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Essays on Patent Value

PhD Thesis

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Abstract

This thesis consists of six chapters which focus on patents and what determines their value. In the first chapter, I present an overview of the thesis. The second chapter provides background information about patents. In the third chapter, I investigate the effect of patent attorney capability on the economic and technological value of patents. I find that attorneys' substantive expertise is positively correlated with both economic and technological value of patents. I further find that substantive expertise of patent attorneys becomes more important for the economic value of patents after the opening of four new regional patent offices. Moreover, the economic value of a firm's new patents increases (decreases) after the company switches to an attorney with a higher (lower) substantive expertise. In the fourth chapter, I investigate the effect of new green patent announcements on shareholder wealth in the short run. I find that green patent announcements do not have a positive effect on shareholder wealth. This result holds regardless of the level of institutional investor ownership or attention, climate risk exposure, or climate change concerns. Moreover, I find no evidence that the number of green patents obtained by a company increases its environmental score, institutional ownership, or Tobin's Q. In the fifth chapter, I study the long-run performance of firms following their green patent announcements. I find that green patenting firms earn negative alphas after obtaining new green patents. This result holds regardless of the portfolio holding period or portfolio type. The underperformance is larger during 1976 to 2005 than during 2006 to 2009. Lastly, firms in the bottom quintile in terms of R&D intensity or R&D efficiency show stronger underperformance than other firms. The final chapter concludes the thesis and offers suggestions for future research.

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List of abbreviations

AIPA	American Inventors Protection Act
AR	Abnormal Returns
BHAR	Buy and Hold Abnormal Returns
CAR	Cumulative Abnormal Returns
CCMT	Climate Change Mitigation Technologies
CMA	Conservative Minus Aggressive
CPC	Cooperative Patent Classification
CRSP	Centre for Research in Security Prices
EPO	European Patent Office
ES	Environmental and Social
ESG	Environmental, Social, and Governance
EUIPO	European Union Intellectual Property Office
FE	Fixed Effects
HML	High Minus Low
IEA	International Energy Agency
IO	Institutional Investor Ownership
IPC	International Patent Classification
IPCC	Intergovernmental Panel on Climate Change
MCCC	Media Climate Change Concerns
MOM	Momentum
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-operation and Development

OLS	Ordinary Least Squares
PAIR	Patent Application Information Retrieval System
PatEx	Patent Examination Research Dataset
R&D	Research and Development
RMW	Robust Minus Weak
ROA	Return on Assets
SIC	Standard Industrial Classification
SIF	Social Investment Forum
SMB	Small Minus Big
TRI	Toxics Release Inventory
UMC	Unexpected Media Climate Change Concerns
US	United States
USPTO	United States Patent and Trademark Office
VC	Venture Capital

1. Introduction

The goal of the United States (US) patent system is to encourage innovation, which is considered critical for economic growth (Kim et al., 2012) and for transitioning the economy to net zero carbon emissions (Aghion et al., 2022). Under the patent system, inventors can receive an exclusive legal right to practice a novel invention for limited time in return for disclosing the invention to the public. Without patents, making the details of the new technologies public would be undesirable for an inventor due to the non-rivalry in the consumption of knowledge (Langinier and Moschini, 2002).

Patents give their owners the right to try to exclude others from commercialising an invention for approximately 20 years from the filing date of the patent application. The United States Patent and Trademark Office (USPTO) issued 391,103 new patents in 2019 alone, which is more than double the 191,927 patents it granted in 2009 (USPTO, 2021a). Companies obtain patents to protect their intellectual property from appropriation (Blind et al. 2006), increase their bargaining power (Mihm et al., 2015), increase their chances of winning in patent litigation (Bessen and Meurer, 2005), and to communicate the successful results of their R&D efforts (Hsu and Ziedonis, 2008). Patents often benefit firms as they can increase companies' employment growth, sales growth, chances of survival, and access to capital (Farre-Mensa et al., 2020; Hegde et al., 2022). Patents can be very valuable. Kogan et al. (2017) estimate that the median economic value of a patent owned by a US public firm is \$3m. Moreover, the economic value of patents can vary depending on the scientific merit of the underlying technology and the scope and validity of the patent (Trajtenberg, 1990; Lemley and Shapiro, 2005; Bessen, 2008). Patents with a broader scope protect a larger number of competing products and processes (Merges and Nelson, 1990), meanwhile patent

validity refers to the probability of a patent being found invalid in court (Lemley and Shapiro, 2005).

