Norwegian School of Economics
Bergen, Spring 2018

NPEs' patent acquisitions

Empirical analysis of patent data

Magne Nilsen and Prakash Raj Paudel

Supervisor: Steffen Juranek

Master Thesis, MSC Economics and Business Administration,
Strategy and Management (STR)

NORWEGIAN SCHOOL OF ECONOMICS

Executive summary

Patent trolls, or NPEs, act as intermediaries in the markets for technology and behave opportunistically to earn profit through patent litigation and licensing. Some researchers claim that NPEs harm the economy and innovation, but few studies address the issue related to the supply side of NPEs' patent acquisitions. Thus, in this thesis, we want to empirically analyze NPEs' patent acquisitions using the USPTO patent assignment dataset to explore who are the patent sellers (firms) to the NPEs and if they are different than the sellers to non-NPEs. Similarly, we investigate what kind of patents do NPEs acquire and whether these patents are different than non-NPEs. The analysis is based on secondary data. After extensive data cleaning, we used the final dataset of 119,777 containing 18,010 patents acquired by NPEs and 101,767 by non-NPEs between 2005 and 2014. Our empirical analysis revealed that the firms and patents are statistically significantly different between NPEs and non-NPEs. In contrast with previous research, our results showed that NPEs are more likely to acquire patents from very large companies. Additionally, on average, NPEs are more likely to acquire significantly higher quality patents (with higher patent scope, forward citations, backward citations and claims) mostly in specific category from non-US based companies than that non-NPEs are likely to acquire. We also found that patents acquired by NPEs have more claims and words adjustments during the grant process than by non-NPEs. Finally, research implications, limitations, and opportunities for future research are discussed.

Keywords: NPEs, Markets for technology, Patent acquisitions, Patent transfer

Acknowledgement

Working on this thesis has been very interesting and rewarding. We feel grateful to be able to work on a topic of our interest, which matched with the research field of our supervisor.

We would like to thank our thesis supervisor, Steffen Juranek, for his encouragement, constructive comments and suggestions during the preparation of this thesis. This thesis would not have been possible without his data regarding non-practicing entities (NPEs). He was always open for questions and provided valuable input and feedback on our work. We truly appreciate all the effort.

Bergen, June 2018

Magne Nilsen and Prakash Raj Paudel

List of abbreviations

comp	Company
Comp & Comm	Computers and Communications
Ele & Elec	Electrical and Electronics
EPO	European Patent Office
GDP	Gross domestic product
ind.	Independent
IP	Intellectual property
IPC	International Patent Classification
IPR	Intellectual property rights
JPO	Japan Patent Office
KIPO	Korean Intellectual Property Office
NBER	National Bureau of Economic Research
NPE	Non-practicing entity
NPL	Non-patent literature
OECD	Organization for Economic Co-operation and Development
PAE	Patent assertion entity
PATSTAT	Worldwide Patent Statistical Database
R&D	Research and development
rf_id	reel-frame identification number
SIPO	State Intellectual Property Office of the People's Republic of China
US	United States
USPTO	United States Patent and Trademark Office
V large	Very large
WIPO	World Intellectual Property Organization

Contents

List of tables and figures

List of tables

List of tables at appendix

List of figures

1. Introduction

1.1 Motivation and purpose

Non-practicing entities (NPEs) are firms or individuals who own patents but have no intention to develop or practice it. Patent trolls are one type of NPEs who own patents and buy patent portfolios from other companies in order to sue practicing firms that they claim have infringed their patents, without fear of being countersued. Reitzig, Henkel, and Heath (2007, p. 134) define “Patent trolls (or sharks) as patent holding individuals or (often small) firms who trap R&D intensive manufacturers in patent infringement situations in order to receive damage awards for the illegitimate use of their technology” (hereafter we use the term NPEs to represent patent trolls). Moreover, the authors further state that NPEs generate profit by selling or licensing patents to manufacturing firms but refuse to provide the license after production start because this will give more pressure to the manufacturer to settle the case in case of patent infringement. This strategy makes NPEs different from practicing firms (hereafter we use the term non-NPEs to represent practicing firms and used interchangeably). These arguments explain the business model of the NPEs and how they operate in the markets for technology.

In recent years, NPEs have received more attention in media and research and attracted a large amount of debate and scrutiny (Feng & Jaravel, 2016). Bessen (2014) argues that patent litigation harms innovation, especially for small businesses. The author further states that the number of firms sued by NPEs has grown by nine times from 2003-2013, which ultimately have a negative impact on innovation and investment in research and development (R&D). This is because NPEs follow the money and sue large innovative and cash-rich companies (Bessen, 2014; Blumenthal, 2013). Research showed that in the US, patent litigations reduce firms’ market capitalization by over $60 billion dollars each year (Bessen, 2014). Similarly, an analysis by RPX Corporation (2014) showed that in 2013 patent trolls filed 67% of all new patent lawsuits. That is up from 28% in 2009.

On the positive side, some researchers argue that NPEs increase market efficiency by providing liquidity in the patent market and it's easier for small patent owner to monetize their patents (Hagiu & Yoffie, 2013; McDonough III, 2006) and serving as patent intermediaries (Feng & Jaravel, 2016). NPEs have also been praised for their ability to evaluate patents and by “reducing information asymmetries between buyers and sellers” (Osenga, 2014, p. 452). NPEs defenders say they promote invention by providing liquid capital, compensation to small inventors and managing risk (Yeh, 2013). Shrestha (2010) states that "NPEs can serve a valuable role in enhancing innovation by identifying and acquiring high-value patents and thereby funding and encouraging some of the most successful inventors" (p. 150). Several researchers and the US Federal Trade Commission note that these benefits are significantly lower than the costs of NPEs (Yeh, 2013). The indirect costs from NPEs also include disruption of innovative activities. Patent litigation lawsuit initiated by NPEs can thus reduce the rate of innovation since more resources are focused on the lawsuit (Bessen & Meurer, 2013).

Importance of the topic

There are mainly three areas of studies have been done addressing NPEs. The first and widely studied area is NPEs and patent litigation (e.g., Bessen & Meurer, 2013; Kiebzak, Rafert, & Tucker, 2016; Lanjouw & Schankerman, 1997; Lanjouw & Schankerman, 2001), the second is the NPEs business model (e.g., Golden, 2006; Henkel & Reitzig, 2010; Reitzig, Henkel, & Schneider, 2010) and a recent study area is NPEs' patent acquisitions (e.g., Feng & Jaravel, 2016; Fischer & Henkel, 2012). The first two areas mostly analyzed NPEs activities and patents in connection with litigation cases. While analyzing NPEs acquisition route, we found interesting research gaps. First, this is a relatively new area of research, and very few studies have been done about NPEs' patent acquisitions (e.g., Feng & Jaravel, 2016; Fischer & Henkel, 2012). Second, Fischer and Henkel (2012) state in their future research section that it is still an open question whether NPEs acquire patents from small or large firms, and they just assume (on the basis of web search) that NPEs acquire most of their patents from small firms. Finally, the authors argue that it also needs to be confirmed whether NPEs acquired higher quality patents than practicing firms or not.

Thus, we tried to fill this research gap by providing empirical evidence by analyzing NPEs' patent acquisitions. For further analysis, we follow Fischer and Henkel (2012) and extend their study by overcoming the limitations and addressing their future research suggestions. They have some limitations regarding the firm size (of the patent sellers) as they argue that "a large percentage of sellers we were unable to determine the firm size" (p.1526). Similarly, they identify only 70 NPEs through web searches. We will attempt to address this research gap using data from the Orbis database. The main difference is that this thesis is to our knowledge the first large-scale empirical study of NPEs' patent acquisitions using multiple sources of secondary data. NPEs' patent acquisitions and characteristics of their patents have not yet been clarified. In addition, research on NPEs' patent acquisitions are scarce (Henkel and Fischer, 2012). Thus, we would like to add more knowledge and contribute to the field of NPEs' patent acquisitions and the markets for technology through this study.

Methodology

To shed light on NPEs' patent acquisitions, we have a unique dataset of 18,010 patents acquired by NPEs between 2005 and 2014, which we compare to our control groups of 101,767 patents that were acquired by non-NPEs in the same technology class and grant year. We used secondary data from the USPTO patent assignment database, OECD Patent Quality Indicators database, Orbis company information database, the NBER patent category classification, the USPTO patent claims dataset and PatentsView data for granted patents between 2005 and 2014. We are in particular motivated to understand where and what kinds of patents do NPEs acquire? "Where" here represent the patent sellers' characteristic and "what" represent the characteristics of the patents (quality parameters). Since previous studies state that NPEs mostly acquired patents from small firms (Fischer & Henkel, 2012; Haus & Juranek, 2017) and relied on dubious and less quality patents (Feng & Jaravel, 2016; Haus & Juranek, 2017), we expect that sellers and patents will be significantly different between NPEs and non-NPEs (hereafter we use the sellers, firms and company interchangeably to represent patent seller).

Results

Since we were interested in analyzing NPEs' patent acquisitions, our findings revealed interesting insights. Our results showed that the probability of patents being acquired by NPEs will increase a) by increasing the number of very large companies, b) increasing the non-US based companies and c) increasing the patents in the chemical, drugs and medical, computers and communications, electrical and electronics and mechanical (than others) category than by non-NPEs. Additionally, the results further revealed that on average patents acquired by NPEs are of significantly higher quality than patents acquired by non-NPEs which is in the same line with the results of Fischer and Henkel (2012) in the case of patent characteristics but not for the size of the firm.

To our knowledge, important contributions to NPEs' patent acquisitions were done by Fischer and Henkel (2012) and Feng and Jaravel (2016) who analyzed NPEs' patent acquisitions by using secondary data sources such as PATSTAT and the USPTO patent examination respectively. We extend the work of Fischer and Henkel (2012) in mainly three ways. First, we analyze more recent patent assignment data from the USPTO (2005 to 2014) while Fischer and Henkel's study was based on data from 1997 to 2006. Our research is important because we have more recent data to analyze NPEs' patent acquisitions and how they operate in the markets for technology. Second, we include data from the Orbis database to analyze the patent sellers' characteristics, which was unclear in the Fischer and Henkel's study. Finally, we use the patent claims dataset in addition to the OCED Patent Quality Indicators database to analyze patent characteristics. Thus, we believe, our research will contribute to the literature on NPEs' patent acquisitions and the field of markets for technology.

1.2 Research questions

This thesis will analyze NPEs' patent acquisitions. Studies have shown that there is a rise of patent litigation by NPEs, but few studies have addressed the where and what kind of patents do NPEs acquire.

This thesis aims to answer the following research questions:

1. ***Where do NPEs acquire patents from? Are the firms (sellers) different than non-NPEs?***

   By answering this research question, we would like to see who are the sellers to NPEs and non-NPEs and whether they are different between NPEs and non-NPEs, in terms of sellers' characteristics (e.g., size of the company, country of origin, types of entity, number of companies in their corporate group and number of subsidiaries).

2. ***What kinds of patents do NPEs acquire? Are patents different than non-NPEs?***

   By answering this research question, we would like to see what kinds of patents do NPEs and non-NPEs acquire and whether these patents are different between NPEs and non-NPEs, in terms of patent quality indicators (e.g., patent scope, family size, grant lag, backward citations, non-patent literature, forward citations, claims, renewal and patent age).

1.3 Outline

This introduction section will be followed by a review of relevant literatures. In chapter 3, we will explain our research methods (research approach, research design, data collection, preparation of data, sample and control groups). In chapter 4, we present the statistical analysis and results interpretation. Chapter 5 includes a discussion about the result of the data analysis and a discussion about NPE and markets for technology. Finally, in chapter 6, we conclude and provide the limitations and opportunities for future research.

Chapter 1	• Introduction
Chapter 2	• Literature review
Chapter 3	• Research methods
Chapter 4	• Result analysis
Chapter 5	• Discussion
Chapter 6	• Conclusion

Figure 1. Outline of the study

2. Literature review

In this chapter, we will review the most relevant research literature related to our research questions. In relation to our research questions, our (main) focus is on innovation, patent, IPR management and strategy, and theories related to these topics. Additionally, we will elaborate more about markets for technology, patent intermediaries, NPEs and hypothesis development. We begin this chapter with a definition and discussion of innovation and patents followed by IPR strategy and markets for technology.

2.1 Innovation

According to the OECD (2005, p. 46) innovation is *"the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations*". Innovation is a vital process for any business and organizations to survive and to create, capture and deliver value for customers, increase productivity and economic output (Edison, Bin Ali, & Torkar, 2013). Thus, managing innovation is of vital strategic importance for companies (Bessant, 2003). From the above definition, we can conclude that innovation could take many forms and is driven by the creation of new ideas to improve products or processes, which becomes an important factor for a firm's competitive advantage. Innovation is associated with the knowledge and idea which is part of intellectual property and protected by intellectual property right. According to wipo.int (2018), "Intellectual property (IP) refers to creations of the mind, such as inventions; literary and artistic works; designs; and symbols, names and images used in commerce". IP is protected by law such as patents, copyrights and trademark which enables the inventor/owner of IPR to practice that innovation for the financial benefit for a certain duration of time (WIPO, 2016) (typically 20 years in the case of patents). Thus, intellectual property right (IPR) plays a very important role to protect and exploit such innovation.

2.2 Patents

WIPO (2018) defines patent as "an exclusive right granted for an invention, which is a product or a process that provides, in general, a new way of doing something, or offers a new technical solution to a problem". Furthermore, Scotchmer (2004) notes that a patent gives its owner the right to sue for infringement if anyone tries to make, use, sell, offer, import or offer to import the invention into the country issuing the patent. Gilbert and Shapiro (1990) note that one of the purposes of a patent system is to reward innovators. Compared to other forms of IP, patents are regarded as a gold standard of IP for its power to use for patent infringement cases.

Intellectual property is central to companies in this digital era, and to protect and exploit the innovation. Intellectual property is part of intangible assets and important resources for firms. They also possess the right to use and trade like physical asset. Arora, Fosfuri, and Gambardella (2004) state that “Without the prospect of being able to capitalize on their innovation by trading the property rights protecting the innovation, many small technology-based firms would not invest in creating new and useful technologies” (p. 14). They argue that IPR grants such right to protect and capitalize the innovation which encourages firms to invest in innovation. Nowadays patents are used as a “competitive weapons” for high-technology firms (Paik & Zhu, 2016, p. 1410).

In 2014, IP-intensive industries accounted for $6.6 trillion in the United States, which was equivalent to 38.2% of US GDP (Antonipillai & Lee, 2016). Thus, for innovative technology-based organizations (e.g., the smartphone industry), patents are the most valuable resource and at the same time a tool to encourage R&D and innovation. Patents can give companies a competitive edge (Bollen, Vergauwen, & Schnieders, 2005) and is important for a company`s valuation (Hall, Jaffe, & Trajtenberg, 2005). For biotech companies, patents play a vital role for its valuation, revenues and provide the possibility of mergers and acquisitions (Burkhart, 2017; Gogoris & Clarke, 2001). In terms of strategy, patents are applied to countersue if sued, thus discouraging lawsuit. Thus, having a good IP strategy with regard to patents is of high importance. A case in point is Google`s $12.5 billion acquisition of Motorola in 2011, and this was in large part undertaken to reduce patent lawsuits from competitors (Womack & Tracer, 2011). The pharmaceutical industry has for decades used patents as a business strategy (Macdonald, 2004). Since R&D is very costly in this industry and few products make it to the market, it is in their interest to use patents as a business strategy. We have seen the same trend in the technology sector. A case in point is the lawsuit between Apple and Samsung Electronics (Kastrenakes, 2017).

According to a report from the World Intellectual Property Organization (WIPO), more than 3 million patent applications were filed worldwide in 2016, and it was 8.3% higher than in 2015[1].

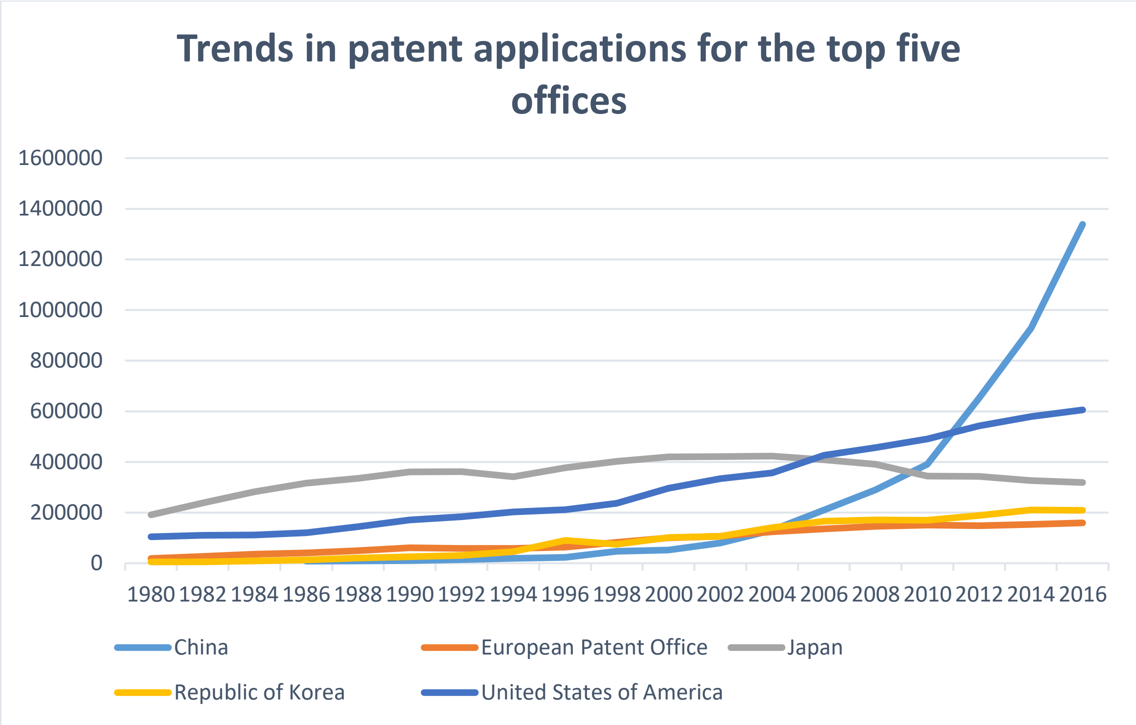

Figure 2. Trends in patent applications for the top five offices[2].

