.16)				
12	0.51**	3	Yes	554	0.41
	(0.15)				
13	0.58**	3	Yes	546	0.44
	(0.18)				
14	0.66**	3	Yes	538	0.47
	(0.23)				
15	0.68**	3	Yes	530	0.50
	(0.27)				

Note: This table presents the results of the local projection model with country fixed effects and cluster-robust standard errors. *h* refers to the number of years in the future. *P* refers to the start of a pandemic. Country fixed effects (*C*) and three lags of innovation output (*L*) are included in each regression (not reproduced here). Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

Table 6.3 Effect of pandemic shocks on patent applications

Dependent variable:	**Ln(Innovation$_{i,t+1}$)**							
Sample	G7				T10			
	(1)		(2)		(3)		(4)	
P^{End}	-0.60***	-0.63***			-0.10	-0.09		
	(0.15)	(0.15)			(0.28)	(0.30)		
P^{Dur}			-2.24***	-2.34***			-2.24***	-2.24***
			(0.19)	(0.19)			(0.23)	(0.23)
N	712	712	712	712	859	859	859	859
Country FEs	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.002	0.114	0.074	0.193	0.001	0.102	0.060	0.166

Note: This table presents the results of the effect of pandemic shocks on next year's innovation output. The dependent variable is the natural logarithm of one plus the number of submitted patent applications at year $t+1$ for each country i. $P_t^{End/Dur}$ refers to the dummy variables of pandemic (P^{End} and P^{Dur}) at time t. P^{End} is 1 if there is a pandemic end, 0 otherwise. P^{Dur} is 1 if there is a pandemic, 0 otherwise. Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