The investment that firms make in innovation is commonly quantified using the R&D expenditures (Rogers, 1998; Bloom et al., 2020). Patents are the most popular measure of the output of this innovative input (Moser, 2013; Lerner and Seru, 2022) for multiple reasons. First, patent data dates back to the second half of the 20th century and it is widely available. Since all granted patents are recorded, the data includes companies from all industries. Second, patent data is rich. It includes detailed information on the inventions, the citations patents make to other patents, and on the inventors, among other information (Lerner and Seru, 2022). Third, innovation that has been disclosed in patents had been validated as useful, novel, and not obvious by an expert (the patent examiner) (Bouchoux, 2013). Not all innovations for which patent protection is sought are successful. Carley et al. (2015) estimate that only 56% of patent applications lead to granted patents without the use of continuation procedures (Carley et al. 2015). Therefore, patents represent the successful output of R&D. The advantages listed above make patents arguably a more useful measure of innovation output than the alternatives, such as new product announcements or industry-specific improvements in productivity.¹

It is important to note that patents are not a perfect measure of innovation and not all R&D investment is made with the goal of obtaining patents for two main reasons. First, not all inventions can be patented. Only inventions that fulfil the USPTO's

¹ The main issue with measuring innovation output using new product announcements is the lack of an official screening process. It can be challenging to distinguish genuine corporate innovations from simple marketing by the companies (Hagedoorn and Cloudt, 2003). Moreover, measuring innovation output using industry-specific improvements in productivity makes it impossible to compare innovation across industries (Moser, 2016).

patentability requirements (see section 2.2) are eligible for patent protection (Bouchoux, 2013). Second, a company may decide not to seek patent protection for its invention(s). Firms can choose to keep the details of their discovery as a trade secret (Cohen et al., 2000). For example, the recipe for Coca-Cola has never been patented and remains a commercial secret (Moser, 2012). Therefore, not all results of R&D manifest as patents.

To obtain a US patent on a new technology, an inventor has to write a patent application describing the invention and submit it to the USPTO. Then, the application undergoes a lengthy examination process at the patent office which lasts on average 3 years (Farre-Mensa et al., 2020). The USPTO recommends hiring a patent attorney to represent a patent application during patent examination, because the process requires both legal and scientific expertise (Reitzig, 2004). Patent attorneys often advise inventors on how to increase the commercial value and the patentability of their invention (Yelderman, 2014). Moreover, patent attorneys, conduct prior art searches, prepare patent applications, and negotiate the grant of patents with patent examiners (Gaudry, 2012; Lu et al., 2017). Over 80% of all inventors hire patent attorneys (Bouchoux, 2013). In Chapter 2, I discuss patents and how the patent attorneys' work influences patents in a much greater detail.

Patent attorneys may differ in how capable they are at working with inventors, preparing patent applications, and negotiating with patent examiners. According to the *attorney capability theory* (McGuire, 1995; Miller et al., 2015), more capable attorneys produce better outcomes for their clients. For example, the capability of conventional attorneys increases the chances of success in litigation before the Supreme Court (McGuire, 1995; Szmer et al., 2007). Similarly, the capability of patent attorneys may

have a positive effect on the patents that they work on. The value of a patent is largely dependent upon skilled preparation of the patent application and navigation of the patent examination process (USPTO, 2020). Despite the important role that patent attorneys' play in obtaining patents, the effect of patent attorney capability on patent value been underexplored. This rationale motivates my third chapter.