Figure 2 shows the trends in the patent applications for the top five patent offices from 1980-2016. From figure 2 we can see that patent applications in China have increased significantly since 2010. Similarly, in the US there has been increased patent applications. There is also a growing patent applications trend for the Korean Intellectual Property Office (Republic of Korea) and the European Patent Office (EPO). Since 2005 there has been a decreasing patent applications trend in Japan. In 2016, China had the highest number of patent applications followed by the United States. The number of additional applications received by Chinese Patent Office (SIPO), was in 2016 higher than the combined patent applications of the European Patent Office (EPO), Japan Patent Office (JPO), the Korean Intellectual Patent Office (KIPO) and the United States Patent and Trademark Office (USPTO). Interestingly,

[1] http://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2017-chapter2.pdf (accessed on April 20, 2018)

[2] https://www3.wipo.int/ipstats/ipslinechart (accessed on April 3, 2018)

Haskel and Westlake (2017) note that countries have for many years tweaked their patent systems to encourage more innovation.

There are many discussions and research on the topic of patents, IPR and innovation. Lerner (2009) concludes that in countries with low patent protection, a positive changes in the patent policy has a positive effect on innovation, while in countries with high protection, a positive change has a lower impact (even negative). This means that patent itself doesn't encourage/discourage the innovation. Similarly, Moser (2013) concludes that patent policies which grant strong IPR to early generations of inventors may discourage innovation. Other researchers (e.g., Moser, 2005; Sakakibara & Branstetter, 1999) also conclude in the same line that there is no exact evidence that changing the patent laws increased the innovation activity. Maskus (2000) also finds similar results as Falvey, Foster, and Greenaway (2006), and concludes that there is a positive impact of IPR on economic growth, but this also depends on the competitive nature of the economy. On the other hand, Galasso and Schankerman (2015) state that patents rights block downstream innovation in electronics, computers and medical instruments, but not in mechanical, drugs or chemical technologies. These above discussions conclude that changing the patent laws are not the only factors that stimulate innovation. Companies' motives towards patent filing, markets for innovation and countries' competitive nature are also important.

IPR strategy

It is not always the case that patent holders have the resources and capabilities to develop a final product or service. As such, Haus and Juranek (2017) argue that the possibility of patent innovators to sell their patents is an incentive for innovation. Thus, IP strategy is becoming an important element for firms nowadays. Patents are used as a complementary asset and a source of a firm's competitive advantage. The markets for technology facilitate firms to commercialize their IP either in the form of licensing or selling. These commercialization strategies also stimulate companies for future innovation. Since patents are used as a strategic weapon, companies patent innovations for different strategic motives. To contribute to the field of markets for technology, Veer and Jell (2012) analyze the patenting motives of individuals investor, small companies and universities and conclude that most universities are willing to license patents, which means to facilitate others to use their patents. Small firms mostly use patents as a signal to investors to gain more access to capital. Individuals mostly use patents for blocking motives, which means that individuals who hold the patent do not produce anything on their own, but they own the patent just to block others from production. Similarly Blind, Edler, Frietsch, and Schmoch (2006) conclude that it was essential to use patents to protect inventions, followed by blockade, reputation, exchange and incentives. Patents are also used as a bargaining chip against rivals (Cohen, Goto, Nagata, Nelson, & Walsh, 2002) and “central to the strategic battle plans” (Thurow, 1997, p. 97).

2.3 Markets for Technology

Markets for technology enables companies to profit from innovation and get access to new technology. As such, companies are interested in trading patents in the markets for technology. Trade in technology (patents) helps to generate private and social gain because it provides a platform where firms with low production capabilities can sell or licence their innovation (patent) to firms with high manufacturing capabilities. Arora et al. (2004) state that markets for innovation represent the creation of new technology and markets for technology refers to the diffusion of technology. Arora et al. (2004) define market for technology as “includes transactions involving full technology packages (patents and other intellectual property and know-how), and patent licensing” (p. 6). The markets for technology have become larger in the last two decades (Arora et al., 2004; Arora, Fosfuri, & Rønde, 2013; Robbins, 2009). Arora et al. (2013) note that the markets for technology have “created new strategic options for firms” (p. 1103). Since Arora, Fosfuri, and Gambardella (2001) study, lots of research has been done in the field of markets for technology (e.g., Arora & Fosfuri, 2003; Arora et al., 2001; Arora et al., 2013; Arora & Gambardella, 2010; De Marco, Scellato, Ughetto, & Caviggioli, 2017; Fischer & Henkel, 2012; Kani & Motohashi, 2012; Rassenfosse, Palangkaraya, & Webster, 2016; Veer & Jell, 2012).

Bryer, Lebson, and Asbell (2011, p. 93) argue that “Effective, business-focused patent strategies can accelerate innovation, improve patent quality, simplify communication, facilitate executive participation and reduce cost”. This argument explains different strategic aspects of patents management in organizations. Rassenfosse et al. (2016) argue that patents facilitate trade in technology due to its role in protection against the infringement of IP. Thus, companies’ strategies are aligned with the IP strategy which mostly involves trades of patents. Arora et al. (2001) argue that the market transaction for technology, ideas, knowledge or information is growing, and the markets for the technology has different implications for the corporate strategy of firms. According to the authors, the markets for technology enhance and broaden the strategic possibility of the firm by providing different ways to commercialize their patents either through licensing or selling. This also has managerial implications, including the development of an effective IP strategy and being focused on further development either through external partnership or acquisition. This implies that trade in patents solve many problems such as access to innovation and reduce cost at the industry-level.

According to the USPTO, there are 8.0 million patent assignments and roughly 13.1 million patents and patent applications in the USPTO Patent Assignment Dataset (uspto.gov, 2018). This further confirms that the size and the markets for technology are growing. Serrano (2006) argues that “a large fraction of patents are traded” (p. 2) and he further mentions that better patents (represent a higher number of citations) are more likely to be traded. This could be true for the firms who are in the creation of IP business but have no commercial manufacturing capabilities, and they can benefit from the markets for technology by trading their patents. Monk (2009) analyzes intellectual property in emerging markets, and he concludes that with the development of IP market, specialized patent intermediaries are introduced, and they are facilitating the market for IP in the markets for technology.

Markets for technology allows firms to access and to commercialize technology easier to foster innovation (De Marco et al., 2017). However, concerns have been raised about the players in the market who acquired patents just for strategic or opportunistic purpose, which adversely affects innovation activity of the practicing firms. This means that the rise of NPEs in the markets for technology as patent intermediaries give rise to a new dimension of the research within the field of markets for technology.

We have discussed innovation, patents, IP strategy and markets for technology because these are the main areas which are affected by NPEs activities and are related to each other. The above discussion provided an overview of innovation, patents and its strategic use, markets for technology, players in the markets for technology and raised concerns about NPEs activities. NPEs acquire patents in the markets for technology for the purpose of suing practicing firms, blocking future innovation and claiming damage awards without the risk of being countersued. Thus, we proposed our research questions to explore the supply side of NPEs’ patent acquisitions.

2.3.1 Patent Intermediaries and NPEs

Patent intermediaries are agents between buyers and sellers in the markets for technology. Hagiu and Yoffie (2013) define patent intermediaries as "an organization (firm or not-for-profit entity) that directly facilitates the sale or licensing of patents from owners-creators to users" (p. 46). Patent intermediaries include patent brokers, patent exchanges, patent aggregators and any other firms or individuals that are exclusively involved in the patent transactions as a part of their core business model.

The increased importance of patents as part of a business strategy has enabled patent intermediaries to grow (Agrawal, Bhattacharya, & Hasija, 2016). Additionally, the development of a market for IP has enabled patents to become a tradeable asset (Monk, 2009). Millien and Laurie (2009) note that the IP marketplace has market-maker intermediaries who try to make IP a more liquid asset class and to profit from it. Wang (2010) states that the "demand for intermediaries has at least three sources: (1) functional requirements of the patent markets; (2) need for assistance with valuation; and (3) general industry trends" (p. 183). The difficulty of patent valuation and increased patent acquisitions create a market for patent intermediaries. In turn, this means higher growth for defensive aggregators and brokerage services.

Firms that are just in the business of creating IP and that have no commercial manufacturing capabilities can use a broker to facilitate the monetization of a firm's IP assets (Monk, 2009). Some universities and inventors lack the resources to develop their IP or to chase infringers. Hence patent intermediaries play an import role since these organizations can sell patents to and through patent intermediaries. Importantly, distressed companies can raise cash by selling some of their patents through patent intermediaries. This can help companies survive during a recession (The Economist, 2009). Haus and Juranek (2017) state that "As long as there are gains from trade, there is a potential role for an intermediary" (p. 48). This could be one, among others, the reason why patent intermediary exists. The authors further argue that the benefits from trade are good for innovation incentives and patent trade is an advantage for patents owned by small innovators. Another reason why patent intermediaries play a larger role in the markets for technology is that patents have evolved into intellectual property assets that are becoming more important for companies' strategy and have value as transactional goods (Wang, 2010).

Wang (2010) categorize patent intermediaries into three groups: defensive aggregators, brokers and offensive aggregators. Brokers are companies that connect patent sellers with potential buyers in exchange for a fee. In other words, brokers play a market-making role for consumers and producers of IP. Brokers also help patentees to license their technology (Hagiu & Yoffie, 2013). Similarly, defensive aggregators "are services that acquire patent rights and license them to subscriber companies" (Wang, 2010, p. 160). An example of a firm that is a defensive aggregator is RPX which provides an IP protection against NPEs for companies (Hagiu & Yoffie, 2013). Defensive patent aggregators play a vital role in the market for IP by serving as buyers of IP assets, increasing demand and in turn, raising the market values of IP assets. Likewise, offensive aggregators acquire patents to collect license fees from alleged patent infringers. Furthermore, Wang (2010) notes that NPEs are an example of an offensive aggregator. The most controversial IP intermediaries are NPEs (Hagiu & Yoffie, 2011). Wang (2010) further argues that offensive aggregators are a classic case of wealth distribution and they do not contribute to innovation.

Non-practicing entities (NPEs)

Peter Dekin claims to have coined the term "patent troll" in 2001, and at the time he was the assistant general counsel for Intel Corporation (Sandburg, 2001). According to Peter Dekin, "patent troll is somebody who tries to make a lot of money off a patent that they are not practicing and have no intention of practicing and in most cases never practiced" (Sandburg, 2001).

NPE, also called patent troll or patent assertion entity (PAE) acquire patent rights with the aim of suing users of the technologies and ideas embodied in previously issued patents. Their main business model is based on patents and enforcement. In other words, NPEs earn profit mainly from IP litigation and licensing. As NPEs grow in the business of IP, it is a big debate among researchers regarding their business model. Feng and Jaravel (2016) state that NPEs defend their business model arguing that they work as a matchmaker (intermediaries) to improve the efficiency of markets for technology, by providing the necessary help and consultation to the small and financial-constrained inventor and firms to enforce their patents against infringement. They further present the criticism of NPEs behaviour on patent acquisition, as NPEs acquire and assert weak patents. The "weak" here refers to patents that are not exactly invalid, but may well be invalid (Farrell & Shapiro, 2008). Addressing NPEs' patent acquisitions, Feng and Jaravel (2016) analyze the patent examination data and argue that by improving the patent examination process and its quality could solve the issue of NPEs activities. Because their findings show that NPEs acquire and assert patents which were examined and granted by specific set of examiners. Moreover, these patents are with vaguely-worded claims. Thus, they conclude that these weak patents are more favourable for the NPEs business model and likely to get more litigation. Additionally, Feng and Jaravel (2016) further note that NPEs acquire patents at bankruptcy auctions where patents of bankrupt companies are offered for sale.

Similarly, Magliocca (2006) argues that NPEs acquire patents which are cheap and hard for a defendant to substitute, and they are more likely to settle the case (settled out of the court without becoming public) rather than providing the licensing to the manufacturer. The author provides the example of NTP vs Research in Motion to explain the scenario. This also concludes that NPEs want to settle the case with a large amount of damage award instead of licensing to the manufacturer. Bessen and Meurer (2008) argue that it is the patent system in the United States which provides good legal environment for NPEs to play in the market. In addition to this, the authors further state that this also could be a reason of low patent quality, and that is because of the less qualified patent examiners. This in sum provides the idea that it is because of the patent system which is not so transparent and it is suitable for the NPE business (Fischer & Henkel, 2012). Cohen, Gurun, and Kominers (2016) also conclude in the same line as Bessen and Meurer (2008) that to reduce litigation case from NPEs, the US needs to change its IP policy. Addressing why NPEs exist, Reitzig et al. (2007) argue that the US IP system grant more power to the patent holder and the courts' unrealistic damage awards (for the patent owner) in case of infringement is the core condition for the NPEs to exist and operate profitably. These arguments are also supported by a PWC litigation report, where it is reported that on average NPEs are awarded three times more damage awards than practicing firms (pwc.com, 2017).

A study by Bessen and Meurer (2013) showed that NPEs in 2011 had an estimated direct, accrued patent assertion cost of $29 billion. Furthermore, Bessen, Ford, and Meurer (2011) estimate the annual cost of NPEs litigation to firms traded on US stock exchanges to be about $80 billion. Watkins (2014) notes that NPEs often target companies in high-tech industries, where technological progress is rapid, and a 20-year patent right is likely worth more to the NPE than to the original innovator. A study by Tucker (2014) showed that health information technology companies sued for patent infringement by NPEs stopped all innovation in that technology.

Existing research on NPE

NPEs are firms that receive revenues from licensing their patents without applying them for their own production (Haus & Juranek, 2017). Many small innovators lack the resources to protect their intellectual property rights and are thus not able to litigate firms that are financially stronger (McDonough III, 2006; Ronspies, 2004) and some of these companies, therefore, sell their patents to NPEs. Patent strategy is an essential tool for companies to generate value and to develop a competitive strategy (Gilardoni, 2007). NPEs try to maximize profit by leveraging their patent portfolio. This can be done by demanding patent license fees from companies or individuals which use their patents and/or suing companies for infringing their patents. NPEs are proactive with regards to patent enforcement. Gilardoni (2007) have five approaches to patent strategy: aggressive, active, passive, selective and reputation-based. By using Gilardoni (2007) five classifications of patent strategy, we would classify NPEs as active, which means that they are trying to maximize the revenue from patents.

Different researchers have conducted research on NPEs by using litigation data. As mentioned before, there is big controversy with the NPEs business model, and therefore different researchers criticize their business model. To address the issue related to the NPEs business model Lemley and Shapiro (2006) discuss how NPEs threaten firms to implement the hold up in practice and demand high settlement fees. Following the same research Golden (2006) analyzes the business model of NPEs. Similarly, Reitzig et al. (2010) conclude that NPEs adopt three main strategies to attack practicing firms: injunction strategy, damage awards and switching cost. And the authors further suggest that these strategies and attacks look sustainable against policy changes. Similarly, Henkel and Reitzig (2008) argue that NPEs mostly operate in the technology field and give particular attention to the patents in computing, telecommunication, and mobile communication. Geradin, Layne-farrar, and Padilla (2012) argue in a different way than other researchers. According to their conclusion, “patents in the hands of non-practicing entities can increase competition, increase innovation, lower downstream prices, and enhance consumer choice” (p. 73).

Thus, there are many discussions going on about the role of NPE and its business model, their impact on innovation such as private and social cost of NPE. Bessen et al. (2011) argue that NPEs activities (opportunistic behaviour) have a negative impact on firm performance and investment. The above literature reviews of NPEs, indicate that there has been little research on NPEs’ patent acquisitions. Hence, we would like to explore this by analysing NPEs’ patent acquisitions. We think this research will contribute to the field of markets for technology and to understand NPEs' patents acquisition.

2.4 Hypothesis development

NPEs and sellers relationship

We have reviewed many previous literatures related to NPEs, and most of the literatures are addressing the issues of the NPEs and patent litigation. These are mostly from law studies and analyzed the case of patent litigation, and in most of the cases addressed what kind of firms do NPEs attack. We could not find that many literatures about where NPEs acquired patents from. Fischer and Henkel (2012) tried to address this issue by analysing the seller's profile, but they lacked access to good data. They only used data from websites and assumed that the sellers are small firms. Feng and Jaravel (2016) state that some of the patents acquired by NPEs were originally assigned to firms which are already bankrupt (such as Kodak and Polaroid).

In the same way, we were not able to find the literature on the country of origin of the patent sellers. Since we have company information from Orbis, we have such information in our dataset, so we would like to analyze the country of origin of the sellers as well. Likewise, we found some literature such as Fischer and Henkel (2012) who also tried to address patents characteristics using the IPC technology classes, but for this thesis, we would also like to analyze the patents using NBER classification. Thus, based on the information from our literature review and the data we have, we propose the following hypotheses:

H1: *The firms (sellers) where NPEs acquired the patents from, will be significantly different than that of non-NPEs:*

H1-a) in terms of their category,

H1-b) in terms of their country of origin.

H2: *The categories of the patents (NBER categories) acquired by NPEs will be significantly different than that of non-NPEs.*

Patent characteristics

Patent characteristics are widely used indicators for a patent's quality. Most of the study related to patent litigation used data from the OECD Patent Quality Indicators. We follow Feng and Jaravel's arguments in the patent characteristics. They argue that on average NPEs acquire patents which are in the core technology area (such as hardware/software), have very different pre and post examination features and are suitable to support the NPEs business model. As the authors suggest, we will use the USPTO patent claims dataset to analyze the changes in the claims (such as number of independent claims, dependent claims, average word length of independent claims and average word length of dependent claims). Their study shows that patents acquired by NPEs are mostly re-assigned and have more adjustment of the claims during the grant process (Feng & Jaravel, 2016).

To analyze the patent characteristics, we use the following variables: patent scope, family size, grant lag, backward citation, forward citations, non-patent literature, and number of claims, renewal and patent age. According to the description of the OECD Patent Quality Indicators database, a higher number (on patent scope, family size, forward citation, backward citations, non-patent literature (NPL) citations, renewal and claims) represent a higher quality patent. Many studies have studied the value of the patents and quality of the patents in litigation cases. However, there are very few literatures that analyze NPEs' patent acquisitions and their patent characteristics.

Lerner (1994) argues that patent scope is positively associated with the firm's value. Merges and Nelson (1990) conclude in the same line that the importance of patents depends on its scope. These arguments provide an overview that patents are positively associated with the firm's value. On the other hand, there is no such research using the variable family size also related to the case of NPEs' patent acquisitions. Few researchers discussed the case of patent citations (backward, forward and NPL) related to the quality of patents (e.g., Hall et al., 2005; Harhoff, Scherer, & Vopel, 2003). Lanjouw and Schankerman (2001) note that litigated patents get more citations than others. Fischer and Henkel (2012) conclude that on average, NPEs acquire higher quality patents than that of non-NPEs. The patent litigation report from PWC[3] reveals that NPEs are mostly focused on specific courts in the US where they have

[3] http://www.ipwatchdog.com/wp-content/uploads/2017/05/2017-Patent-Litigation-Study_PwC.pdf (accessed on April 2, 2018)

higher success rate but in other courts they are not so successful (which is less than 15%), but on average the success rate was 33%. This provides some room to doubt the results from the Fischer and Henkel (2012) that if NPEs acquired higher quality patents, they should have won more litigation cases.