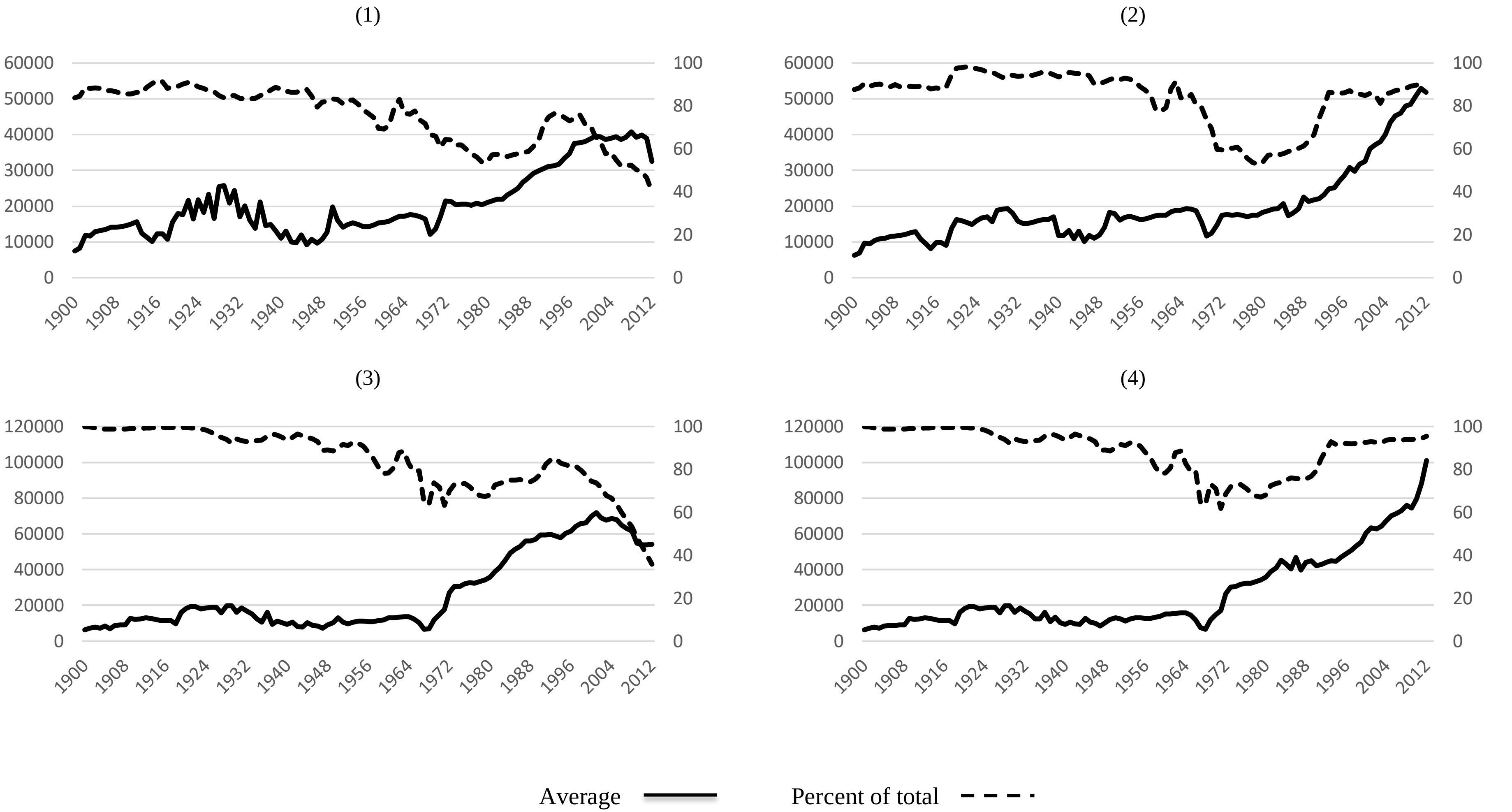
Table 6.4 Robustness tests

	(1)		(2)		(3)		(4)	
h	*P*	R^2	*P*	R^2	*P*	R^2	*P*	R^2
1	0.03	0.07	0.06*	0.10	0.05	0.07	-0.11	0.04
	(0.05)		(0.03)		(0.07)		(0.11)	
2	0.03	0.11	0.10**	0.19	0.14*	0.11	-0.28	0.04
	(0.05)		(0.04)		(0.06)		(0.16)	
3	0.21	0.12	0.14**	0.12	0.04	0.12	-0.54**	0.07
	(0.19)		(0.06)		(0.2)		(0.2)	
4	0.04	0.13	0.17*	0.10	0.31	0.13	-0.39	0.08
	(0.19)		(0.09)		(0.17)		(0.23)	
5	-0.56*	0.19	0.05	0.12	0.15	0.18	-0.58*	0.08
	(0.27)		(0.11)		(0.21)		(0.25)	
6	-0.62	0.23	-0.45**	0.15	-0.46	0.22	-1.32***	0.12
	(0.5)		(0.18)		(0.29)		(0.23)	
7	0.39*	0.25	-1.01*	0.20	-0.83	0.26	-1.50***	0.13
	(0.17)		(0.48)		(0.54)		(0.38)	
8	0.45*	0.27	0.40***	0.20	0.50**	0.27	-0.73	0.10
	(0.19)		(0.09)		(0.16)		(0.4)	
9	0.49**	0.30	0.41***	0.20	0.53**	0.29	-0.85**	0.12
	(0.18)		(0.1)		(0.17)		(0.29)	
10	0.51**	0.33	0.41***	0.22	0.19	0.32	-0.67*	0.11
	(0.2)		(0.12)		(0.49)		(0.3)	
11	0.51*	0.38	0.41***	0.25	0.61***	0.38	-0.36	0.12

	(0.23)		(0.12)		(0.16)		(0.28)	
12	0.58*	0.41	0.41***	0.27	0.60***	0.41	-0.47	0.13
	(0.27)		(0.12)		(0.16)		(0.31)	
13	0.65	0.44	0.42***	0.29	0.68**	0.44	-0.4	0.13
	(0.34)		(0.13)		(0.2)		(0.23)	
14	0.61	0.47	0.40**	0.31	0.74**	0.47	-0.33	0.14
	(0.38)		(0.13)		(0.25)		(0.3)	
15	0.57	0.50	0.40**	0.32	0.74**	0.50	-0.44	0.15
	(0.34)		(0.13)		(0.28)		(0.29)	