In Chapter 3, I examine whether the capability of patent attorneys impacts the economic and technological value of patents owned by publicly listed firms in the US. Similar to Kogan et al. (2017), I measure the economic value of patents based on the three-day (0,+2) cumulative abnormal market reaction to patent announcements.² A large (small) market reaction to a patent announcement arguably reflects the shareholders' expectation that the patent will (will not) significantly increase future cashflows of a company. More commercially and/or technologically important patents elicit higher market reactions (Kogan et al., 2017). Using the market valuation of announcements to measure the economic patent value is a common practice in the literature (Boscaljon et al., 2006; Kogan et al., 2017; Chen et al., 2018). I capture the technological value of patents based on the number of patent citations they receive (Hall et al., 2005).³ To investigate attorney capability, I draw on the *attorney capability theory* (McGuire, 1995; Miller et al., 2015). Based on the theory, I expect more capable patent attorneys to obtain more valuable patents for their clients. Moreover, the *attorney capability theory* distinguishes between process experience and substantive expertise of attorneys. I measure process experience of patent attorneys using the

² New patents are announced by the USPTO every Tuesday, which is when the market first learns about the successful patent application. Moreover, the market reacts to new patent announcements during the (0,+2) window as shown by the increasing share turnover during this time (Kogan et al., 2017).

³ Citations that patents receive from other patents are commonly used to proxy for their technological quality because new patents need to cite previous patents if they are building upon their technology (Hirschey and Richardson, 2004; Trajtenberg, 1990).

cumulative number of patent applications filed by an attorney, and I capture substantive expertise using the attorneys' success rate in obtaining patents from the patent office.

First, I explore the relationship between patent attorney capability and the economic and technological value of patents in a multivariate analysis. I find that patent attorney substantive expertise (success rate) is positively related to both the economic and technological value of patents. This suggests that successful attorneys are more capable at pursuing patent applications. I further find that attorneys' process experience (number of applications filed) does not matter for the economic or technological value of patents. This suggests that attorneys do not gain valuable experience by simply submitting more patent applications to the USPTO.

A company may choose to use different patent attorneys depending on the characteristics of technology the firm wants to patent (de Rassenfosse et al., 2023). I conduct two additional tests to address the potential selection issues arising from a plausibly non-random matching between patent attorneys and inventions, and to explore the effect of patent attorney substantive expertise on patent value in more detail. First, I investigate how the opening of new regional offices by the USPTO affected the patent attorneys located in the states in which the new offices opened. These patent attorneys benefit from an easier access to patent examiners with whom they can meet in-person to discuss and negotiate the grant of a patent (Lemley and Sampat, 2010). I find that the new USPTO offices increased the positive impact of substantive expertise of the affected attorneys on the economic value of patents. Moreover, the new offices had no impact on the technological value of patents. This is consistent with the fact that an in-person meeting with a patent examiner can only

occur at a late stage of the patent examination process, when the technological aspects of an invention described in a patent application have already been finalised (Lemley and Sampat, 2010). Second, I study how the changes in a company's patent attorney relate to the economic and technological value of patents. I find that when firms switch to a patent attorney with a higher (lower) substantive expertise, the patents represented by these attorneys experience a higher (lower) stock market reaction at announcement and receive more (fewer) patent citations. Moreover, the size of this effect increases as the gap in substantive expertise (success rate) between the new and the old patent attorney widens. This suggests that the impact of patent attorney substantive expertise on the value of patents is causal.

Overall, the evidence presented in Chapter 3 shows that it is the substantive expertise of patent attorneys that matters, and not simple process experience. Only successful patent attorneys increase the economic and the technological value of patents. In the last part of Chapter 3, I investigate whether successful patent attorneys are recognized for their positive effect on patent value in the annual Legal500 patent attorney firm rankings. I find that there is a negative correlation between a firm's ranking and patent attorney substantive expertise. I further find that there is no statistically significant relation between the top ranked patent attorney firms and the economic and technological value of patents that they have worked on. This suggests that patent attorney rankings are poor predictors of patent value, and that successful patent attorneys are not recognized for their substantive expertise.