Thus, previous studies either focused on the patents quality (e.g., Allison, Lemley, & Walker, 2010; Chen & Chang, 2010; Wagner, 2009), patent value (Reitzig, 2003), legal aspects of NPEs business (e.g., Golden, 2006; Henkel & Reitzig, 2010; Pohlmann & Opitz, 2013; Reitzig et al., 2007), analyzing the patent hold up and royalty stacking (Lemley & Shapiro, 2006), or NPEs patent litigation (e.g., Bessen, 2014; Bessen et al., 2011; Kiebzak et al., 2016; Lanjouw & Schankerman, 1997; Lanjouw & Schankerman, 2001; Lerner, 2006). In patent litigation studies researchers only analyzed the litigated side (about the characteristics of the litigated patents). They did not analyze NPEs activities on the supply side (that is: where and what kind of patents they acquire). NPEs are more successul in specific Federal District Courts in the US, and they only acquire patents in specific categories (Feng & Jaravel, 2016) that are suitable for their businesses. Based on the literature we propose the following hypothesis:

H3: *Patents acquired by NPEs will be significantly different (in terms of their characteristics) than patents acquired by non-NPEs*.

Our analysis in this thesis will go beyond the testing of hypothesis. We will analyze NPEs' patent acquisitions in depth, and we believe that these hypotheses will be a good reference point to start with.

3. Research methods

3.1 Methodology

In this chapter, we will elaborate more on research methods, design and strategy we have used to answer our research questions. This chapter elaborates on the rationale for the research design, concentrating on how the study accomplished the research goals and why the design was the optimum choice for this thesis.

Wilson (2010) defines research as a "step-by-step process that involves the collecting, recording and interpreting of information" (p. 306). In other words, this means that research is about generating answers to research questions and thus to increase and advance knowledge (Saunders, Lewis, & Thornhill, 2012). Furthermore, Wilson (2010) defines business research as "The systematic and objective process of collecting, recording, analyzing and interpreting data for aid in solving managerial problems" (p. 300). This definition states that research is a systematic and objective process to find out things, which have different characteristics such as there should be a systematic way to collect and interpret the data. Moreover, there should be clear objectives to solve the problems. Our aim in this thesis is to analyze NPEs' patent acquisitions. We would like to analyze where and what kind of patents do NPEs acquire and whether these patents and companies are different than practicing entities (non-NPEs).

3.2 Research approach

There are two different research approaches to draw a conclusion from the research. Saunders et al. (2012) make a distinction between deductive and inductive research approaches. A deductive research approach is when you have a theory that you want to test through the collection of data. More specifically, "a theory and hypothesis/hypotheses are developed, and a research strategy designed to test the hypothesis" (Saunders et al., 2012, p. 150). On the other hand, an inductive research approach is when you want to develop a theoretical explanation or to explore a topic. This thesis is based on existing literature, theory and secondary data (quantitative), and we will conclude the result by developing and testing the hypotheses. Thus, principally starting from theory to conclusion, we conclude that this research follows a deductive research approach.

Qualitative and quantitative methods

Quantitative and qualitative methods are two major methods used in research. Quantitative research is associated with numbers, data collection and the use of statistics and diagrams (Saunders et al., 2012). Qualitative research is associated with words, classification of non-standardized data into categories and analysis is conducted through the use of conceptualization. Saunders et al. (2012) note that quantitative research examines data that are numerical while qualitative research tries to understand a situation or a phenomenon. Furthermore, quantitative research is associated with deductive research and qualitative research is related to inductive research.

For this thesis, all the analysis will be based on secondary quantitative data. Thus we are going to use a quantitative research method for this thesis.

3.3 Research design

Research design is a description of how the entire analysis process should be set up to answer the research question (Gripsrud, Olsson, & Silkoset, 2010). In this regard, it is important to know what kind of data we need, how to get these data, and finally, how to analyze the data. According to Gripsrud et al. (2010), it is common to distinguish between three main types of research design: explanatory design (cause-effect), exploratory design (explorative) and descriptive design.

Explanatory research design

Studies that establish causal relationships between variables may be regarded as explanatory research. The main focus of explanatory design is on studying a problem or a situation in order to explain the relationships between variables (Saunders et al., 2012). Examples of explanatory design are experimental design and semi-structured interviews.

Exploratory research design

Zikmund, Babin, Carr, and Griffin (2012) state that exploratory research design is most useful when the situation is more ambiguous. There are several ways to conduct exploratory research. More specifically, the most popular are literature search, conducting interviews or focus group interviews (Saunders et al., 2012).

Descriptive research design

Descriptive research design is most appropriate when the purpose of the research is to describe the characteristics of people, object, organizations, environment or groups (Zikmund et al., 2012). This research design addresses the what, who, where, when and how questions (Wilson, 2010). However, descriptive research does not determine cause and effect relationship (Saunders et al., 2012). Furthermore, Zikmund et al. (2012) note that descriptive design is carried out to describe past or existing phenomena. This type of research can be either quantitative or qualitative, and a survey is typically used to gather data and by using different descriptive statistics.

The main objective of this thesis is to analyze NPEs' patent acquisitions. We used quantitative data from secondary sources. To conclude, we use quantitative research methods and descriptive design to conduct this thesis.

3.3.1 Reliability of the data source

For this study, we use data from multiple secondary sources. Our main dataset is the USPTO patent assignment dataset. We have found that many researchers already used the USPTO patent assignment dataset for their research (e.g., De Marco et al., 2017; Figueroa & Serrano, 2013; Galasso, Schankerman, & Serrano, 2013; Serrano, 2011; Serrano, 2010). All these studies address the patent transactions in the markets for technology. In addition to that, the USPTO patent assignment dataset description provides a good overview of how the data were recorded and its limitations. Furthermore, we also use data from the USPTO patent claims database and PatentsView. Both datasets contain the record derived from the USPTO. All the datasets have complementary data description reports. Using these descriptions, we could select the data according to the purpose of our research. Thus, we use these datasets and apply different assumptions to clean the data according to our requirements.

We use secondary data from Orbis to obtain company information. Orbis is Bureau van Dijk's company database, and in 2017 Moody's acquired Bureau van Dijk (Hufford, 2018). Orbis is an extensive business database that contains more than 300 million companies across the globe (Bvdinfo, 2018). Bvdinfo (2018) states that "We are committed to capturing, treating and delivering the highest quality private company information available". Many researchers, analysts at financial institutions and governments use and rely on reliable data from Orbis. Hence, we think that the quality and reliability of Orbis data is high.

Similarly, we use patent quality data from the OECD Patent Quality Indicators database. This dataset provides different patent quality indicators for the USPTO patents which could be used to measure patent quality as described by the OECD Patent Quality Indicators description (Squicciarini, Dernis, & Criscuolo, 2013). Different researchers already used this data for their studies, and the data description reports provide a good overview of the quality indicators. Thus, we think the reliability of the OECD Patent Quality Indicators database is high and suitable for research purpose.

Thus, we believe the reliability of our study is quite high, and there is a possibility to replicate our study using the same dataset and procedure as we apply.

External validity

External validity is related to if the research findings can be generalized to other relevant context (LeCompte & Goetz, 1982). Since we are using NPEs based in the US, it will be difficult to generalize our results to other countries, because, among other things, other countries have different economic and industrial characteristics than the US. For example, few countries have so many high technology patents as in the US. Additionally, the US financial markets are well known for breadth and depth in providing liquidity to new and established firms (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1997; Moyo, 2017). Hence, it is easier for NPEs in the US to acquire patents than NPEs in other countries. Likewise, the court case in the US and Europe are also different regarding legal fees. Unlike the US, in Europe, even the loser has to pay the legal fee, which could be the reason that there are few NPE litigation cases in Europe compared to the US (Fusco, 2013). Due to these circumstances, it is difficult to generalize the results from our thesis in another context, but there is still a possibility to extend our study.

3.4 Data collection

3.4.1 Secondary data sources

To answer our research questions, we use data obtained from multiple secondary sources. These secondary data sources include the USPTO assignment database, the OECD Patent Quality Indicators Database, and Orbis for the company information, PatentsView, the USPTO patent claims dataset and NPE data from Cotropia, Kesan, and Schwartz (2014), Haus and Juranek (2017) and Stanford NPE Litigation Dataset (Stanford Law School, 2017).

The USPTO patent assignment dataset contains all the transactions related to the patent transfer (uspto.gov, 2018). This dataset records all kinds of transfer including a name change, internal transfer, and ownership transfer and so on. According to the dataset information, the latest updated dataset contains information about 7.2 million patent assignments since 1970 and involving roughly 12.2 million patents and patent applications (uspto.gov, 2018). We thoroughly follow the information as described by the authors regarding the description of the patent assignment datasets (Marco, Myers, Graham, D'Agostino, & Apple, 2015). The authors provide concise information on how all the records were recorded in the dataset, which helped us to clean the data according to our requirement.

The OECD Patent Quality Indicators dataset contains the quality characteristics of patents, which we have matched with the USPTO patent assignment dataset for our analysis. To analyze the patent characteristics further, we use the USPTO patent claims dataset. This dataset contains the information about claims characteristics such as number of independent claims and their average word length.

Orbis company information database provides information about companies. Since we are interested in the companies' (sellers) characteristics, we matched the assignor data from the USPTO assignment dataset with the Orbis dataset to make sure that we have companies that exist in both datasets. The detail description will be discussed later in this chapter.

Using these datasets listed above, we would like to analyze NPEs' patent acquisitions. In connection to that, we want to explore the patent sellers' characteristics and patents characteristics associated with NPEs and test whether these sellers and patents are different than that of non-NPEs.

3.5 Preparation of data

3.5.1 USPTO patent assignment database

The main dataset for our research is the USPTO assignment dataset. When the patent is transferred, all the transaction records are recorded in the USPTO patent assignment database. De Marco et al. (2017) state that "An assignment is a transfer, by a seller to a buyer, of the rights, title and interest in one or more granted patents or patent applications" (p. 1647).

The USPTO assignment dataset contains six different files related to the patent transfer transactions records, and we used four out of six which are: assignment, assignee, assignor and documentid. As described by Marco et al. (2015), the USPTO assignment data file contains a record of every single transaction which is uniquely identifiable by a reel-frame identification number (rf_id). The reel-frame identification number is a combination of reel number ("microfilm reel number of the assignment entry in physical USPTO records") and frame number ("location of the assignment entry on the reel number in physical USPTO records") (Marco et al., 2015, p. 10). In the same way, the assignor, assignee and documentid files contain the records of each assignor, assignee and document (patent) information such as application date, patent number and so on, linking records to each rf_id data file. Since this is our main dataset and it contains 7.2 million patent assignment records, we, therefore, had to do a substantial amount of data cleaning. Due to our limited time, we could not include all 7.2 million patent assignment transactions. Therefore, we formulate different assumptions to clean the data as per our requirement. The brief description of each four datasets and assumptions used to clean data are as follows:

1. **Assignment data file**: The assignment data file contains the records of each transaction with a unique rf_id number (approximately 7.2 million patent assignment transaction). In addition to the rf_id number, the file contains other fields which hold the records of what kind of assignment was that, such as name change, mergers and acquisitions, assignment of assignor's interest and so on. Since we are only interested in patent transfer transactions, we only keep those records which contain the convey type as an 'assignment of assignor's interest'. Furthermore, we are not able to include all the records. Thus, we restrict our assumptions and include only those recorded transaction between 2005 and 2014. These criteria gave us approximately 3.9 million unique assignment transactions.

2. **Assignee data file:** The assignee data file contains data captured for the assignee(s) for each rf_id in the assignment data file. Along with the rf_id it includes the assignee(s) name and address. In this file, we are restricted to US-based assignee(s) only, so we only keep those records. Because the US is a growing market for the NPEs and we are interested to analyze NPEs' patent acquisitions. Additionally, we are mostly interested in analyzing the assignee(s) who owns 100% of the patent, so we drop all those records which have multiple assignee(s). By doing this, we have approximately 3.8 million unique assignee(s) from the US.

3. **Assignor data file**: The assignor data file contains the data for each assignor(s) for each rf_id in the assignment data file. Along with the rf_id, the assignor data file includes the assignor(s) name and execution date of the transaction. Here, we also restrict our assumption to include only those transactions that took place between 2005 and 2014. Furthermore, we only keep those records which have only one assignor. These criteria gave us approximately 1.5 million unique assignors.

4. **Documentid data file**: The documentid is the most comprehensive data file which contains approximately 12.2 million patents and patent applications (uspto.gov, 2018). To make the data more organized, we first deleted all those records which have no patent number. Secondly, since we are interested in analysing transactions that took place between 2005 and 2014, we only keep patents that were granted between 1985 and 2014. Because patents granted before 1985 have already expired by 2005, so we need to include patents with valid years. These criteria gave us approximately 8.2 million unique patents.

3.5.2 PatentsView

The PatentsView database was sourced from the USPTO (PatentsView, 2017). This database contains data for patents applications from 2001 and granted patents from 1976. We want to make sure that we are working with the US granted patents, so we have downloaded all the patent applications and granted patents data from PatentsView and matched it with the documentid data file using the key patent number and application number. We found all the patents recorded in the documentid data file that are matched with the granted patent datafile. After this preliminary cleaning, we merged these four files (assignment, assignor, assignee and documentid), using the rf_id keywords and we got 512,158 unique matched observations.

After that, we used other data cleaning strategies to clean the data. First, we dropped all the observations where the execution date (date on which the actual transaction took place) was before the patent grant date because we found that these kinds of transactions are mostly internal transfer. Second, we identified the age of the patent and execution date. We have calculated the year difference by subtracting the patent grant date from execution date and dropped all those records where the difference was greater than 20 years because this indicates that the patents have already expired. Third, we matched the name of the assignor and assignee and dropped all those observations which gave matching results, because that indicates the transfer is within organizations. After these steps, we made sure that we have the last owner of that patent as an assignee, so we kept the last transaction of that patent, assignor and assignee. These criteria gave us 190,556 number of observations as unique patent transfer between 2005 and 2014.

To further clean the dataset, we downloaded data from PatentsView. The main data files were patent, inventor and assignee. According to the information on patentsview.org (2018), the inventor is the one who invents and applies for the patent, and the assignee is either an organization or individual whom the patent was assigned after grant. This first assignment is also recorded in the USPTO patent assignment database. Thus, we matched the inventor name (from PatentsView) and assignor (seller) name (from the USPTO assignment), and assignee (PatentsView) and assignee (buyer) (the USPTO assignment), and we dropped all the observations which gave matched results. We did this because these transactions were the first assignment transfers. Name matching is very crucial, so we first made all the name in the same letter (upper case), and we dropped all the comma (,) and dot (.) from the name, and matched the name with the Stata command. Furthermore, we have analyzed that most of the names contain maximum 20 characters, so we made the same length of the name and matched again. In addition to the name matching, we also used other word matching to find similar companies. After this process, we had a total of 169,748 unique observations. These 169,748 observations are unique patent numbers that were traded between different companies between 2005 and 2014.

After this stage, we made two different data files from the total of 169,748 observations to fit the data for our research. These data files combine all the variables from those four separate files. Since we are interested in analysing the 'where' and 'what' questions regarding NPEs' patent acquisitions, we made two separate datasets, where one dataset contains the unique assignor (seller) information and the other dataset contains the unique patent information.

Unique assignor dataset

The assignor data file contains information of unique assignors. In our dataset, we found that from 2005 to 2014 there are a total of 24,749 unique assignors. This data file is very important for us to answer the first research question 'where do NPEs acquire patents from?' To answer this question, we would like to further analyze the characteristics of the sellers, such as the size of the companies, country of origin of the sellers, type of entity, number of subsidiaries and number of companies under the corporate group. Thus, using this dataset, we have accessed the Orbis database to download these information.

Patent characteristics dataset

On the other hand, to answer the research question 'what kinds of patents do NPEs acquire?' we matched the patents data with the OECD Patent Quality Indicators database. The database contains information about different characteristics of the patents quality such as number of claims, forward citations, backward citations, originality and others (Squicciarini et al., 2013). And to further analyze the patent characteristics more closely we also used data from the USPTO patent claims dataset.

3.5.3 Orbis company information database

With the assignor data file, we have 24,749 unique assignor names, and we select all those unique assignor names and matched the name to the Orbis database using the batch search. This is a time-consuming process because it took approximately 4 hours per 1,000 names to generate the matched results. Once the matched process is completed, we have the BvDid number (which is the unique number that the Orbis database created from its national company number)[4] and matched company name. Once we have the BvDid number, then we can use the BvDid number to access other information. Although we have 24,749 unique sellers name, we got only 15,510 (62%) matched results from the Orbis database. Thus, we have 15,510 unique assignor names in the assignor data file, which has all the company information that we can use to answer our first research question.

3.5.4 OECD Patent Quality Indicators database

The OECD Patent Quality Indicators database is a comprehensive database for the patent dataset. For this research, we have used the OECD Patent Quality Indicators for the USPTO file. This file contains all the (published and granted) patent information from the USPTO. Since we are mostly interested in analysing the transfer of granted patents, we dropped all the observation containing published patents. In the same way, the OECD Patent Quality Indicators database contains only the records of utility patents, and we also restrict our search strategy to that limitation and use only utility patents. This dataset only contains those

[4] http://biblioteka.vdu.lt/files/Orbis.pdf (page 7) (accessed on March 16, 2018).

observations which have matched with the USPTO assignment database and the OECD Patent Quality Indicators database. By doing this, we have a total of 155,762 number of unique patents. The main parameters included in this quality database are patent scope, family size, grant lag, backward citations, citations to non-patent literature (NPL), claims, forward citations, breakthrough inventions, generality, originality, radicalness and patent renewal (Squicciarini et al., 2013). However, for our analysis, we choose only eight parameters: patent scope, family size, grant lag, backward citations, citations to non-patent literature (NPL), claims, forward citations (first five years after patent grant) and patent renewal.

Once we got the company matched result from the Orbis database, we decided to include only those companies here in the quality data file as well. Then, we matched the assignor name in both tables and kept only patents of those companies which have matched results because we think this will give more consistent results. By doing this, we have a total of 119,777 number of unique patents in the quality data file.

After getting all the information about patent transfers from the USPTO patent assignment database, the sellers from Orbis and Patent Quality Indicators from the OECD, we have combined all the information in one file with 119,777 unique patent transactions between 2005 and 2014. So, we have now one single file containing information for both company information and quality parameters. This dataset contains observation at the patent level (each row contains unique patents and related information).

3.5.5 Identification of NPEs and NPEs data

To define the NPEs and find the names of NPEs we follow three main sources as follows. First, we used the data used by Haus and Juranek (2017) to study the role of non-practicing entity (NPE) as an enforcement specialist. The authors analyzed patent litigation cases of NPEs in different US courts. We used the same data for NPEs which they have prepared manually and collected from different sources for their research, which contains more than 3000 names of NPEs (including the holding companies). Similarly, we used the data from npedata (2014) where Cotropia et al. (2014) analyzed patent litigation cases between 2010 and 2012 and made the data available on the website npedata.com. In the same way, Stanford Law School (2017) conducted a study on patent litigation and made the data available on their website. For this study, we combine all the data from these three sources which gave us 3,348 number of unique NPEs.