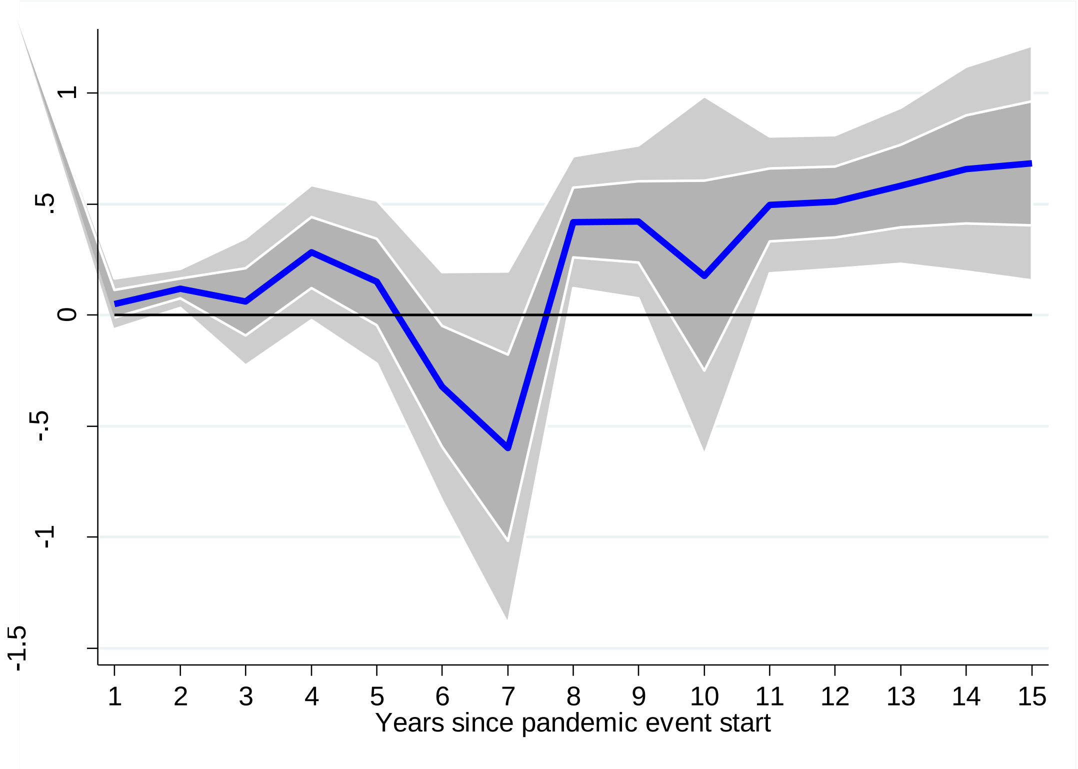
Note: This table presents the results of the robustness tests. We estimate a set of local projection models with country fixed effects and cluster-robust standard errors. *h* refers to the number of years in the future. Country fixed effects (*C*) and three lags of innovation output (*L*) are included in each regression (not reproduced here). In (1), *P* refers to the end of a pandemic period. In (2), (3) and (4), *P* refers to the start of a pandemic. In (2), we reproduce the results using the top 10 most innovative countries over the sample period. In (3), we do not account for the HIV pandemic. In (4), we use the patent owner's country of residence. Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

Figure 6.1 Time series of innovation from 1900 to 2012



Note: In (1), the solid line refers to the average number of applications granted for the G7. The dashed line refers to the proportion of successful applications granted in G7 countries as a percentage of total global activity. In (2), we replace G7 with T10. In (3), the solid line refers to the average number of applications submitted for the G7. The dashed line refers to the proportion of applications submitted in G7 countries as a percentage of total global activity. In (4), we replace G7 with T10.