In my third chapter, I do not explicitly differentiate between the different types of innovations that can be protected by patents.⁴ However, environmental technologies

⁴ I control for the fact that patents can cover different technologies by including patent technology class fixed effects in alternative model specifications in Chapter 3, and the results remain the same.

can be important to firms and investors, who are concerned about environmental risks (Krueger et al., 2020; Sautner et al., 2022). In my fourth chapter, motivated by the importance of green innovation in addressing climate risks (Nordhaus, 2021; Stern, 2022), I distinguish between patents that cover environmentally friendly technologies (green patents) and patents that do not (grey patents). Green technologies play a crucial part in climate change mitigation and adaptation and in decarbonizing the economy (United Nations, 2021). Green patents, which protect environmental technologies, can be important to investors, who call for more green innovation (McCormick, 2021; US Chamber of Commerce, 2019), and push firms to make more environmentally friendly decisions (Dyck et al., 2019). Environmental innovation can also be valuable to firms because it can lower their exposure to climate risks (Miao and Popp, 2014), and help them capture climate-related opportunities (Sautner et al., 2022). Moreover, the number of green patents is growing rapidly. The annual number of green patents granted in the US increased by 301% from 2009 to 2019, compared with a 97% increase in the annual number of grey patents.

In Chapter 4, I investigate whether investors reward companies for developing new green innovations by studying how the announcements of new green patents obtained by US public firms affect shareholder wealth. I apply the *signalling theory* (Spence, 1973) to corporate green patent announcements. The theory is helpful in describing communication between two or more parties, and it is primarily concerned with how the information asymmetry between the parties can be reduced (Connelly et al., 2011). I argue that green patents can decrease the information asymmetry between a firm and its (potential) investors about the level of a company's environmental commitment (Berrone et al., 2017). Green patents are credible signals of a firm's commitment to

the environment because engaging in green innovation is often risky and expensive (Gaddy et al., 2017). To develop a new green technology, a firm has to redirect its research and development (R&D) efforts from other projects. Moreover, any green innovation has to undergo the patent examination process, which can be both lengthy and costly to the firm (Lemley, 2001; Farre-Mensa et al., 2020). If a company is successful at obtaining a green patent, it is credible proof of an environmental progress (Hascic and Migotto, 2015). Therefore, I expect green patent announcements to increase shareholder wealth.

First, I conduct an event study to measure the market reaction to patent announcements, and I differentiate between announcements that include a green patent (green announcements) and ones that do not (grey announcements). I find that green announcements do not increase shareholder wealth. This result contrasts with the positive market reaction to the grey announcements. I conduct additional sub-sample event study analysis to investigate this in more detail. I expect that green patents may be more valuable to firms operating in polluting industries, because these firms can benefit more from adopting environmental technologies (Carrion-Flores and Innes, 2010). Moreover, green patent announcements may be more valuable during times of increased climate change concerns (Ardia et al., 2022), when the benefits of green innovation become more salient. Also, green patents may be more valued by institutional investors, who care about environmental risks (Ilhan et al., 2021) and engage with firms on environmental issues (Dimson et al., 2015; Hoepner et al., 2022). I find that green patents granted to polluting firms do not increase shareholder wealth. I also find that there is no market reaction to green patents regardless of whether I

focus only on green announcements associated with high climate concerns, high institutional investor ownership, or high institutional investor attention.

Second, to control for potential confounding factors, I investigate what impacts the relationship between green patent announcements and shareholder wealth in a multivariate setting. The results are similar to my earlier findings. I find no evidence that green patent announcements increase shareholder wealth regardless of a firm's climate risk exposure, the level of climate change concerns, and institutional investor ownership or attention. Moreover, I test whether the market reaction to green patents changed after the 2015 Paris Agreement, which increased investor attention to climate change (Kruse et al., 2020). I find that the impact of green patent announcements on shareholder wealth has not changed after the Paris Agreement.

The lack of a market reaction to new green patents motivates me to investigate the possible reasons for this result. In the last part of Chapter 4, I study whether changes in a firm's green patenting activity impact a company's environmental score, level of institutional investor ownership, and Tobin's Q. I find no evidence that an increase in the number of green patents obtained by a company increases institutional investor ownership and Tobin's Q. Meanwhile, there is no consistent evidence that green patenting activity improves a firm's environmental score.

Overall, Chapter 4 shows that, in contrast to grey patent announcements, green announcements do not increase shareholder wealth. To the degree that firms which obtain green patents can be seen as being environmentally-responsible (Berrone et al., 2017), the findings are consistent with Pástor et al. (2021), who argue that investors can prefer holding green firms because they generate positive externalities for the environment. This increases their valuations relative to grey firms and decreases their

future returns. The results also support the view that the returns to environmental technologies can be low, because green technologies may be in their infancy stages (Aghion et al., 2014; IEA, 2021).