After collecting the names for NPEs, we matched the NPE names with the assignees in our combined dataset which has 119,777 unique patent transactions. This yields a total of 1,047 unique assignees matched with a total of 18,010 unique patent transactions (acquired) by NPEs. Then we made a dummy variable called “NPE” which is equal to “1” if that matched with the data and “0” otherwise. We will then have all the detailed information in a single dataset.

3.5.6 Patent claims dataset

According to the USPTO,[5] the patent claims dataset contains information about the claims of US granted patents from 1976 to 2014 and patent applications from 2001 to 2014. Claims play an essential role during litigation, as stated by Marco et al. (2016): “The claims represent the legal metes and bounds of the invention”(p. 9). Different researchers state that one of the key parameters of patents’ quality is its claims, thus, patents with a higher number of claims are considered to have higher quality patents. Marco et al. (2016) conducted a study using the patent claims dataset to analyze patent quality. The authors argued that claims represent the bounds of the invention through different dependent and independent claims. Dependent claims are the extension of the independent claims which means that if the claims contain a direct reference to another claim, then that is regarded as dependent claim otherwise it is an independent claim. The scope of the patent depends on the length and number of independent claims. The change in count and length of independent claims from publication to grant indicates broader and narrower patents claims (Marco et al., 2016).

Here for our analysis, we follow the description of the patent claims data from Marco et al. (2016). We use the patent claims dataset just as a supplement for the patent quality and claim characteristics associated with patents acquired by the NPEs and non-NPE, because Feng and Jaravel (2016) argue that NPEs mostly acquired patents with vaguely-word claims that are suitable for litigation and support their business model. Thus, we would further like to analyze whether this argument is true in the case of NPEs’ patent acquisitions or not. The patent claims dataset contains information regarding the number of independent claims, dependent claims, average word length on the independent claims and average word length on the dependent

[5] https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-claims-research-dataset (accessed on April 10, 2018)

claims. By using this dataset, we would like to analyze whether the patents acquired by NPEs and non-NPEs have similar number of claims and word counts.

Therefore, we have downloaded the patent claims dataset from the USPTO. To use the patent claims dataset, we matched the patents number from our existing dataset (patent level) with the patent number at the patent claims dataset. The patent claims dataset contains both information about the patents (pre-grant and after grant). Once we matched two datasets, we were able to get 49,680 unique patents. We employ descriptive statistics and t-test on this dataset to analyze the claims characteristics.

Standardization

All the observations of the patent quality parameters and claims characteristics were in absolute value. We have two groups with different number of observations and it may be difficult to interpret the statistical results using the absolute value. Thus, we have standardized (converted into a relative value) the numerical variable (the OECD Patent Quality Indicators and patent claims dataset) using the NBER subcategories and patent grant year. We will provide more description in chapter 4.

3.6 Sample and control groups

3.6.1 Patent level analysis

As mentioned earlier, the final dataset contains information at the patent level. To answer our research questions, we made two groups of the firm according to the ‘NPE’ variable, where NPE (with 1) represents NPEs and zero represents non-NPEs. At the patent level, the total number of observations is 119,777 which contains 18,010 NPEs and 101,767 non-NPEs. This approach will allow us to analyze NPEs’ patent acquisitions criteria in relation to patent sellers including different variables: the category of the company, entity of the company and country of origin of the patent seller. Similarly, this will further allow us to analyze are the sellers different between NPEs and non-NPEs. Likewise, this approach will allow us to investigate characteristics of the patents acquired by NPEs and non-NPEs and analyse whether the patents are different between NPEs and non-NPEs.

3.6.2 Transaction level analysis

To make the analysis more robust, we made different dataset from the patent level dataset. The data at the patent level dataset represent unique patents that are not the same as a unique transaction, because there may be many patents in a single transaction between companies. The transaction record was recorded in the assignment data file (which we already discussed earlier in this chapter), and each transaction was uniquely identified by the reel-frame identification number (rf_id). The company information from Orbis will not be changed because that is at the assignor level. Moreover, we did some calculation for the patent quality indicator variables. We made a new variable for each quality indicator which contains the average of all patents included in that specific transactions (e.g., if there are three patents included in one transaction, then we calculated the average of claims for these three patents). We believe that we could use the results from this dataset to cross-check the results from the patent level. Using these criteria, we have 24,784 unique transactions that took place between 2005 and 2014, where 22,739 transactions with non-NPEs and 2,045 with NPEs. For the analysis, we present the results from both levels of analysis.

3.7 Research variables

3.7.1 Dependent variable

NPEs

The dependent variable for our model is the dummy variable that captures the information about whether the patent was acquired by NPEs or not. It is a binary variable that takes the value one (1) if the patent was acquired by NPEs and zero (0) otherwise.

3.7.2 Independent variables

For the company information

This data file contains information about companies. For the analysis purpose, we made five different variables (all categorical variables). We have made the dummies for all individual categories for the statistical analysis.

Category of the company

The Orbis database provides information for each company, and a company's size is classified into one of the following four categories: small, medium, large and very large company. We made the dummies for all categories (small, medium, large and very large company) for the statistical analysis. These variables will allow us to investigate the category (size) of the company. So, we could analyze whether the sellers associated with NPEs and non-NPEs are different or not. According to the Orbis database, the criteria for categorizing the companies are as follows:

Orbis classifies a company very large when a company matches at least one of the three following conditions: 1) Total assets is equal or larger than 260 million USD, 2) operating revenues for a company is equal or more than 130 million USD and 3) the company has equal or more than 1000 employees (Orbis, 2018). To be classified as a large company, Orbis states that the company must match at least one of the following three conditions: 1) Total assets is equal or larger than 26 million USD, 2) operating revenues for a company is equal or more than 13 million USD and 3) the company has equal or more than 150 employees. Likewise, Orbis states that a medium sized company is a company that matches at least one of the three following conditions: 1) Total assets is equal or larger than 2.6 million USD, 2) operating revenues for a company is equal or more than 1.3 million USD and 3) the company has equal or more than 15 employees. Finally, Orbis classifies a small company when the company is not included in another listed category (Orbis, 2018).

Country of origin

The country of origin represents the origin of the patent seller. Since we are interested in analysing the seller's profile, it is important to know whether that seller is based in the US or not. Therefore, we made a dummy variable to represent this variable, and a binary value 1 represent companies that are from the US and 0 represent companies that are not from the US.

Type of entity

Type of entity is another important categorical variable, which classifies firms into three different entities: banks and financial company, corporate and research institute and others. We have made the dummies for all entities (bank and financial, corporate and research institute and others) for the statistical analysis. These categorical variables will also allow us to analyze what kind of entity are the main sources for NPEs and non-NPEs.

Number of companies in the corporate group

Number of subsidiaries

These variables contain the number of companies within that company group, and the number of subsidiaries of that company, respectively. We have decided to include these variables because these will give us some additional explanation power to analyze patent seller. This means that we could analyze how many companies and how many subsidiaries the patent sellers have under the same corporate group.

These variables are also categorical variables, and there are mainly four categories recorded. The first category is 1 and represents '0' in both variables, which means that there are no other companies under the corporate group or no subsidiaries, the second category represents the companies which have 2 to 50 (number of companies or subsidiaries), third from 51-100 and fourth 100+. Likewise, we have converted all the categories to dummies for the statistical analysis.

NBER category

National Bureau of Economic Research (NBER) classifies technology class into six main categories: chemical, computers and communications, drugs and medical, electrical and electronics, mechanical and others. Furthermore, NBER classify 37 subcategories. We have downloaded the NBER category and subcategory data file from PatentsView and matched with our existing dataset. Therefore, we make the dummies of NBER categories and used these variables as independent variables. We used these variables because it would allow us to investigate categories of patents acquired by NPEs and non-NPEs and whether they are different or not between NPEs and non-NPEs.

For the OECD Patent Quality Indicators data file

Patent scope

It contains the numbers of 4-digit subclasses of the international patent classifications (IPC) the invention is allocated to, and a larger number represent a broader scope of the patent. Lerner (1994) studied the importance of patent scope and concluded that it has an impact on the valuation of the firm, and broad patents are more valuable than patents in the same class. Furthermore, a broad scope is better to protect for early disclosure of the invention as well (Matutes, Regibeau, & Rockett, 1996). Matutes et al. (1996) further state that "a broad scope is equivalent to a wide range of potential applications being protected for some period of time" (p. 70).

Family size

Squicciarini et al. (2013) define patent family size as: “The set of patents filed in several countries which are related to each other by one or several common priority filings is generally known as patent family” (p. 15). This means that patents which are protected in more countries for the same inventions are regarded as valuable patents (Harhoff et al., 2003). Some studies used the family size as a proxy to study the value of patents. Lanjouw, Pakes, and Putnam (1998) analyzed the family size as a proxy for the value of IP.

Backward citations

Forward citations

Backward and forward citations are key quality indicators for the patent characteristics. According to the rules to be eligible to be granted a patent, the inventor must disclose all the information related to the patent and the patent examiner checks all the references and information before granting a patent. This includes the citation of all the published, granted patents, scientific works, and other non-patent literatures (Squicciarini et al., 2013). The backward citations are also used to access the degree of novelty of the invention as well as the patterns of knowledge transfer among new inventions (OECD, 2009).

Forward citations are the number of citations the patent gets, which means that how many other innovations use the patent as a source for the inventions which is also part of knowledge diffusion on the subsequent invention (Duguet & MacGarvie, 2005). Forward citations are associated with the importance of the innovation and technology and its social value (Trajtenberg, 1990). Lanjouw and Schankerman (1999) argue that forward citations are the least noisy indicator to analyze patent quality. This could be the reason that forward citations are the most used patent quality indicator for research purpose. Patents with a higher number of forward citations are regarded as valuable patents. For our analysis, we include the forward citation for the first five years after a patent is granted.

Claims

The number of claims is associated with the technological and economic value of the inventions. We already mentioned that to be eligible to grant a patent, the inventor must disclose all the information related to the invention. Patent claims are a list of descriptions which defines the scope or boundaries of the patents. Thus patents with a larger number of claims are regarded as valuable patents. Hong (2013) states that claims are the heart of the patents from the owner’s viewpoint because it defines the scope of legal protection. Because of this, most patent agents and/or inventors would like to draft the claims as broad as possible, to cover all the inventions. Like forward citations, claims are also regarded as a less noisy indicator (Lanjouw & Schankerman, 1999) and measure the size of an innovation (Tong & Frame, 1994).

References to non-patent literature (NPL)

NPL includes all the basic research from universities, journals and non-journals and published articles cited by patents (OECD, 2009). Usually, a higher number of NPL share in the citation represents a valuable patent. NPL could be the outcome of basic research, just developed by the university and the inventions citing this reference could be more complex and novel inventions (Squicciarini et al., 2013). The OECD (2009) states that mostly in the biotechnology and pharmaceutical related patents have more NPL citation than other patents. Callaert, Van Looy, Verbeek, Debackere, and Thijs (2006) analyze the share of NPL citation on the granted patent with application year between 1991 and 2001 and conclude that 34% of US patents contain non-patent literature references, and 39% of EPO (European Patent Office) patents contain NPL. The authors claim that patents with a higher share of NPL are complex and contain basic research (Cassiman, Veugelers, & Zuniga, 2008) and are of higher quality (Branstetter & Ogura, 2005).

Grant lag

Grant lag is the time difference between application and grant dates of the patent. This is closely related to the quality of the patent in the sense that the application which is well documented and contains proper referencing will get faster approval. In contrast, the application which has ambiguous claims construction, and is not well documented takes a longer time before a patent is granted (Squicciarini et al., 2013).

Patent renewal

Age of the patent

Patentees must pay a renewal fee to keep their patents in force (Pakes, 1986). Patent renewal represents the patent and its claims are still valid and useful. Patent renewal is associated with the quality of the patent, which means that if the patent gets a higher number of forward citations, then the patent is more likely to be renewed and will have a higher probability that it will be traded in the future (Serrano, 2010). The age of the patent is associated with the patent renewal. Patent renewal also represents the chances of patents being commercialized and valuable patents are renewed for longer periods (Pakes, 1986). We have calculated the age of the patent by subtracting the grant date from transaction date, which represent the age of the patent on the date of the transaction.

As already mentioned in chapter 3.5.4, we chose eight out of twelve quality parameters for this study. Since we are interested in analyzing the patents acquired by NPEs and non-NPEs and whether these patents are different or not according to these parameters. Hence, the selected parameters will allow us to compare the value of patents. According to Squicciarini et al. (2013), patents with a higher number of scope, family size, claims, citations (backward, forward and NPL), higher renewal and shorter grant lag are considered as valuable patents. Based on these quality parameters we would like to analyze whether patents acquired by NPEs are more valuable than that of non-NPEs. These are the mostly used parameters to analyze the patents quality, so we decided to use these parameters as independent variables in our study.

Summary and description of variables used in this research

Variable name	Description
Dependent variable	
NPE	Dummy variable equals 1 if the patent was acquired by a NPE (if the assignee is NPE) and 0 otherwise
Independent variables (company information from Orbis)	
Category of the company	Categorical variable contains the category of the company (seller). In addition, we have dummies for all the categories: Small, medium size, large and very large company
Country of origin	Categorical variable contains the country code of the origin of assignor (seller) and dummies for that category: Non-US, US
Entity	Categorical variable contains the entity type of the assignor and dummies for each entity: Bank and financial, corporate and research institute and others
Number of companies in the group	Categorical variable contains the number of companies of the assignor in the corporate group and dummies for each category
Number of subsidiaries	Categorical variable contains the number of subsidiaries companies of the assignor and dummies for each category
NBER category	This is a categorical variable, representing the patent category according to the NBER classifications. And dummies for each category
Independent variables patent characteristics (OECD Patent Quality Indicators)	
Patent scope	A numerical variable which counts the number of different 4-digit IPC classification
Family size	A numerical variable that counts the patent filed in several countries and which are related to each other
Backward citations	A numerical variable that counts the number of backward citations the patent use
Forward citations	A numerical variable that counts the number of forward citations (first five years) the patents get
Claims	A numerical variable that counts the number of claims which defines the scope and boundaries of patents
Non-patent literature (NPL)	A numerical variable that counts the non-patent literature that the patent cites
Grant lag	A numerical variable that indicates the time difference between application and grant dates of the patent
Patent renewal	A numerical variable that represents the patent and its claims are still valid and useful. It contains information about how long the patent owner pays the renewal fee for that patent
Patent age	A numerical variable that represents the age of the patent on the date of the transaction

Table 1. Summary of variables used in this research

4. Result analysis

In this chapter, we are dealing with the data analysis and interpretation of the results. To do the analysis, we start with the descriptive analysis, correlation analysis and finally will do the regression analysis. Since our dependent variable is a dummy variable, we will use logistic regression in this study.

4.1 Models for the analysis

4.1.1 Total observations for the study

Group	Patent level (Model 1)		Transaction level (Model 2)	
	Frequency	**Percent**	**Frequency**	**Percent**
Non- NPE	101,767	84.96	22,739	91.75
NPE	18,010	15.04	2,045	8.25
Total	**119,777**	100	**24,784**	100

Table 2. Total observations for analysis

Table 2 shows the total observations for the two different models used in this thesis.

Model 1. Patent level observations

In model 1, we have 18010 observations for NPEs, 101,767 non-NPEs and a total of 119,777 observations at the patent level. In this dataset, each observation represents a unique transfer patent.

Model 2. Transaction level observations

In model 1, we have all the observations at the patent level. In most of the cases, bundles of patents were included in one transaction and, therefore, we made a new dataset from those 119,777 observations with the unique transaction number. Thus, in the new dataset, there are 24,784 unique transactions in total with 22,739 non-NPEs and 2,045 NPEs transactions between 2005 and 2014.

4.2 Descriptive statistics results

For the descriptive results, we produce the results of model 1 and model 2 together and compare those two results together. As mentioned earlier, the observations in the model 1 are at the patent level and in model 2 at the transaction level. We use descriptive analysis along with t-test for the categorical variables as well as numerical variables.

4.2.1 Descriptive results for company information

For the company information, we use data extracted from the Orbis database. We use this dataset to answer our first research question. To answer this research question, we use the following variables: category of the company, country of origin of the company, and supplement tables in the appendix with information for types of entity, number of companies in the corporate group and number of subsidiaries of the company. Since all the variables used in the company information are categorical variables, thus, we made dummy variables for all the categories to calculate summary statistics such as mean, standard deviation and t-test.

Category of the company

Patent level

Category of the company	Non-NPE (Obs. 101,767)		NPE (Obs. 18,010)		Combined (Obs. 119,777)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Small company	0.435	0.496	0.228	0.420	0.404	0.491	52.798***
Medium size company	0.135	0.342	0.113	0.316	0.132	0.338	8.214***
Large company	0.090	0.285	0.048	0.215	0.083	0.276	18.391***
Very large company	0.340	0.474	0.611	0.488	0.381	0.486	-70.318***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table 3. Category of companies (patent level)

Transaction level

Category of the company	Non-NPE (Obs. 22,739)		NPE (Obs. 2,045)		Combined (Obs. 24,784)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Small company	0.543	0.498	0.439	0.496	0.535	0.499	9.076***
Medium size company	0.170	0.376	0.156	0.363	0.169	0.375	1.666
Large company	0.099	0.299	0.086	0.281	0.098	0.298	1.926
Very large company	0.187	0.390	0.319	0.466	0.198	0.398	-14.417***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table 4. Category of companies (transaction level)

The results from table 3 and 4 reveal the categories of the sellers' profile. In chapter 3, we already defined the criteria for a company to be defined as either a small, medium size, large or very large company.

The result from table 3 shows that in first three categories (small, medium and large) non-NPEs are associated with statistically significantly larger mean than NPEs, except for the fourth category (very large) which has statistically significantly lower mean than NPEs. This concludes that at the patents level companies are statistically significantly different between NPEs and non-NPEs. This indicates that on average NPEs acquired most of the patents from very large companies and less patents from small, medium size, and large companies than that of non-NPEs.

On the other hand, at the transaction level, we could see that only two categories (small and very large) are statistically significantly different between NPEs and non-NPEs, where non-NPEs are associated with a statistically significantly higher mean on small companies and lower mean on very large companies than NPEs. This means that on average NPEs have more transaction with very large companies than that of non-NPEs while non-NPEs have more transactions with small companies than NPEs. This could be true in the sense that mostly non-NPEs are looking for small innovative companies, and they acquire either the whole company or patents from small companies, while NPEs may acquire a bundle of patents from very large and sometimes bankrupt companies. These results conclude that NPEs acquired overproportion of patents from very large companies than that of non-NPEs.