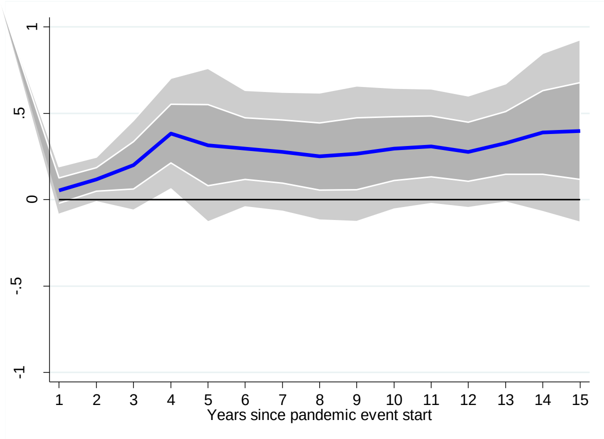
Figure 6.2 The impulse response of innovation output to a pandemic episode



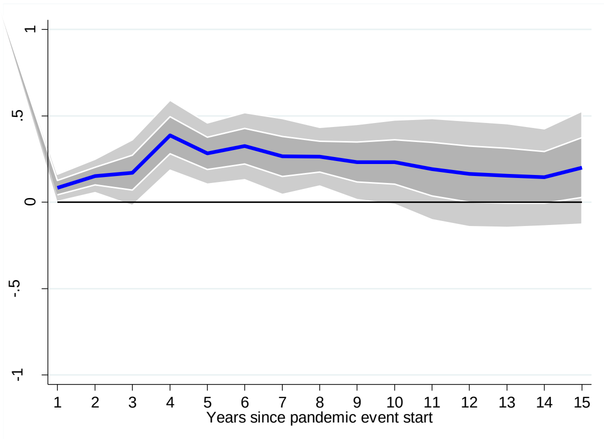
Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

Figure 6.3 The impulse response of innovation output to a pandemic episode by sector of economic activity