To supplement these results, we have further analyzed two different variables: number of companies in the corporate group and number of subsidiaries. While we generate the results, we have noticed that the results are in the same line as a category of the company (e.g., non-NPEs mostly acquired patents from small firms which can have only one company and no subsidiaries). Therefore, we have moved these tables to the appendix as table A1, A2, A3 and A4. The results may not be the same because the criteria to categorize small, medium, large and very large company is different than the number of companies in the corporate group or number of subsidiaries, but still, all these tables reveal similar results. The associated t-value shows that the companies are statistically significantly different in terms of these variables (number of companies in the corporate group and number of subsidiaries) as well. Similarly, we add one more variable: type of entity, and the associated tables to the appendix (table A5 and A6), which concludes that more than 90% of the sellers are corporate for both groups. The descriptive statistics and t-value associated with the results show that non-NPEs are associated with a significantly higher mean on the corporate firms than NPEs. This means that NPEs may search for patents from other sources such as bank and financial companies, bankrupt companies, and research institution and other where non-NPEs are associated with a statistically significantly lower mean than NPEs. Since the results from these variables (number of companies under corporate group, number of subsidiaries and types of entity) are not so noticeable, we decided not to use these variables for further analysis. Thus, for the further analysis (e.g., correlation and regression analysis) we will not use these variables.

Country of origin

Patent level

Country of origin	**Non-NPE (Obs. 101,767)**		**NPE (Obs. 18,010)**		**Combined (Obs. 119,777)**		**t-value**
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	
Non-US	0.205	0.404	0.306	0.461	0.220	0.414	-30.291***
US	0.795	0.404	0.694	0.461	0.780	0.414	30.291***

A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Country of origin of companies (patent level)

Transaction level

Country of origin	**Non-NPE (Obs. 22,739)**		**NPE (Obs. 2,045)**		**Combined (Obs. 24,784)**		**t-value**
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	
Non-US	0.235	0.424	0.359	0.480	0.245	0.430	-12.509***
US	0.765	0.424	0.641	0.480	0.755	0.430	12.509***

A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Country of origin of companies (transaction level)

Table 5 contributes to answer research question one. Since we are analysing NPEs based in the US, it is interesting for us to see whether NPEs acquired most of their patents from US-based company or not. From table 5, we can see that in both groups the main sellers are based in the US and on average non-NPEs acquired more of the patents from US-based companies than the NPEs and fewer patents from non-US companies. The results further show that patent sellers to the NPEs and non-NPEs are statistically significantly different in terms of their country of origin. In addition to this, table 6 (transaction level) also reveals the results are in the same line that on average non-NPEs have more transactions with the US-based companies and less transactions with non-US companies than NPEs. A rationale that most of the patent sellers are from the US could be that the US patent market is more liquid and bigger than other patent markets and more high technology patents are traded in the US.

NBER patent classifications

Patent level

NBER category titles	Non-NPE (Obs. 101,767)		NPE (Obs. 18,010)		Combined (Obs. 119,777)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Chemical	0.111	0.314	0.027	0.162	0.099	0.298	35.071***
Comp & Comm	0.306	0.461	0.612	0.487	0.352	0.478	-81.333 ***
Drugs & Medical	0.115	0.318	0.024	0.153	0.101	0.301	37.417 ***
Ele & Elec	0.176	0.380	0.251	0.433	0.187	0.390	-23.834***
Mechanical	0.148	0.355	0.063	0.242	0.135	0.342	30.976 ****
Others	0.144	0.352	0.024	0.152	0.126	0.332	45.366 ***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table 7. NBER patent classifications (patent level)

Transaction level

NBER category titles	Non-NPE (Obs. 22,739)		NPE (Obs. 2,045)		Combined (Obs. 24,784)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Chemical	0.120	0.325	0.011	0.103	0.111	0.314	15.104 ***
Comp & Comm	0.236	0.425	0.734	0.442	0.277	0.448	-50.687***
Drugs & Medical	0.164	0.370	0.010	0.101	0.151	0.358	18.674 ***
Ele & Elec	0.138	0.345	0.156	0.362	0.139	0.346	-2.223**
Mechanical	0.141	0.348	0.061	0.239	0.134	0.341	10.201***
Others	0.202	0.402	0.028	0.166	0.188	0.391	19.440 ***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table 8. NBER patent classifications (transaction level)

Table 7 contributes to answer research question two. NBER classifies the technology class into six different categories as presented in the above table. The results from table 7 show that the patents in the computers and communications categories are mostly traded followed by electrical and electronics in both groups. We can see that on average non-NPEs acquired more patents in chemical, drugs and medical, mechanical and others category than that of NPEs and less in computers and communications and electrical and electronics category. The similar results can be seen at the transaction level (table 8). Especially for the NPEs, they acquired overproportionate of patents in the field of computers and communications. This may be due to that NPEs see more value in patents in computer and communication and electrical and electronics categories because these are growing sectors and have many patents applied in these two categories.

The t-test results further conclude that non-NPEs were associated with a statistically significantly larger mean of NBER categories in chemical, drugs and medical, mechanical, and others than NPEs and lower mean on computers and communications and electrical and electronics. Thus, these results conclude that patents in each NBER category are statistically significantly different between NPEs and non-NPEs in both datasets (patent level and transaction level).

To further clarify the analysis of NBER categories, and the categories of the firms, we used crosstabs, which is also known as the contingency table. Normally the contingency table (crosstabs) is used to describe and analyze the relationship between two or more categorical variables (Torres-Reyna, 2007). Table 7 provides some interesting results that mostly NPEs acquired patents from two categories. So, we would further like to explore what kind (category) of companies are associated with this kind (NBER category) of patents. The results of the crosstabs are available in the appendix as table A7 and A8. From the results (table A7 and A8), we could see that, at both (patent and transaction) level NPEs acquired more patents in computers and communications, and electrical and electronics categories from very large company than that of non-NPEs. Additionally, at the transaction level in electrical and electronics category, NPEs acquired more patents from medium and large companies also than that of non-NPEs.

Thus, along with the above results, we are able to answer our first research question. We were interested to know who are the sellers (who feeds the patent trolls (Feng & Jaravel, 2016)) to the NPEs and are they different than non-NPEs or not. And the results from above tables (table 2 to table 7) conclude that the firms (sellers) are statistically significantly different between NPEs and non-NPEs and NPEs acquired more patents from non-US based very large firms in the field of computers and communications and electrical and electronics than those of non-NPEs. Our result contradicts with the result of Fischer and Henkel (2012) as they conclude that NPEs mostly acquire patents from small firms.

In the next section, we will analyze the patent characteristics (patent quality parameters) and will discuss these two results together.

4.2.2 Descriptive results of patent characteristics

Patent level analysis

To answer our second research question, we used data from the OECD Patent Quality Indicators database and used the following variables: NPE, patent scope, family size, grant lag, backward citations, number of claims, non-patent literature, forward citations, patent renewal and patent age.

Standardize the variables

The initial dataset contains the absolute value of each variable for all observations. To make the interpretation and comparison easier, we standardize the data using the mean. To do this, we use the NBER subcategories and patent grant year to take out the effect of technology class and year. And by NBER subcategories and grant year we have calculated the mean of each quality indicator and get the relative value (obs/mean) for each observation. For further analysis, we will use relative value instead of the absolute value. Still, we present the results from the absolute value and transaction level for comparison. The results are available in the appendix.

Furthermore, to explain the patent characteristics, we will analyze the patent claims dataset at the patent level. The dataset contains the average numbers of the claims word count, dependent claims and independent claims. Since the dataset contains data on pre-grant and grant level of each patents, we could analyze the changes in the independent claims, dependent claims, average word count of independent and dependent claims on the patents acquired by NPE and non-NPE. The results of this analysis will further help us to understand what kind of patents do NPEs acquire and how are they different than that of non-NPEs (in terms of scope and quality)?

Patent characteristics	**Non-NPE (Obs. 101,767)**		**NPE (Obs. 18,010)**		**Combined (Obs. 119,777)**		**t-value**
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	
Patent scope	0.991	0.584	1.052	0.596	1	0.586	-13.029***
Family size	0.991	0.954	1.049	0.967	1	0.956	-7.47***
Grant lag	0.996	0.413	1.025	0.511	1	0.429	-8.381***
Backward citations	0.980	1.037	1.110	1.247	1	1.072	-14.987***
Non-patent literature	0.993	2.793	1.039	2.617	1	2.767	-2.051**
Claims	0.998	0.765	1.013	0.786	1	0.768	-2.395**
Forward citations	0.983	1.681	1.097	2.111	1	1.753	-8.044***
Renewal	0.999	0.180	1.007	0.160	1	0.177	-5.817***
Patent age	1.004	0.485	0.979	0.385	1	0.472	6.59***

A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Patent characteristics (standardized patent level data)

Table 9 summarizes the descriptive statistics results of the patent quality indicators from the OECD. The result from table 9 reveals that on average patents acquired by NPEs have a higher scope, family size, number of claims, took a long time to grant, have higher forward and backward citations, NPL citations and are renewed for a longer period of time. Similarly, the result shows that on average non-NPEs are associated with a lower mean on eight out of nine patent characteristics than NPEs, and all the results are statistically significant ($p<0.05$). This concludes that patents acquired by NPEs are more valuable than those acquired by non-NPEs, which is in the same line as Fischer and Henkel (2012).

For the cross-check, we have calculated the descriptive statistics of the absolute value of patent quality indicators and at the transaction level. Those tables are available in the appendix (table A9 and A10) for more information. From the results of table A9, we could see that on average non-NPEs were associated with a statistically significantly larger mean on patent scope, family size and NPL citation and lower mean on grant lag, backward citation (which is not statistical significant), claims, forward citations, renewal, and patent age than NPEs. The results of table A10 also presents similar results as table A9, except backward citations, where non-NPEs are associated with significantly higher mean than NPEs. Overall, the results conclude that patents acquired by NPEs and non-NPEs are statistically significantly different in terms of their quality indicators. The results of the standardized data and absolute data look different because of some effect of technology class and year. Thus, though we have different results, we can probably rely on the results of the standardized data (table 9).

Along with these results, we are very close to answering our second research question: are the patents acquired by NPEs and non-NPEs different? Thus, summarizing the results from table 9, by comparing the quality indicators of patents acquired by NPEs to those of non-NPEs, we find a highly significant difference at ($p<0.01$) for seven out of nine characteristics and a significant difference at ($p<0.05$) for the remaining two characteristics. Patents acquired by NPEs, on average, have higher patents scope, family size, grant lag (took a longer period to grant), backward citations, NPL citations, claims, forward citations and renewed longer period of time than patents acquired by non-NPEs. In addition, the results show that patents acquired by NPEs are on average younger than patents acquired by non-NPEs. This concludes that on average patents acquired by NPEs seem significantly higher quality than the patents acquired by non-NPEs.

Our results are in the same line as Fischer and Henkel (2012), where they conclude that NPEs mostly acquired patents in the communication and IT field, and they are of relatively higher quality than that of non-NPEs. However, our results contradict with the size of the sellers, as they conclude that sellers are small and new firms. Our results show that NPEs acquired most of their patents from very large companies than that of non-NPEs. On the other hand, our findings also contradict with the result of Feng and Jaravel (2016), as they conclude that on average patents acquired by NPEs have vague word length claims, are not technologically innovative but fruitful for the litigation. On the contrary, we found the opposite. However, this paper motivated us to look further into the patent claims dataset to find some supplement results that 'are the patents acquired by NPEs and non-NPEs different in terms of claims characteristics?'

In the next section, we will look at the patent claims dataset and analyze the different claims characteristics such as a number of independent claims, dependent claims, average word length of independent claims, and average length of dependent claims for the patents for each case (published and granted). The purpose of analyzing the patent claims dataset is that we could analyze the changes in the number of claims while the patent was applied (published) and while it was granted. Similarly, we could also analyze the changes in the independent claims and word length.

Patent claims dataset

As described in the methodology chapter, we have matched our existing patent level data with the patents claims data (patent level) and found 49,680 matched results. Now we use this dataset to run the descriptive statistics of claims characteristics. All the data values were standardized using the same mechanism as we employed in the patent characteristics. While we standardized the variables, it generates missing values in some of the variables. For the clarity, we include the observations for each variable in the descriptive statistics.

Variable (claims characteristics)		Non-NPE			NPE			Combined			t-value
		Obs.	Mean	Std. dev	Obs.	Mean	Std. dev	Obs.	Mean	Std. dev	
Pre-grant publication	Count of independent claims	43,036	0.988	0.766	6,644	1.080	1.091	49,680	1	0.817	-8.55***
	Count of dependent claims	43,036	0.994	0.842	6,644	1.039	0.878	49,680	1	0.846	-4.037***
	Avg. word count in ind. claims	42,977	0.999	0.833	6,630	1.006	0.776	49,607	1	0.825	-0.606
	Avg. word count in dependent claims	42,189	1.000	1.384	6,462	0.997	1.459	48,651	1	1.394	0.195
Granted patent	Count of independent claims	43,036	0.993	0.718	6,644	1.048	0.872	49,680	1	0.740	-5.622***
	Count of dependent claims	43,036	0.995	0.812	6,644	1.033	0.887	49,680	1	0.822	-3.477***
	Avg. word count in ind. claims	43,034	1.005	0.583	6,644	0.971	0.466	49,678	1	0.569	4.521***
	Avg. word count in dependent claims	42,049	1.003	0.509	6,506	0.982	0.450	48,555	1	0.501	3.185***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.											

Table 10. Claims characteristics

Table 10 shows the results of claims characteristics of the patents before grant and after grant. We can see that during the pre-grant publication non-NPEs were associated with a statistically significant smaller mean of count of independent claims and count of dependent claims. Moreover, there is no significant difference on the mean of average word count in independent claims and average word count in dependent claims. On the other hand, if we analyze the same variables after patent grant, we could see that all the parameters are statistically significant where non-NPEs were associated with smaller mean on count of independent claims and dependent claims while higher on average word count in independent and dependent claims. Marco et al. (2016) indicate that the length and count of independent claims determine the importance of patents. In this result, we could see that during the examination both count of independent and dependent claims are reduced for patents acquired by both group. And still, we can conclude that on average patents acquired by NPEs have wider scopes than by non-NPEs because they have higher number of independent and dependent claims even after the patent grant. On the other hand, we could see that the proportion of changes of average word counts in the independent claims and dependent claims are higher for the patents acquired by NPE than patents acquired by non-NPEs. In this case, one could argue that there is some association between the claims' word length and NPEs' patent acquisitions. Because we can see that the word formation of the claims' of the patents acquired by NPEs changed significantly during the grant process.

From this result (table 10), we could summarize that NPEs still acquired patents with higher number of claims, but the claims have more adjustment on the average word length of independent claims than that of non-NPEs. The reason could be that patents acquired by NPEs may have some extra lines of comment, or some fuzzy boundaries which are suitable for their business model. These results provide a good supplement for the claims parameters as we can argue that NPEs are not only acquiring patents with higher number of claims than that of non-NPEs, but NPEs also analyze the word formation of the claims which is in the same line as suggested by Feng and Jaravel (2016).

Correlation analysis (with all the observations)

VARIABLES	NPE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
NPE	1.00																					
Small comp (1)	-0.15	1.00																				
Medium comp (2)	-0.02	-0.32	1.00																			
Large (3)	-0.05	-0.25	-0.12	1.00																		
Very large (4)	0.20	-0.65	-0.31	-0.24	1.00																	
Non-US (5)	0.09	0.03	-0.05	-0.03	0.02	1.00																
US (6)	-0.09	-0.03	0.05	0.03	-0.02	-1.00	1.00															
Chemical (7)	-0.10	0.03	0.03	0.02	-0.06	-0.03	0.03	1.00														
Comp & Comm (8)	0.23	-0.09	-0.04	-0.07	0.16	0.03	-0.03	-0.24	1.00													
Drugs & Medical (9)	-0.11	0.08	0.05	0.03	-0.13	0.01	-0.01	-0.11	-0.25	1.00												
Ele & Elec (10)	0.07	-0.07	-0.01	-0.02	0.09	0.01	-0.01	-0.16	-0.35	-0.16	1.00											
Mechanical (11)	-0.09	0.01	-0.01	0.04	-0.02	-0.02	0.02	-0.13	-0.29	-0.13	-0.19	1.00										
Others (12)	-0.13	0.10	0.02	0.04	-0.14	-0.02	0.02	-0.13	-0.28	-0.13	-0.18	-0.15	1.00									
Patent scope (13)	0.04	0.01	0.00	0.01	-0.01	0.04	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	1.00								
Family size (14)	0.02	0.03	-0.01	0.01	-0.03	0.07	-0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.29	1.00							
Grant lag (15)	0.02	-0.01	-0.01	0.00	0.02	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.03	1.00						
Backward citations (16)	0.04	0.02	0.03	0.05	-0.06	-0.09	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.23	0.06	1.00					
NPL citations (17)	0.01	0.01	0.03	0.04	-0.05	-0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.14	0.07	0.41	1.00				
Claims (18)	0.01	0.01	0.02	0.03	-0.04	-0.06	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.09	0.06	0.17	0.14	1.00			
Forward citations (19)	0.02	0.00	0.02	0.03	-0.03	-0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.19	0.02	0.23	0.17	0.12	1.00		
Renewal (20)	0.02	-0.01	-0.02	-0.01	0.03	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.04	0.63	0.04	0.05	0.05	0.02	1.00	
Patent age (21)	-0.02	0.03	0.00	-0.03	-0.02	-0.04	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	-0.04	-0.02	-0.01	0.00	0.08	1.00

Table 11. Correlation matrix

The correlation matrix (table 11) provides an overview of collinearity of the parameters included in the analysis. Correlation analysis is the first step for the regression analysis. Furthermore, it shows the magnitude of the relationship between two variables. In the above table (table 11), we could see that more variables have a positive relationship. We cannot conclude any specific result from the correlation analysis except the sign/magnitude of the relationship. From the correlation matrix, we could observe that our independent variables do correlate between -0.65 and 0.63. But we found the dummies of country of origin (origin US and non-US) do correlate very high (-1). These are the dummy variables and while we run logistic regression one variable will be base variable. Thus, we think it will not be an issue to run logistic regression. Since there is no other such strong correlation (which is close to either 1 or -1), we could argue that there is no case of multicollinearity and we can then conduct regression analysis.

Regression analysis

We can analyze the impact of each variable on NPEs' patent acquisitions with a logistic regression model because the response variable is binary. The variable NPE would be equal to 1 if the patent was acquired by NPEs and 0 otherwise. Logistic regression is a statistical method to analyze the dataset when there is a binary dependent variable. UC_Rstats (2018) notes that logistic regression allows the user to estimate the probability of categorical response based on the independent variable. UC_Rstats (2018) further clarifies that logistic regression "allows one to say that the presence of a predictor increases (or decreases) the probability of a given outcome by a specific percentage". The coefficient in the logistic regression represents the probability of the event occurring, given by:

$$P(Y=1|X) = P\ (Y=1|X_1, X_2, X_3 \ldots X_n) = F\ (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n)$$

Where y is the dependent variable and x denote the set of independent variables. Here for the regression analysis, we use all the variables used in the correlation matrix, where NPE is the dependent variable with value either 1 or 0.

Interpreting the logistic coefficient

Interpreting the logistic regression is different than the linear regressions (O'Halloran, 2005). In the case of logistic regression, the logistic slope coefficient represents the effect of a unit change in the X variable on the predicted value while other variables being held constant. That means how one unit change in X effects the log of odds when other things being held constant.

The odds ratio in the logistic regression is represented as the ratio of favourable to the unfavourable case.

Odds=p/ (1-p) =probability of the event occurring / probability of the event not occurring.

And, the logit transformation is defined as log of odds:

logit (P) = ln (p/ (1-p))

The odds ratio in logistic regression is interpreted as the effect of one unit change in X in the predicted odds ratios, while other things being held constant.

Thus, in this research, since the NPE is a binary variable, the odds ratio is given by:

$$\text{Odds ratio (OR)} = \frac{\text{Odds (patent acquisition} \mid \text{NPE)}}{\text{Odds (patent acquisition} \mid \text{non-NPE)}}$$

We use the logit model and use all the coefficient and marginal effect to describe the results. We already mentioned that we could not read and interpret the logit coefficient in the same way as linear regression because they are in the log of odds units. On the other hand, we can use the Z and p-values in the same way. To make the interpretation easier, researchers use the odds ratios, which means they convert the result to the odds ratios. When the coefficients are converted into odds ratio, then that represent the odds of Y=1 when X increases by 1 unit. These are the exp (logit coeff). Odds equal to 1 means that the event is equally likely to occur. Odds greater than one means the event is more likely to occur and odds less than 1 means the event is less likely to occur. The odds ratios are constant, so a change in the odds does not describe/explain any change in the probabilities of the event to occur. In the same way, the marginal effect is "the predicted increment of the of the response variable associated with a unit increase in one of the covariates keeping the others constant"[6].

Here, for the analysis, we use all the variables (including category dummies) as in the correlation matrix and related value at the patent level. For the cross-check, we have also

---

[6]https://stats.stackexchange.com/questions/175287/predicted-probabilities-vs-marginal-effects-using-at-means-or-asobserved-in-sta (accessed on May 19, 2018: The author further states that i*n linear regression, it is just the beta parameter. In logistic regression, it depends on the value of the covariate. The predicted probability is just the predicted probability for the outcome to be 1 (the label associated with the value 1)*

calculated the regression on the absolute value and dataset at the transaction level analysis as well, and the results from those two are available in the appendix as table A11 and A12.

Logistic regression

(NPE=1) **VARIABLES**	(Model 1) Coefficient	(Model 2) Coefficient	(Model 3) Coefficient	(Model 4) Coefficient	(Model 5) Coefficient	(Model 6) Coefficient	(Model 7) Coefficient	(Model 8) Coefficient	(Model 9) Marginal effect
Small company	-0.958***			-0.464***	-0.513***	-0.515***		-0.514***	-0.048***
	(0.019)			(0.029)	(0.029)	(0.030)		(0.030)	(0.003)
Large company		-0.657***		-0.432***	-0.447***	-0.347***		-0.374***	-0.035***
		(0.036)		(0.043)	(0.043)	(0.043)		(0.044)	(0.004)
V large company			1.113***	0.767***	0.733***	0.444***		0.478***	0.044***
			(0.017)	(0.026)	(0.026)	(0.027)		(0.028)	(0.003)
Origin US					-0.554***	-0.503***		-0.536***	-0.050***
					(0.018)	(0.019)		(0.020)	(0.002)
Chemical						0.304***		0.301***	0.028***
						(0.067)		(0.067)	(0.006)
Comp & Comm						2.255***		2.257***	0.210***
						(0.051)		(0.051)	(0.004)
Drugs & Medical						0.199***		0.196***	0.018***
						(0.071)		(0.071)	(0.007)
Ele & Elec						1.923***		1.926***	0.179***
						(0.052)		(0.052)	(0.004)
Mechanical						0.807***		0.804***	0.075***
						(0.058)		(0.058)	(0.005)
Patent scope							0.133***	0.147***	0.014***
							(0.013)	(0.014)	(0.001)
Family size							0.009	0.006	0.001
							(0.009)	(0.010)	(0.001)
Grant lag							0.116***	0.127***	0.012***
							(0.024)	(0.028)	(0.003)
Backward citations							0.098***	0.144***	0.013***
							(0.008)	(0.008)	(0.001)
NPL citations							-0.018***	-0.015***	-0.001***
							(0.003)	(0.004)	(0.000)
Claims							-0.008	0.040***	0.004***
							(0.011)	(0.011)	(0.001)
Forward citations							0.015***	0.020***	0.002***
							(0.004)	(0.005)	(0.000)
Renewal							0.071	-0.029	-0.003
							(0.051)	(0.062)	(0.006)
Patent age							-0.098***	-0.078***	-0.007***
							(0.015)	(0.017)	(0.002)
Constant	-1.419***	-1.688***	-2.260***	-1.914***	-1.467***	-2.991***	-2.060***	-3.358***	
	(0.009)	(0.008)	(0.013)	(0.024)	(0.028)	(0.055)	(0.045)	(0.075)	
Observations	119,777	119,777	119,777	119,777	119,777	119,777	119,777	119,777	119,777

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. Regression at the patent level standardardized data

Table 12 provides the main results of our study. In addition to this table, we have two supplement tables available in the appendix as table A11 and A12. Table A11 contains the results from the absolute value (from dataset at patent level), and table A12 contains the results from the transaction level dataset. In table 12, the numbers (the heading) represent different models with different independent variables where models from 1 to 8 represent the coefficient from the logistic regression while model 9 represents the marginal effect. We include the marginal effect to interpret the coefficient of the logistic regression better. We run different models with different combinations of independent variables to see how the effect of one variable will change while adding other independent variables. As we can see from the regression output from models from 1 to 4, that adding more variables will change the effect of the previous variable (medium size company is the base group). By adding two dummy variables of the category (large and very large), the coefficient of the small companies changed significantly (which was as expected) because we already saw from the descriptive statistics that NPEs acquired more patents from very large company than that of non-NPEs. The results further show that the probability of patents being acquired by NPEs (rather than non-NPEs) will increase as the number of very large company (than base group) increase.

In the same way, when we add country of origin dummy (non-US origin is the base group) in model 5, and the NBER category dummies (others category is the base group) in model 6 and still we could not see any change in the magnitude of the coefficient. But at the same time, we have noticed a significant change in the coefficient of very large company and small changes in the medium company when we add the NBER category dummies in model 6. Models from 1 to 6 represent the results of all categorical variables in our study and all the coefficients are statistically significant at the 1% level. From the results of model 6 (table 12), we noticed that all the coefficients are significant, and six out of nine variables are positive, and the remaining three have a negative magnitude. Here, we would like to include the results of a categorical variable from appendix table A12 (transaction level). As noted from the results of table A12, almost all the results are in the same line (as table 12) except some magnitude. The results of all the variables look significant except for large company. The magnitudes of chemical and drugs and medical patents categories are also negative. This means that at the transaction level a unit increase in the computers and communications, electrical and electronics, mechanical category patents and a unit increase in very large company will increase the probability of patents being acquired by NPEs. But, at the patent level the result looks interesting. Though, we found NPEs are associated with significantly higher mean in computers and communications and electrical category than non-NPEs from descriptive statistics, we found all the coefficients (chemical, computers and communications, drugs and medical, electrical and electronics and mechanical making others as a base group) are positive and significant in the regression analysis. This indicates that though NPEs acquired more patents in two (computers and communications and electrical) categories than that of non-NPEs, the likelihood of patents being acquired by NPEs increase with the increase patents in the chemical, computers and communications, drugs and medical, electrical and electronics and mechanical (than others) category rather than the likelihood of patents being acquired by non-NPEs.

In model 7 (table 12), we include only quality indicators, and the results show that patent scope, grant lag, backward citations and forward citations are positive and significant at ($p<0.01$), NPL citations and patent age are negative and significant and family size, claims and renewal are not significant. Similarly, in model 8, we include all the patent characteristics variables along with the categorical variables and it is the final model of our study. The results of model 8 show that all the independent variables are significant at ($p<0.01$) except for family size and renewal. The one thing to note is that while we add categorical variables (variables used in model 6) in model 8, the coefficient of the claims changes significantly and shows a significant and positive impact. Model 9 represents the marginal effect, and can easily be interpreted (e.g., patents increase in the field of computer and communications are 21% more likely to be acquired by NPEs than that of non-NPEs).

Thus, comparing the NPEs' patent acquisitions to non-NPEs, in final model (table 12, model 8), we found that the coefficient and marginal effect of very large company, NBER categories (chemical, computers and communications, drugs and medical, electrical and electronics and mechanical), patent scope, grant lag, backward citation, claims and forward citations are positive and highly significant at ($p<0.01$). That means that a unit increase in these independent variables will increase the relative probability of patents being acquired by NPEs rather than that of non-NPEs. On the other hand, the coefficient and marginal effect of a small company, large company, country of origin, NPL citations, and patent age are negative and highly significant ($p<0.01$) and family size and renewal are not significant though family size has a positive and renewal has a negative coefficient. These results conclude that patents acquired by NPEs and non-NPEs are significantly different in terms of quality parameters and on average NPEs acquired significantly higher quality patents than that of non-NPEs.

5. Discussion

In this thesis, we wanted to analyze NPEs' patent acquisitions. To conduct the analysis, we proposed hypotheses and used quantitative method to test the hypotheses. We have used company (seller) data from the Orbis database and patent category data from the NBER, and sellers (assignor) details from the USPTO patent assignment database to answer the first research question and test the first hypothesis. Our first hypothesis (H1–a): the firms where NPEs acquired the patents from, would be significantly different than that of non-NPEs. Our findings revealed results in the same line with this hypothesis and showed that firms are statistically significantly different between NPEs and non-NPE. Further results revealed that on average NPEs are associated with significantly higher mean on very large companies and lower mean on small, medium and large company than that of non-NPEs. Similar results can also be seen from the regression analysis. We did not find previous studies in this field using the same kind of data, thus, we are unable to compare it with past results.

Similarly, we have proposed hypothesis (H1-b) that firms will be significantly different between NPEs and non-NPEs in terms of country of origin. The results revealed that the country of origin of the company (non-US and US) are statistically significantly different between NPEs and non-NPEs and on average NPEs acquired more patents from non-US companies than that of non-NPEs, which is also in the same line with our hypothesis. Similar results can be seen in the regression analysis, that increasing one additional US firm will decrease the probability of patents being acquired by NPEs.

Likewise, we have proposed our second hypothesis (H2): The categories of the patents (NBER categories) acquired by NPEs will be significantly different than that of non-NPEs. Moreover, the empirical analysis revealed the results are in the same line with this hypothesis that patents in all the NBER categories (chemical, computers and communications, drugs & medical, electrical and electronics, mechanical and others) are significantly different between NPEs and non-NPEs. The results concluded that on average NPEs are associated with a significantly larger mean in computers and communications and electrical and electronics patents than non-NPEs. The results from regression analysis showed that all the NBER category dummies (others as a base group) are positive and significant.

Similarly, we have proposed our third hypothesis (H3): Patents acquired by NPEs will be significantly different than patents acquired by non-NPEs. To test this hypothesis, we used data from the USPTO patent assignment database and the OECD Patent Quality Indicators database. According to the information provided by Squicciarini et al. (2013) higher number represents higher quality except for grant lag. We found that the characteristics of patents are in the same line with this hypothesis. And the results show that on average non-NPEs are associated with statistically significantly lower mean (on eight out of nine parameters) than NPEs and higher mean on patent age. The results (from regression table 12, model 8 and 9) showed all the quality indicators are significant at ($p<0.01$), except for family size and renewal. The coefficient of patent scope is positive and significant which means that increasing the patent scope will increase the probability of patents being acquired by NPEs rather than that of non-NPEs. The larger the number of patent scope, the broader the scope of the patents. Merges and Nelson (1990) state that the broader the scope of the patents, the larger the number of processes and products that will infringe the patents. Fischer and Henkel (2012) argue that patents with a broader scope are more attractive for NPEs because it provides more rooms for licensing and cover more areas to find the infringed product and processes. In addition to that, the authors argue that patents with a broader scope are more valuable as it provides a good opportunity for cross-licensing and deterrence. Lerner (1994) also concludes in the same line that patents with broad scope are more likely to have been litigated. The results from our study also revealed similar results and the reason could be the same as stated by Merges and Nelson (1990), Fischer and Henkel (2012) and Lerner (1994). Because the NPEs business model is based on licensing and litigation and for that they need patents with broader scope which is suitable for them to sue other companies.

Similarly, citations play an important role in the quality of patents. Harhoff et al. (2003) note that a number of references to the patent literature and forward citations have a positive impact on the value of the patent. Hall, Thoma, and Torrisi (2007) note that forward citations received by patents indicate that the patents and it’s contained information are important for future innovation. Hence, it makes reasonable sense for NPEs to acquire patents that have a higher number of forward citations because when the patents get cited more, there will be more rooms for NPEs to sue other companies (more chances the patents are being infringed). In line with these results, we also found a positive and significant impact of forward citations on NPEs’ patent acquisitions.

Most of the researchers used different quality indicators together to analyze the patent value, patent quality or litigation cases. Our results (table 12, model 8) revealed that both backward citations, forward citations and claims have a positive and significant impact on the NPEs decision to acquire patents. This is in the same line as Lanjouw and Schankerman (1997), who conclude that litigated patents have higher forward citations than others. Similarly, Lanjouw and Schankerman (2004) also conclude that forward citations are an important factor in the drugs and medical category of patents, while the claim is considered an important determinant in other NBER categories. Furthermore, the authors note that backward citations are also one factor of patent quality but large number of citations of other patents are sometimes perceived that the innovation is not novel. Due to these features, the patents could be suitable for NPEs. Similarly, patents claims are another important piece of information in patents which determine its value. Claims are mostly correlated with citations (forward and backward) and technologies in the categories of drugs and medical, chemicals and electronics have more claims per patent while mechanical and others have less (Lanjouw & Schankerman, 1999). We also found a similar result that the probability of patents being acquired by NPEs will increase as the number of claims increase.

From our study, we found no significant impact of renewal on NPEs' patent acquisitions but found a negative and significant results on patent age. In addition to that, we found a positive and significant coefficient on grant lag, which indicates that increasing the patents which took a longer time to grant will increase the probability of being acquired by NPEs. There could be a link between the patent scope (regarding claims construction) and patent grant. If the patents acquired by NPEs have higher claims than that of non-NPEs then it is expected that it may take a longer time period to be granted. Furthermore, we found a negative and significant coefficient on the NPL citations and are not able to find previous research on the NPL citations and NPEs patent acquisitions to compare our results.

Furthermore, to supplement our results, we have conducted a descriptive analysis of the patent claims data. The data contains information about the patent claims characteristics. From the results, we found that NPEs mostly acquired patents which have more claims than the non-NPEs and that have more word adjustment during the grant process.

5.1 NPE and the Markets for technology

We already discussed in chapter two that there is a growing trend of NPEs and patent litigation. Many economists, politicians and researchers are concerned about the NPEs' business model. Henkel and Reitzig (2010) argue that as long as NPEs acquire patents which are sufficient to justify in the court and produce significant long-term switching cost for practicing firm after infringement, their business model looks sustainable.

NPEs are important players in the market for technology and in most of the time working as an intermediaries/brokers. Fischer and Henkel (2012) argue that transaction involving NPEs took place in the market for patents not in the markets for technology. This is an interesting argument where the authors note that NPEs are only acquiring patents for their own benefit not for social benefits. Because NPEs do not want to make the technology available for all like practicing entities who either buy/sell patents, form pool if necessary or do cross-licensing to commercialize the new technology. Since NPEs acquired more valuable patents than that of non-NPEs and played an active role in the markets for technology, we could argue that the role of NPEs will also be growing as the markets for technology grows.

6. Conclusion

The purpose of this thesis was to analyze NPEs' patent acquisitions through the supply side. It is important to understand who the sellers to the NPEs are and what kinds of patents did they sell and how sellers to the NPEs and patents are different those of non-NPEs. Thus, we proposed two research questions and used secondary data and quantitative methods to answer those questions. To our knowledge this is the first large-scale empirical study of NPEs' patent acquisitions using multiple sources of secondary data.

We believe this research contributes to the field of markets for technology and NPEs' patent acquisitions. We conducted this study by extending and overcoming the limitations of Fischer and Henkel's study. We used the recent USPTO patent assignment data from 2005 to 2014 and analyzed NPEs' patent acquisitions. We analyzed patent sellers' characteristics using data from Orbis database, NPEs data from previous empirical study, and patent characteristics data from the OECD Patent Quality Indicators database and the USPTO patent claims dataset. Thus, we believe this study opens the door for future research in this field.

The results from our empirical analysis revealed that companies are statistically significantly different between NPEs and non-NPEs and the likelihood of a patent being acquired by NPEs increase as the number of very large and/or non-US based companies increase. In addition to that, we have noticed that NPEs are associated with statistically significantly higher mean on computers and communications and electrical and electronics category than non-NPEs. Furthermore, the regression results revealed that all the NBER categories (making others base group) are positive and significant, making the probability of patents being acquired by NPEs higher. This indicates that NPEs are pickier regarding patent acquisitions. They acquire more patents in specific categories and from very large non-US based company rather than patents acquired by non-NPEs.

We found interesting conclusions from our results that NPEs acquired most of the patents from very large companies which contradict the results by Fischer and Henkel (2012) and Haus and Juranek (2017) where they argue that NPEs acquired most of the patents from small companies. For the quality parameters, our finding showed that NPEs acquired most of the patents which have higher number of patent scope, backward citations, forward citations, claims and grant lag than the patents acquired by non-NPEs which is in the same line with the results of Fischer and Henkel (2012). Similarly, our results further revealed that NPEs are more strategically active in the markets for technology than non-NPEs. Because, NPEs are not only acquiring patents in the field of technology and with higher number of claims, scope, citations but also analyzed the claims construction (word formation of the claims). Moreover, NPEs mostly acquired patents which have vaguely word and lengthy claims than that of non-NPEs, that are suitable for their business model. We found significant and negative impact of small and large company, US origin sellers, NPL citations and patent age and no significant impact of family size and renewal.