Manufacturing



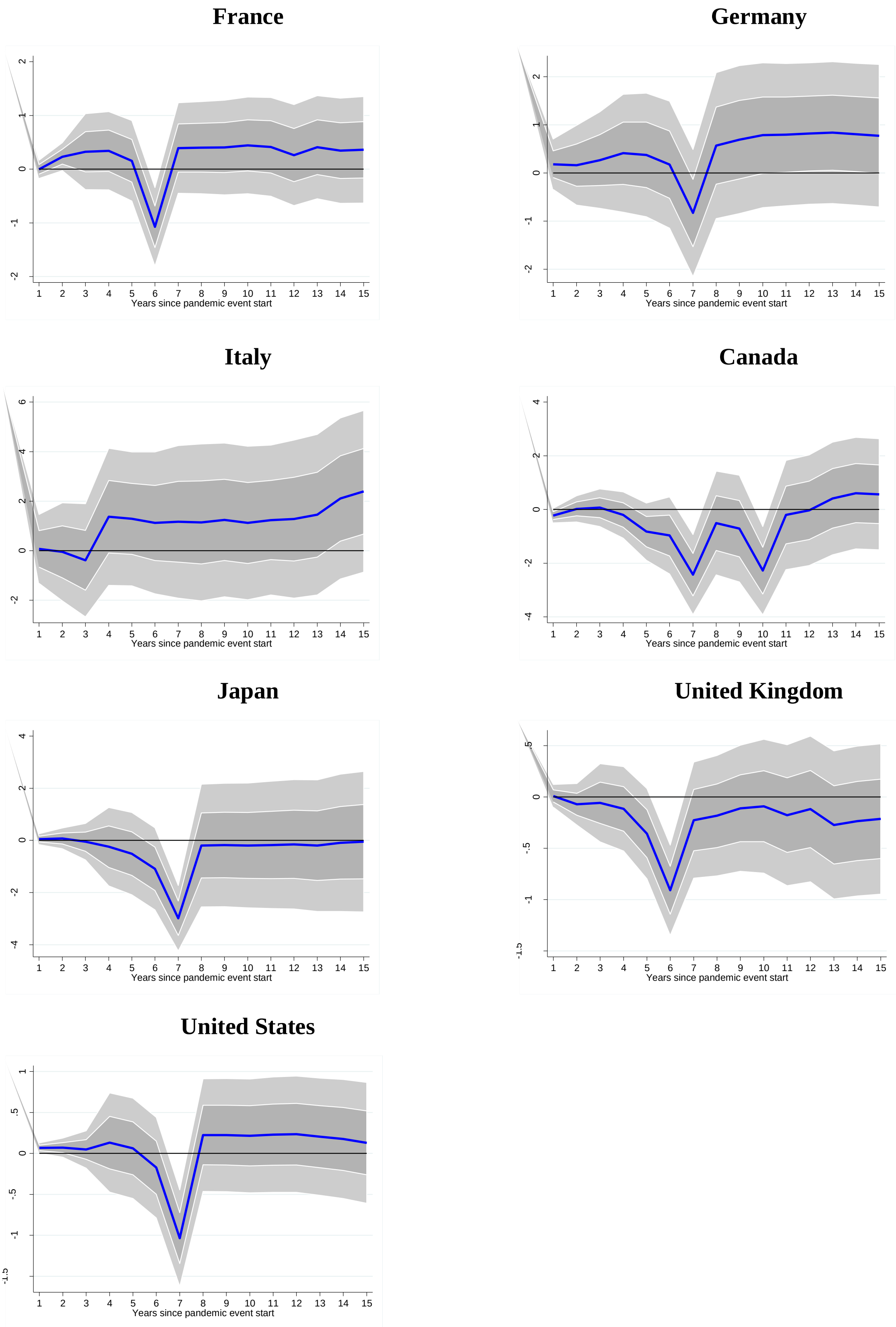
Construction



Information and communication

Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

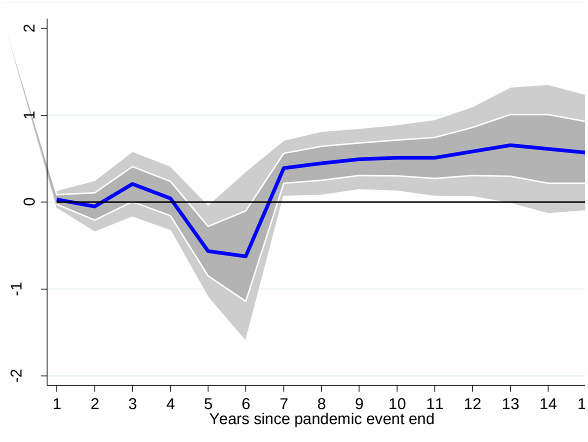
Figure 6.4 The impulse response of innovation output to a pandemic episode by country



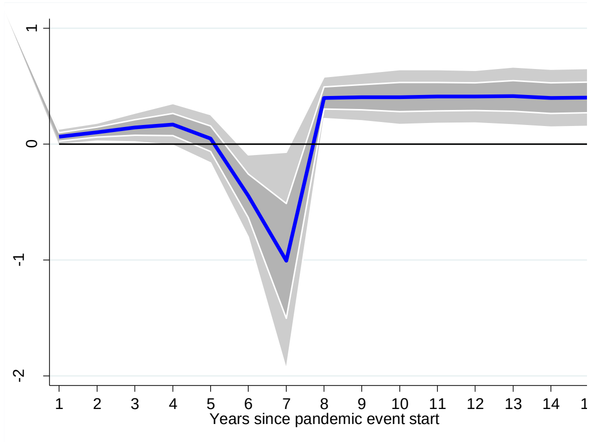
Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

Figure 6.5 Robustness tests: impulse responses of innovation output to a pandemic episode