Our findings have a number of managerial implications. First, practicing firms should be proactive and find patents related and riskier to the company and acquire patents before NPEs. To do that, practicing firms could cooperate and exchange their innovation with each other. Second, addressing the patent examination process, hiring more knowledgeable patent examiners could also help to minimize the risk of being litigated by NPEs. Finally, minimizing the damage awards (awarded by courts) for the infringement case by NPEs could also help to minimize the patent litigation by NPEs.

6.1 Limitations and suggestions for future research

First, this research was conducted for the partial fulfilment of the master's degree and should be completed within the time frame of one semester. Because of this, we were not able to do everything that we wanted. Within this short time period, we have conducted an empirical study on patent data using secondary sources: the USPTO patent assignment dataset, PatentsView, the OECD Patent Quality Indicators database, Orbis and the USPTO patent claims dataset. Due to time constraints, we have only included data from 2005 to 2014 from the USPTO patent assignment database. There is always a possibility to extend our study by including most recent data. In the beginning, we would like to analyze the sellers (who sold the patents to NPEs) and their innovation activity before and after the transaction with NPEs. But because of time limitation, we were not able to do that. Hence, this could be interesting to analyze.

Second, we used patents that firms own 100% (for both assignee and assignor). Thus, we dropped all the patents which were not 100% owned by a company. Therefore, extending the study using all (partial ownership) patents could provide different results.

Lastly, we were interested in analysing the patent sellers, what kind of companies were involved in the patent transactions with NPEs and non-NPEs, so we matched the assignor name to the Orbis database and extracted company information and used only the matched companies. We did not include individuals and those companies whose data are not available in Orbis.

There are many avenues for future research in the field of markets for technology and NPEs' patent acquisitions. First, we were very restricted by the time limit, and therefore it is always a possibility to extend our study by overcoming the limitations. Second, this field (NPEs' patent acquisitions) is in its infancy and therefore further research needs to clarify and explore NPEs' patent acquisitions. Third, we did not analyze the litigation side of NPEs. Thus it would be interesting to explore what percentage of acquired patents do the NPEs used for litigations. Finally, a study on the role of NPEs past, present and future would be interesting to explore.

Appendix: Supplement tables

Number of companies under the corporate group (sellers' profile)

Patent level

No. of comp. under corporate group	Non-NPE (Obs. 101,767)		NPE (Obs. 18,010)		Combined (Obs. 119,777)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
1	0.416	0.493	0.279	0.449	0.396	0.489	34.856***
2 to 50	0.183	0.387	0.149	0.356	0.178	0.382	10.999***
51 to 100	0.046	0.210	0.243	0.429	0.076	0.265	-95.39 ***
100+	0.354	0.478	0.329	0.470	0.350	0.477	6.666***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A1. Number of companies under the corporate group (patent level)

Transaction level

No. of comp. under corporate group	Non-NPE (Obs. 22,739)		NPE (Obs. 2,045)		Combined (Obs. 24,784)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
1	0.570	0.495	0.462	0.499	0.561	0.496	9.472***
2 to 50	0.209	0.406	0.223	0.417	0.210	0.407	-1.555
51 to 100	0.030	0.170	0.117	0.321	0.037	0.188	-20.223***
100+	0.192	0.394	0.198	0.399	0.192	0.394	-0.712
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A2. Number of companies under the corporate group (transaction level)

Number of subsidiaries (sellers' profile)

Patent level

No of subsidiaries	Non-NPE (Obs. 101,767)		NPE (Obs. 18,010)		Combined (Obs. 119,777)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
0	0.540	0.498	0.335	0.472	0.509	0.500	51.216 ***
1 to 50	0.251	0.434	0.191	0.393	0.242	0.429	17.499 ***
51 to 100	0.032	0.175	0.228	0.420	0.061	0.240	-110 ***
100+	0.177	0.382	0.245	0.430	0.187	0.390	-21.767 ***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A3. Number of subsidiaries (patent level)

Transaction level

Variables	Non-NPE (Obs. 22,739) Mean	Non-NPE Std. dev.	NPE (Obs. 2,045) Mean	NPE Std. dev.	Combined (Obs. 24,784) Mean	Combined Std. dev.	t-value
0	0.696	0.460	0.585	0.493	0.687	0.464	10.425***
1 to 50	0.214	0.410	0.206	0.404	0.213	0.409	0.817
51 to 100	0.015	0.120	0.065	0.246	0.019	0.136	-15.951***
100+	0.075	0.264	0.145	0.352	0.081	0.273	-11.013***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A4. Number of subsidiaries (transaction level)

Types of entity (sellers' profile)

Patent level

Types of entity	Non-NPE (Obs. 101,767) Mean	Non-NPE Std. dev.	NPE (Obs. 18,010) Mean	NPE Std. dev.	Combined (Obs. 119,777) Mean	Combined Std. dev.	t-value
Bank and Financial Company	0.016	0.126	0.039	0.193	0.020	0.139	-20.011 ***
Corporate	0.971	0.167	0.948	0.222	0.968	0.177	16.104 ***
Research institute and others	0.013	0.112	0.013	0.114	0.013	0.112	-0.671 ***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A5. Types of entity of the company (patent level)

Transaction level

Types of entity	Non-NPE (Obs. 22,739) Mean	Non-NPE Std. dev.	NPE (Obs. 2,045) Mean	NPE Std. dev.	Combined (Obs. 24,784) Mean	Combined Std. dev.	t-value
Bank and Financial Company	0.018	0.134	0.033	0.179	0.019	0.138	-4.702***
Corporate	0.958	0.200	0.939	0.239	0.957	0.203	4.035***
Research institute and others	0.023	0.151	0.027	0.163	0.024	0.152	-1.121
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A6. Types of entity of the company (transaction level)

Crosstabs for NBER and category of the company (patent level)

NBER Category	Non-NPE					NPE				
	Small	Medium	Large	V Large	Total	Small	Medium	Large	V large	Total
Chemical	5,204	1,849	1,179	3,080	11,312	75	11	15	387	488
	46	16	10	27.23	100	15.37	2.25	3.07	79.3	100
	11.75	13.45	12.94	8.89	11.12	1.83	0.54	1.72	3.52	2.71
Comp & Comm	**11,920**	**3,327**	**1,840**	**14,089**	**31,176**	**2,609**	**1,398**	**506**	**6,511**	**11,024**
	38	**11**	**6**	**45.19**	**100**	**23.67**	**12.68**	**4.59**	**59.06**	**100**
	26.92	**24.21**	**20.2**	**40.68**	**30.63**	**63.51**	**69**	**57.96**	**59**	**61**
Drugs & Medical	5,801	2,180	1,302	2,370	11,653	406	8	0	17	431
	50	19	11	20.34	100	94.2	1.86	0	3.94	100
	13.1	15.86	14.29	6.84	11.45	9.88	0.39	0	0.15	2.39
Ele & Elec	**6,891**	**2,248**	**1,387**	**7,344**	**17,870**	**593**	**510**	**237**	**3,172**	**4,512**
	39	**13**	**8**	**41.1**	**100**	**13.14**	**11.3**	**5.25**	**70.3**	**100**
	15.56	**16.36**	**15.23**	**21.21**	**17.56**	**14.44**	**25.15**	**27.15**	**29**	**25**
Mechanical	6,547	1,866	1,694	4,950	15,057	235	73	92	729	1,129
	43.48	12.39	11.25	32.88	100	20.81	6.47	8.15	64.57	100
	14.78	13.58	18.6	14.29	14.8	5.72	3.6	10.54	6.63	6
Others	7,920	2,274	1,707	2,798	14,699	190	28	23	185	426
	53.88	15.47	11.61	19.04	100	44.6	6.57	5.4	43.43	100
	17.88	16.55	18.74	8.08	14.44	4.63	1.38	2.63	1.68	2.37
Total	44,283	13,744	9,109	34,631	**101,767**	4,108	2,028	873	11,001	**18,010**
	43.51	13.51	8.95	34.03	100	22.81	11.26	4.85	61.08	100
	100	100	100	100	100	100	100	100	100	100

Table A7. Crosstabs for NBER and category of the company (patent level)

Crosstabs for NBER and category of the company (transaction level)

NBER Category	Non-NPE					NPE				
	Small	Medium	Large	V Large	Total	Small	Medium	Large	V Large	Total
Chemical	1,415	462	301	543	2,721	7	2	1	12	22
	52	16.98	11.06	19.96	100	31.82	9.09	4.55	54.55	100
	11.45	11.92	13.33	12.78	11.97	0.78	0.63	0.57	1.84	1.08
Comp & Comm	**2,660**	**873**	**442**	**1,390**	**5,365**	**693**	**203**	**107**	**499**	**1,502**
	49.58	**16.27**	**8.24**	**25.91**	**100**	**46.14**	**13.52**	**7.12**	**33.22**	**100**
	21.52	**22.53**	**19.57**	**32.72**	**23.59**	**77.17**	**63.64**	**60.8**	**76.53**	**73.45**
Drugs & Medical	1,957	595	455	711	3,718	17	2	0	2	21
	52.64	16	12.24	19.12	100	80.95	9.52	0	9.52	100
	15.84	15.35	20.15	16.74	16.35	1.89	0.63	0	0.31	1.03
Ele & Elec	**1,643**	**568**	**290**	**631**	**3,132**	**102**	**92**	**31**	**93**	**318**
	52.46	**18.14**	**9.26**	**20.15**	**100**	**32.08**	**28.93**	**9.75**	**29.25**	**100**
	13.3	**14.66**	**12.84**	**14.85**	**13.77**	**11.36**	**28.84**	**17.61**	**14.26**	**15.55**
Mechanical	1,842	582	294	482	3,200	47	12	35	30	124
	57.56	18.19	9.19	15.06	100	37.9	9.68	28.23	24.19	100
	14.91	15.02	13.02	11.35	14.07	5.23	3.76	19.89	4.6	6.06
Others	2,841	795	476	491	4,603	32	8	2	16	58
	61.72	17.27	10.34	10.67	100	55.17	13.79	3.45	27.59	100
	22.99	20.52	21.08	11.56	20.24	3.56	2.51	1.14	2.45	2.84
Total	12,358	3,875	2,258	4,248	**22,739**	898	319	176	652	**2,045**
	54.35	17.04	9.93	18.68	100	43.91	15.6	8.61	31.88	100
	100	100	100	100	100	100	100	100	100	100

Table A8. Crosstabs for NBER and category of the company (transaction level)

Patent quality descriptive statistics at the patent level (absolute value)

Variables	Non-NPE (Obs. 101,767)		NPE (Obs. 18,010)		Combined (Obs. 119,777)		t-value
	Mean	Std. Dev.	Mean	Std. dev.	Mean	Std. dev	
Patent scope	1.880	1.221	1.839	1.128	1.873	1.207	4.158***
Family size	3.877	4.381	3.283	3.146	3.787	4.224	17.411***
Grant lag	977.249	519.592	1045.285	601.757	987.479	533.309	-15.797***
Backward citations	21.029	25.718	21.383	28.044	21.083	26.081	-1.676
Non-patent literature	4.870	13.960	4.021	11.316	4.743	13.599	7.724***
Claims	19.500	15.830	20.435	16.506	19.640	15.937	-7.257***
Forward citations	14.909	41.324	20.646	49.977	15.771	42.786	-16.605***
Renewal	11.711	3.012	12.380	2.783	11.812	2.988	-27.764***
Patent age	6.841	4.728	7.511	4.656	6.942	4.724	-17.566***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A9. Descriptive statistics of patent characteristics at the patent level (absolute value)

Patent quality descriptive statistics at the transaction level (absolute value)

Variables	Non-NPE (Obs. 22,739)		NPE (Obs. 2,045)		Combined (Obs. 24,784)		t-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Patent scope	1.915	1.164	1.833	0.944	1.908	1.148	3.088***
Family size	4.001	4.544	3.333	3.091	3.946	4.445	6.521***
Grant lag	1009.248	506.549	1137.547	498.850	1019.834	507.138	-10.984***
Backward citations	22.493	25.575	19.835	24.477	22.274	25.496	4.518***
Non-patent literature	6.217	15.877	4.614	11.040	6.085	15.541	4.47***
Claims	20.159	15.467	21.534	14.486	20.273	15.392	-3.869***
Forward citations	17.243	63.431	25.954	47.856	17.962	62.339	-6.056***
Renewal	11.258	3.087	12.443	2.594	11.356	3.067	-16.83***
Patent age	5.931	4.358	6.602	4.267	5.986	4.354	-6.681***
A ***, **, or * represents (two-sided) statistical significance at the 1%, 5%, and 10% levels, respectively.							

Table A10. Descriptive statistics of patent characteristics at the transaction level (absolute value)

Regression at the patent level (absolute value)

(NPE=1) **VARIABLES**	(Model 1) Coefficient	(Model 2) Coefficient	(Model 3) Coefficient	(Model 4) Coefficient	(Model 5) Coefficient	(Model 6) Coefficient	(Model 7) Coefficient	(Model 8) Coefficient	(Model 9) Marginal effect
Small company	-0.958***			-0.464***	-0.513***	-0.515***		-0.539***	-0.049***
	(0.019)			(0.029)	(0.029)	(0.030)		(0.030)	(0.003)
Large company		-0.657***		-0.432***	-0.447***	-0.347***		-0.379***	-0.034***
		(0.036)		(0.043)	(0.043)	(0.043)		(0.044)	(0.004)
V large company			1.113***	0.767***	0.733***	0.444***		0.457***	0.042***
			(0.017)	(0.026)	(0.026)	(0.027)		(0.028)	(0.003)
Origin US					-0.554***	-0.503***		-0.571***	-0.052***
					(0.018)	(0.019)		(0.020)	(0.002)
Chemical						0.304***		0.300***	0.027***
						(0.067)		(0.068)	(0.006)
Comp & Comm						2.255***		2.338***	0.213***
						(0.051)		(0.052)	(0.004)
Drugs & Medical						0.199***		0.214***	0.019***
						(0.071)		(0.074)	(0.007)
Ele & Elec						1.923***		1.995***	0.182***
						(0.052)		(0.052)	(0.004)
Mechanical						0.807***		0.831***	0.076***
						(0.058)		(0.058)	(0.005)
Patent scope							0.009	0.051***	0.005***
							(0.007)	(0.008)	(0.001)
Family size							-0.050***	-0.011***	-0.001***
							(0.002)	(0.003)	(0.000)
Grant lag							0.000***	-0.000***	-0.000***
							(0.000)	(0.000)	(0.000)
NPL citations							-0.008***	-0.007***	-0.001***
							(0.001)	(0.001)	(0.000)
Backward citations							0.004***	0.010***	0.001***
							(0.000)	(0.000)	(0.000)
Claims							0.003***	0.002***	0.000***
							(0.000)	(0.001)	(0.000)
Forward citations							0.003***	0.001***	0.000***
							(0.000)	(0.000)	(0.000)
Renewal							0.060***	0.060***	0.005***
							(0.003)	(0.004)	(0.000)
Patent age							0.029***	0.036***	0.003***
							(0.002)	(0.002)	(0.000)
Constant	-1.419***	-1.688***	-2.260***	-1.914***	-1.467***	-2.991***	-2.887***	-4.164***	
	(0.009)	(0.008)	(0.013)	(0.024)	(0.028)	(0.055)	(0.041)	(0.070)	
Observations	119,777	119,777	119,777	119,777	119,777	119,777	119,777	119,777	119,777

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11. Logistic regression at the patent level (absolute value)

Regression at the transaction level (absolute value)

(NPE=1) VARIABLES	(Model 1) Coefficient	(Model 2) Coefficient	(Model 3) Coefficient	(Model 4) Coefficient	(Model 5) Coefficient	(Model 6) Coefficient	(Model 7) Coefficient	(Model 8) Coefficient	(Model 9) Marginal effect
Small company	-0.419***			-0.125*	-0.173**	-0.143**		-0.183**	-0.006**
	(0.047)			(0.068)	(0.068)	(0.072)		(0.073)	(0.002)
Large company		-0.158*		-0.055	-0.076	0.050		-0.027	-0.001
		(0.082)		(0.098)	(0.098)	(0.106)		(0.107)	(0.003)
V large company			0.712***	0.623***	0.557***	0.295***		0.165**	0.005**
			(0.050)	(0.072)	(0.072)	(0.076)		(0.079)	(0.003)
Origin US					-0.576***	-0.586***		-0.586***	-0.019***
					(0.048)	(0.052)		(0.054)	(0.002)
Chemical						-0.500**		-0.476*	-0.016*
						(0.251)		(0.254)	(0.008)
Comp & Comm						3.031***		3.109***	0.101***
						(0.136)		(0.140)	(0.005)
Drugs & Medical						-0.852***		-0.799***	-0.026***
						(0.257)		(0.265)	(0.008)
Ele & Elec						2.037***		2.135***	0.069***
						(0.145)		(0.146)	(0.005)
Mechanical						1.107***		1.126***	0.037***
						(0.161)		(0.161)	(0.005)
Patent scope							-0.012	0.031	0.001
							(0.021)	(0.023)	(0.001)
Family size							-0.048***	-0.004	-0.000
							(0.007)	(0.008)	(0.000)
Grant lag							0.000***	-0.000**	-0.000**
							(0.000)	(0.000)	(0.000)
NPL citations							-0.010***	-0.007***	-0.000**
							(0.002)	(0.003)	(0.000)
Backward citations							-0.003**	0.003**	0.000**
							(0.001)	(0.001)	(0.000)
Claims							0.004***	-0.001	-0.000
							(0.001)	(0.002)	(0.000)
Forward citations							0.003***	0.000	0.000
							(0.000)	(0.000)	(0.000)
Renewal							0.132***	0.134***	0.004***
							(0.010)	(0.011)	(0.000)
Patent age							0.013**	0.015**	0.000**
							(0.007)	(0.007)	(0.000)
Constant	-2.203***	-2.394***	-2.586***	-2.497***	-2.048***	-3.916***	-4.371***	-5.522***	
	(0.031)	(0.024)	(0.028)	(0.058)	(0.068)	(0.148)	(0.125)	(0.192)	
Observations	24,784	24,784	24,784	24,784	24,784	24,784	24,784	24,784	24,784

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A12. Logistic regression at the transaction level (absolute value)

References

Agrawal, A., Bhattacharya, S., & Hasija, S. (2016). Cost-Reducing Innovation and the Role of Patent Intermediaries in Increasing Market Efficiency. *Production and Operations Management*, *25*(2), 173-191.

Allison, J. R., Lemley, M. A., & Walker, J. (2010). Patent quality and settlement among repeat patent litigants. *Geo. LJ, 99*, 677.

Antonipillai, J., & Lee, M. (2016, September). Intellectual property and the US economy: 2016 update. *Washington, DC, Economics & Statistics Administration and US Patent and Trademark Office*. Retrieved from https://www.uspto.gov/sites/default/files/documents/IPandtheUSEconomySept2016.pdf

Arora, A., & Fosfuri, A. (2003). Licensing the market for technology. *Journal of Economic Behavior and Organization, 52*(2), 277-295. doi:10.1016/S0167-2681(03)00002-7

Arora, A., Fosfuri, A., & Gambardella, A. (2001). Markets for technology and their implications for corporate strategy. *Industrial and Corporate Change, 10*(2), 419-451.

Arora, A., Fosfuri, A., & Gambardella, A. (2004). *Markets for technology: The economics of innovation and corporate strategy*: MIT press.

Arora, A., Fosfuri, A., & Rønde, T. (2013). Managing licensing in a market for technology. *Management Science, 59*(5), 1092-1106.

Arora, A., & Gambardella, A. (2010). Ideas for rent: an overview of markets for technology. *Industrial and Corporate Change, 19*(3), 775-803.

Bessant, J. (2003). Challenges in innovation management. In *The international handbook on innovation* (pp. 761-774): Elsevier.

Bessen, J. (2014). The evidence is in: Patent trolls do hurt innovation. *Harvard business review*, 1-4.

Bessen, J., Ford, J., & Meurer, M. J. (2011). The private and social costs of patent trolls. *Regulation, 34*, 26.

Bessen, J., & Meurer, M. J. (2008). *Patent failure: How judges, bureaucrats, and lawyers put innovators at risk*: Princeton University Press.

Bessen, J., & Meurer, M. J. (2013). The direct costs from NPE disputes. *Cornell L. Rev., 99*, 387.

Blind, K., Edler, J., Frietsch, R., & Schmoch, U. (2006). Motives to patent: Empirical evidence from Germany. *Research Policy, 35*(5), 655-672.

Blumenthal, R. G. (2013, January 12). Patently Obvious? Score One for the Big Guys. *Barron's*. Retrieved from https://www.barrons.com/articles/SB50001424052748703792204578219670953944296

Bollen, L., Vergauwen, P., & Schnieders, S. (2005). Linking intellectual capital and intellectual property to company performance. *Management Decision, 43*(9), 1161-1185.

Branstetter, L., & Ogura, Y. (2005). *Is academic science driving a surge in industrial innovation? Evidence from patent citations*. Retrieved from http://www.nber.org/papers/w11561

Bryer, L. G., Lebson, S. J., & Asbell, M. D. (2011). *Intellectual property strategies for the 21st century corporation: a shift in strategic and financial management*: John Wiley & Sons.

Burkhart, F. S. (2017, November 6). Infringers handed new tools to attack patents. Retrieved from https://www.ft.com/content/d35623e8-bfda-11e7-b8a3-38a6e068f464

Bvdinfo. (2018). Orbis - comparable company data | Bureau van Dijk.
Callaert, J., Van Looy, B., Verbeek, A., Debackere, K., & Thijs, B. (2006). Traces of prior art: An analysis of non-patent references found in patent documents. *Scientometrics, 69*(1), 3-20.
Cassiman, B., Veugelers, R., & Zuniga, P. (2008). In search of performance effects of (in) direct industry science links. *Industrial and Corporate Change, 17*(4), 611-646.
Chen, Y.-S., & Chang, K.-C. (2010). The relationship between a firm's patent quality and its market value—the case of US pharmaceutical industry. *Technological Forecasting and Social Change, 77*(1), 20-33.
Cohen, L., Gurun, U. G., & Kominers, S. D. (2016). The growing problem of patent trolling. *Science, 352*(6285), 521.
Cohen, W. M., Goto, A., Nagata, A., Nelson, R. R., & Walsh, J. P. (2002). R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research Policy, 31*(8), 1349-1367.
Cotropia, C. A., Kesan, J. P., & Schwartz, D. L. (2014). Unpacking patent assertion entities (PAEs). *Minn. L. Rev., 99*, 649.
De Marco, A., Scellato, G., Ughetto, E., & Caviggioli, F. (2017). Global markets for technology: Evidence from patent transactions. *Research Policy, 46*(9), 1644-1654.
Duguet, E., & MacGarvie, M. (2005). How well do patent citations measure flows of technology? Evidence from French innovation surveys. *Economics of Innovation and New Technology, 14*(5), 375-393.
Edison, H., Bin Ali, N., & Torkar, R. (2013). Towards innovation measurement in the software industry. *Journal of Systems and Software, 86*(5), 1390-1407.
Falvey, R., Foster, N., & Greenaway, D. (2006). Intellectual property rights and economic growth. *Review of Development Economics, 10*(4), 700-719.
Farrell, J., & Shapiro, C. (2008). How Strong Are Weak Patents? *The American Economic Review, 98*(4), 1347-1369.
Feng, J., & Jaravel, X. (2016). Who feeds the trolls? Patent trolls and the patent examination process.
Figueroa, N., & Serrano, C. J. (2013). *Patent trading flows of small and large firms*. Retrieved from http://www.nber.org/papers/w18982.pdf
Fischer, T., & Henkel, J. (2012). Patent trolls on markets for technology - An empirical analysis of NPEs' patent acquisitions. *Research Policy, 41*(9), 1519-1533.
Fusco, S. (2013). Markets and Patent Enforcement: A Comparative Investigation of Non-Practicing Entities in the United States and Europe. *Mich. Telecomm. & Tech. L. Rev., 20*, 439.
Galasso, A., & Schankerman, M. (2015). Patents and Cumulative Innovation: Causal Evidence from the Courts. *The Quarterly Journal of Economics, 130*(1), 317-369.
Galasso, A., Schankerman, M., & Serrano, C. J. (2013). Trading and enforcing patent rights. *The RAND Journal of Economics, 44*(2), 275-312.
Geradin, D., Layne-farrar, A., & Padilla, A. J. (2012). Elves or trolls? The role of nonpracticing patent owners in the innovation economy. *Industrial and Corporate Change, 21*(1), 73-94. doi:10.1093/icc/dtr031
Gilardoni, E. (2007). Basic approaches to patent strategy. *International Journal of Innovation Management, 11*(03), 417-440.
Gilbert, R., & Shapiro, C. (1990). Optimal patent length and breadth. *The RAND Journal of Economics*, 106-112.
Gogoris, A. C., & Clarke, P. J. (2001). Patent due diligence in biotechnology transactions. In: Nature Publishing Group.
Golden, J. M. (2006). Patent trolls and patent remedies. *Tex. L. Rev., 85*, 2111.

Gripsrud, G., Olsson, U., & Silkoset, R. (2010). Metode og Dataanalyse. Besluttningsstøtte for bedrifter ved bruk av JMP. 2 utg. Høyskoleforlaget. In: Norwegian Academic Press.

Hagiu, A., & Yoffie, D. (2011). Intermediaries for the IP market. *Working Paper, 12*(023).

Hagiu, A., & Yoffie, D. B. (2013). The new patent intermediaries: platforms, defensive aggregators, and super-aggregators. *Journal of Economic Perspectives, 27*(1), 45-66.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *The RAND Journal of Economics, 36*(1), 16-38.

Hall, B. H., Thoma, G., & Torrisi, S. (2007). *The market value of patents and R&D: Evidence from European firms.* Paper presented at the Academy of Management Proceedings.

Harhoff, D., Scherer, F. M., & Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy, 32*(8), 1343-1363.

Haskel, J., & Westlake, S. (2017). *Capitalism Without Capital: The Rise of the Intangible Economy*: Princeton University Press.

Haus, A., & Juranek, S. (2017). Non-practicing entities: Enforcement specialists? *International Review of Law and Economics*.

Henkel, J., & Reitzig, M. (2008). Patent sharks. *Harvard business review*, 129-133.

Henkel, J., & Reitzig, M. G. (2010). Patent Trolls, the sustainability of 'locking-in-to-extort'strategies, and implications for innovating firms.

Hong, S. (2013). Claiming what counts in business: drafting patent claims with a clear business purpose. *SMEs Division, WIPO*.

Hufford, A. (2018, May 15). Moody's Buys Dutch Data Provider Bureau van Dijk. Retrieved from https://www.wsj.com/articles/moodys-buys-dutch-data-provider-bureau-van-dijk-1494850109

Kani, M., & Motohashi, K. (2012). Understanding the technology market for patents: New insights from a licensing survey of Japanese firms. *Research Policy, 41*(1), 226-235.

Kastrenakes, J. (2017, November 6). Apple has finally won $120 million from Samsung in slide-to-unlock patent battle. Retrieved from https://www.theverge.com/2017/11/6/16614038/apple-samsung-slide-to-unlock-supreme-court-120-million

Kiebzak, S., Rafert, G., & Tucker, C. E. (2016). The effect of patent litigation and patent assertion entities on entrepreneurial activity. *Research Policy, 45*(1), 218-231.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1997). Legal determinants of external finance. *Journal of finance*, 1131-1150.

Lanjouw, J. O., Pakes, A., & Putnam, J. (1998). How to count patents and value intellectual property: The uses of patent renewal and application data. *Journal of Industrial Economics, 46*(4), 405-432.

Lanjouw, J. O., & Schankerman, M. (1997). Stylized facts of patent litigation: Value, scope and ownership. *National Bureau of Economic Research Working Paper Series, No. 6297*.

Lanjouw, J. O., & Schankerman, M. (1999). The quality of ideas: measuring innovation with multiple indicators.

Lanjouw, J. O., & Schankerman, M. (2001). Characteristics of Patent Litigation: A Window on Competition. *The RAND Journal of Economics, 32*(1), 129-151.

Lanjouw, J. O., & Schankerman, M. (2004). Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. *The Economic Journal, 114*(495), 441-465.

LeCompte, M. D., & Goetz, J. P. (1982). Problems of reliability and validity in ethnographic research. *Review of educational research, 52*(1), 31-60.

Lemley, M. A., & Shapiro, C. (2006). Patent holdup and royalty stacking. *Tex. L. Rev., 85*, 1991.

Lerner, J. (1994). The importance of patent scope: an empirical analysis. *The RAND Journal of Economics*, 319-333.

Lerner, J. (2006). Trolls on State Street?: The litigation of financial patents, 1976-2005. *Boston, MA: Harvard Business School, manuscript*.

Lerner, J. (2009). The Empirical Impact of Intellectual Property Rights on Innovation: Puzzles and Clues. *The American Economic Review, 99*(2), 343-348.

Macdonald, S. (2004). When means become ends: considering the impact of patent strategy on innovation. *Information Economics and Policy, 16*(1), 135-158.

Magliocca, G. N. (2006). Blackberries and barnyards: Patent trolls and the perils of innovation. *Notre Dame L. Rev., 82*, 1809.

Marco, A. C., Myers, A. F., Graham, S. J., D'Agostino, P. A., & Apple, K. (2015). The USPTO patent assignment dataset: Descriptions and analysis.

Marco, A. C., Sarnoff, J. D., & deGrazia, C. (2016). *Patent Claims and Patent Scope (October 2016)*. Retrieved from https://ssrn.com/abstract=2844964

Maskus, K. E. (2000). Intellectual property rights and economic development. *Case W. Res. J. Int'l L., 32*, 471.

Matutes, C., Regibeau, P., & Rockett, K. (1996). Optimal patent design and the diffusion of innovations. *The RAND Journal of Economics*, 60-83.

McDonough III, J. F. (2006). The myth of the patent troll: an alternative view of the function of patent dealers in an idea economy. *Emory LJ, 56*, 189.

Merges, R. P., & Nelson, R. R. (1990). On the Complex Economics of Patent Scope. *Columbia Law Review, 90*(4), 839-916.

Millien, R., & Laurie, R. (2009). A survey of established and evolving IP monetization models, 984 PLI. *Pat, 1033*, 1038.

Monk, A. H. B. (2009). The emerging market for intellectual property: drivers, restrainers, and implications. *Journal of Economic Geography, 9*(4), 469-491.

Moser, P. (2005). How do patent laws influence innovation? Evidence from nineteenth-century world's fairs. *American Economic Review, 95*(4), 1214-1236.

Moser, P. (2013). Patents and Innovation: Evidence from Economic History. *Journal of Economic Perspectives, 27*(1), 23-44.

Moyo, D. (2017, December 13). America’s economic unique selling points are at risk. Retrieved from https://www.ft.com/content/d8f76c56-d8eb-11e7-a039-c64b1c09b482

npedata. (2014). NPE Data | Non-Practicing Entity Data. Retrieved from http://npedata.com/

O’Halloran, S. (2005). Lecture 10: logistical regression II—multinomial data. *Columbia University, New York*, 1-73.

OECD. (2005). Oslo Manual. *Guidelines for Collecting and Interpreting Innovation Data*.

OECD. (2009). *OECD Patent Statistics Manual*: OECD Publishing.

Orbis. (2018, April). Company size categories. Retrieved from https://help.bvdinfo.com/mergedProjects/68_EN/Data/Coverage/CompSizeCat1.htm

Osenga, K. (2014). Formerly manufacturing entities: Piercing the patent troll rhetoric. *Conn. L. Rev., 47*, 435.

Paik, Y., & Zhu, F. (2016). The impact of patent wars on firm strategy: evidence from the global smartphone industry. *Organization Science, 27*(6), 1397-1416.

Pakes, A. (1986). Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. *Econometrica, 54*(4), 755-784.

PatentsView. (2017, December 26). PatentsView Data Download. Retrieved from http://www.patentsview.org/download/

patentsview.org. (2018). PatentsView Data Download. Retrieved from http://www.patentsview.org/download/

Pohlmann, T., & Opitz, M. (2013). Typology of the patent troll business. *R and D Management, 43*(2), 103-120. doi:10.1111/radm.12003

pwc.com. (2017). 2017 Patent Litigation Study. Retrieved from https://www.pwc.com/us/en/services/forensics/library/patent-litigation-study.html

Rassenfosse, G. d., Palangkaraya, A., & Webster, E. (2016). Why do patents facilitate trade in technology? Testing the disclosure and appropriation effects. *Research Policy, 45*(7), 1326-1336.

Reitzig, M. (2003). What determines patent value?: Insights from the semiconductor industry. *Research Policy, 32*(1), 13-26.

Reitzig, M., Henkel, J., & Heath, C. (2007). On sharks, trolls, and their patent prey-Unrealistic damage awards and firms' strategies of "being infringed". *Research Policy, 36*(1), 134-154. doi:10.1016/j.respol.2006.10.003

Reitzig, M., Henkel, J., & Schneider, F. (2010). Collateral damage for R&D manufacturers: how patent sharks operate in markets for technology. *Industrial and Corporate Change, 19*(3), 947-967.

Robbins, C. A. (2009). Measuring payments for the supply and use of intellectual property. In *International trade in services and intangibles in the era of globalization* (pp. 139-171): University of Chicago Press.

Ronspies, J. A. (2004). Does David Need a New Sling-Small Entities Face a Costly Barrier to Patent Protection. *J. Marshall Rev. Intell. Prop. L., 4*, i.

RPX Corporation. (2014). 2013 NPE Litigation Report. Retrieved from https://www.rpxcorp.com/wp-content/uploads/2014/01/RPX-2013-NPE-Litigation-Report.pdf

Sakakibara, M., & Branstetter, L. (1999). Do stronger patents induce more innovation? Evidence from the 1988 Japanese patent law reforms. *National Bureau of Economic Research Working Paper Series, No.7066*.

Sandburg, B. (2001, July 30). You may not have a choice. Trolling for Dollars. *the recorder*.

Saunders, M., Lewis, P., & Thornhill, A. (2012). *Research methods for business students* (6th ed. ed.). Harlow, England ; New York: Pearson.

Scotchmer, S. (2004). *Innovation and incentives*: MIT press.

Serrano, C. (2011). Estimating the gains from trade in the market for patent rights.

Serrano, C. J. (2006). The Market for Intellectual Property: Evidence from the Transfer of Patents. *Working Paper, University of Toronto*, 1-47.

Serrano, C. J. (2010). The dynamics of the transfer and renewal of patents. *RAND Journal of Economics, 41*(4), 686-708.

Shrestha, S. K. (2010). Trolls or market-makers? An empirical analysis of nonpracticing entities. *Columbia Law Review, 110*(1), 114-160.

Squicciarini, M., Dernis, H., & Criscuolo, C. (2013). Measuring patent quality: Indicators of Technological and Economic Value.

Stanford Law School. (2017). Stanford NPE Litigation Dataset | Stanford Law School. Retrieved from https://law.stanford.edu/projects/stanford-npe-litigation-dataset/

The Economist. (2009, September 10). Trolls demanding tolls. Retrieved from https://www.economist.com/node/14416641

Thurow, L. C. (1997). Needed: a new system of intellectual property rights. *Harvard business review, 75*, 94-107.

Tong, X., & Frame, J. D. (1994). Measuring national technological performance with patent claims data. *Research Policy, 23*(2), 133-141.

Torres-Reyna, O. (2007). Getting Started in Data Analysis using Stata. In: Princeton: Princeton University.

Trajtenberg, M. (1990). A penny for your quotes: patent citations and the value of innovations. *The RAND Journal of Economics*, 172-187.

Tucker, C. E. (2014). Patent trolls and technology diffusion: The case of medical imaging.

UC_Rstats. (2018). Logistic Regression Â· UC Business Analytics R Programming Guide. Retrieved from http://uc-r.github.io/logistic_regression

uspto.gov. (2018). Patent Assignment Dataset. Retrieved from https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-assignment-dataset

Veer, T., & Jell, F. (2012). Contributing to markets for technology? A comparison of patent filing motives of individual inventors, small companies and universities. *Technovation, 32*(9-10), 513-522. doi:10.1016/j.technovation.2012.03.002

Wagner, R. P. (2009). Understanding patent-quality mechanisms. *University of Pennsylvania law review*, *157*(6), 2135-2173.

Wang, A. W. (2010). Rise of patent intermediaries. *Berkeley Technology Law Journal, 25*(159), 159-200. doi:10.15779/Z386D8Z

Watkins, W. J. (2014). *Patent trolls: Predatory litigation and the smothering of innovation*: Independent Institute.

Wilson, J. (2010). *Essentials of business research : a guide to doing your research project*. London: SAGE.

WIPO. (2016). Understanding Industrial Property. Retrieved from http://www.wipo.int/publications/en/details.jsp

WIPO. (2018). WIPO IP Facts and Figures 2017. Retrieved from http://www.wipo.int/publications/en/details.jsp

wipo.int. (2018). What is Intellectual Property? Retrieved from http://www.wipo.int/about-ip/en/index.html

Womack, B., & Tracer, Z. (2011, August 15). Google Agrees to Acquire Motorola Mobility for $12.5 Billion. Retrieved from https://www.bloomberg.com/news/articles/2011-08-15/google-agrees-to-acquisition-of-motorola-mobility-for-about-12-5-billion

Yeh, B. T. (2013). An overview of the "patent trolls" debate. In: Congressional Research Service.

Zikmund, W., Babin, B., Carr, J., & Griffin, M. (2012). *Business research methods*: Cengage Learning.