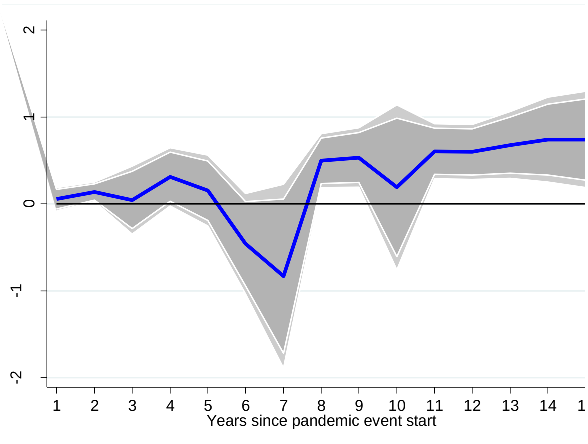
(1)



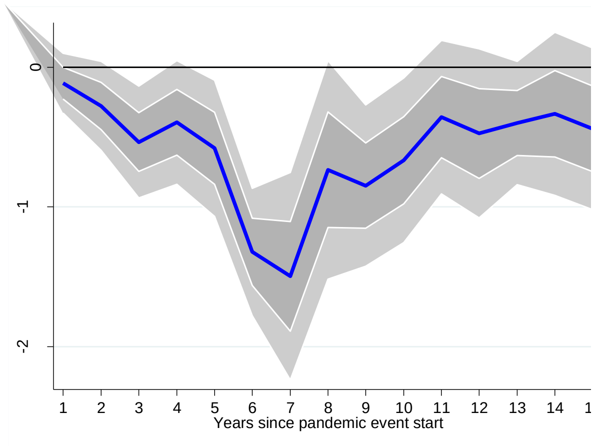
(2)



(3)



(4)



Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands. In (1), we use the end of a pandemic period. In (2), we reproduce the results using the top 10 most innovative countries over the sample period. In (3), we do not account for the HIV pandemic. In (4), we use the patent owner's country of residence.

Chapter 7 Thesis Conclusion

In this thesis, we investigate factors that may impact on innovation activities from the perspective of financial literature. More specifically, by using an international sample, we consider both micro (firm-level) and macro (country-level) factors and discuss how they affect innovation performance.

In Chapter 3, we merge the patent-based data from the PATSTAT database with firm account information from Datastream. It provides a more accessible dataset by which to investigate the relationship between financial markets and firm innovation from an international perspective. Compared with previous researches, this dataset includes patents from patent authorities worldwide rather than just USPTO. Thus, it is less like to underestimate the number of patents per company in non-US countries. In addition, we collect and calculate patent data in different countries with the same standard, which provides a basis for global innovation research through innovation outputs.

In Chapter 4, we investigate the R&D-patent relationship from the perspective of stock liquidity. While stock liquidity causes a significant negative influence on firm R&D investment, it is much lighter than the impact on firm innovation outputs. Thus, we argue that although stock liquidity can affect firm innovation through R&D investment, the most impact of stock liquidity on firm innovation comes from the direct impact of stock liquidity itself. It emphasises the importance of stock liquidity on firms innovation performance and improves the understanding of the R&D-patents relationship from the perspective of stock liquidity. It also provides a basis for our next chapter that focuses on the impact of stock liquidity on firm innovation performance.

In Chapter 5, we explore the relationship between stock liquidity and firm innovation performance. Our empirical evidence shows continuously increased positive impacts of stock liquidity on firms' patent-based indicators. More specifically, we find that stock liquidity mainly contributes to a firm's efficiency in producing high-quality patents rather than more patents. In addition, we assert that firms tend to produce more patents in larger economies with a higher level of international trading and economic freedom. These results provide evidence to policymakers in the financial area who expect to encourage innovation outputs through financial systems. In addition, public companies could be more confident to continue their R&D activities following policies that increase stock liquidity.

In Chapter 6, we investigate the long-term consequences of pandemic shocks on innovation output and demonstrate that following a pandemic, innovation output is disrupted for approximately seven years. We show that the main result of the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in innovative activity in the Information and Communication technology sector. Furthermore, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. Pandemic shocks lead to a short-term drop in the number of patent applications. Crucially, the duration of a pandemic has a strong effect on innovation output. Our results support the policies designed to reduce the effect of the "Great lockdown" on research productivity. Governments need to be prepared to support innovators in the immediate aftermath of the pandemic, and patent offices may have to speed up the process of approving new patents. In addition, we recommend adopting policies that target the more innovative firms as this is expected to help reduce the time it will take for innovation to recover from the effects of COVID19.

Overall, we specifically emphasise the influence of two factors on innovation activities in this thesis. The first is stock liquidity. We provide a deep understanding of these factors by exploring how it affects innovation outputs and what impact it has on innovation performance. The second is the pandemic shocks. We provide an original view by which to analyse the response of innovation activities to pandemic spreads and discuss how financial markets affect innovation as a channel of exogenous shock. In terms of this, we show that financial systems could improve innovation performance by boosting its efficiency, such as increasing stock liquidity. It could also affect innovation activities as a channel of exogenous shocks.

While we make several original contributions to this literature, several limitations should be noticed. Although patent-based data is widely used to represent innovation activities, this indicator shows several shortcomings (Becheikh *et al.*, 2006). First, not all innovators apply for patents to protect their innovation. Different sectors tend to have different patenting propensities and innovation cycles (Michie, 1998; Archibugi and Sirilli, 2000; Cao *et al.*, 2015). Companies may choose other ways to protect their profits due to various reasons, such as high costs, week intellectual property right protection rules and cumbersome patenting procedures (Mansfield, 1985; Archibugi and Planta, 1996; Kleinknecht *et al.*, 2002). For instance, Coca Cola holds its formula in the vault as business secrets. In this thesis, we include a series of firm and country characters, fixed effects, robustness test for specific industry and countries to control for heterogeneity in different firms and industries. Although we may not be able to figure out this problem completely, we believe these adequate control variables and robustness tests could lead to proper deduction applicable firms in different industries and countries.

Besides, some researchers argue that innovation is the procedures of transforming invention into marketable products or process (Coombs *et al.*, 1996; OECD., 1997; Flor and Oltra, 2004). They propose that the patent-based measurements may overestimate innovation outputs by including inventions that are not translated to products or process. However, the patent-based date is still difficult to be replaced in innovation research at the current stage. In particular, we are doing international research in this thesis. Patents are still one of the most direct measures of innovation's extent and quality, and widely accepted by recent finance literature (such as Chemmanur and Tian, 2018; Fang *et al.*, 2014; Chang *et al.*, 2015; Luong *et al.*, 2017; Zhu and Zhu, 2017). Although some literature employs other indicators, such as innovation count, firm-based surveys, to measure innovation activities, they subject to idiosyncratic bias and surveys' answer rate separately (Archibugi and Planta, 1996; Archibugi and Sirilli, 2000). It is also less likely to construct the long term sample of these indicators for international study.

In Chapter 4 and 5, we include the firm accounting information rather than corporate governance indicators. Although a growing body of literature demonstrates that firm innovation can be affected by ownerships (Battaggion and Tajoli, 2000; Lee, 2005) and human characters (Liu et al., 2017; Chemmanur et al., 2019; Chang et al., 2015), we do not include them as firm-level control variables. One of the reason is that we are restricted by the available data at Datastream. For example, Datastream only provides the current ownership structure of the company rather than recording the history of firm ownership transformation. We expect to include corporate governance indicators in future research to consider their impacts on firm innovation.

For future research, this thesis recommends continuing investigation in finance and innovation fields. There are still few studies covering the impact of trading and exchange structures on firm innovation activities. For instance, derivative tradings are highly relevant to firms' long-term earnings (Blanco and Wehrheim, 2017). They could encourage employees to take the risk (Chang *et al.*, 2015), improve information transmission about long-term investments (Blanco and Wehrheim, 2017). However, there are still few literature studies in this area. We expect to consider these characters in future research.

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