It is possible that investors are mispricing green patent announcements in the short-run or realizing the value of green patents with a delay. To test this, in Chapter 5, I investigate the long-run performance of companies following their green patent announcements. Investors may be initially mispricing green patent announcements because green patents are on average more complex and novel than other patents (De Marchi, 2012; Barbieri et al., 2020). This can make it more difficult for investors to value green technologies accurately (Hirshleifer et al., 2013).

The literature does not offer a clear prediction on the direction of the potential mispricing. On the one hand, green patents may improve companies' long-term stock performance since green technologies can reduce the physical and regulatory climate risks faced by firms (Carrion-Flores and Innes, 2010; Miao and Popp, 2014). These long-term benefits may not be recognized by the investors in the short-run, because investors can underestimate the long-run risks associated with climate change (Hong et al., 2019; Stroebel and Wurlger, 2021). On the other hand, green patenting firms may underperform in the long-run if the costs of developing new green technologies outweigh the value created by them. Arguably, the benefit of addressing environmental issues and reducing pollution is shared with the society as a whole (Hall and Helmers, 2010), which can impede a firm's ability to profit from green innovation (Soltmann et al., 2015). Moreover, green innovations can be less developed than other technologies because they have fewer prior innovations to build upon (Aghion et al., 2016).

I apply the calendar portfolio approach to measure the long-term performance of firms following their green patent announcements. I find that firms consistently underperform after obtaining new green patents. I also find that firms do not consistently underperform after obtaining new grey patents. The results hold across alternative portfolio holding periods and portfolio types. This suggests that investors are mispricing green patent announcements in the short-run and that firms do not profit from engaging in green innovation in the long run.

Moreover, I explore whether the performance of green patenting firms changed after the release of the Stern Review and the launch of the Principles for Responsible Investment in 2006, which increased climate attention (Painter, 2020; Kim and Yoon, 2022). I find that before (after) 2006, the underperformance of green patenting firms is more (less) pronounced. I also differentiate between firms based on whether they operate in a CO₂ intensive industry, their R&D intensity, and their R&D efficiency, respectively. I find that alphas earned by CO₂ intensive companies are more negative, which suggests that their green innovation is shunned by investors (Cohen et al., 2022). Moreover, firms with low R&D intensity or companies with low R&D efficiency also earn alphas that are more negative. This suggests that firms which are not focused on innovation produce green technologies that can decrease shareholder wealth in the long run.

Overall, the evidence presented in Chapter 5 shows that investors misprice green patent announcements in the short run and that firms underperform after obtaining new green patents. This is consistent with the argument that engaging in green innovation may not be profitable for firms (Soltmann et al., 2015; Malen and Marcus, 2019). Moreover, the results support the view that green innovation is arguably less developed

than grey innovation (Aghion et al., 2014). The underperformance of green patenting firms may be partially explained by the asset pricing literature on the green tastes of investors. High demand for holding firms that obtain green patents can potentially increase their valuations and lower their expected returns (Pástor et al., 2021).

The main contribution of this thesis can be summarized as follows. First, Chapter 3 is the first study to examine the impact of patent attorney capability on the economic and technological value of patents. I am the first to apply the *patent attorney capability theory* to the work of patent attorneys. Specifically, I show that it is the substantive expertise of patent attorneys that matters for patents, and not simple process experience. Moreover, to my knowledge, this is the first study to investigate the relation between patent attorney rankings and the economic and technological value of patents. I show that that the Legal500 rankings of patent attorney firms are not a useful proxy for patent value. Second, to my knowledge, Chapter 4 is the first study to investigate the impact of green patent announcements on shareholder wealth. I show that there is no market reaction to green patent announcements in the short run, regardless of a firm's climate change exposure, the level of climate change concerns, and institutional investor ownership or attention. Despite investors' calls for climate action and green innovation (McCormick, 2021; US Chamber of Commerce, 2019), I find that, on average, new green patents do not increase shareholder wealth. . Third, Chapter 5 is the first study to examine the long-run stock performance of firms following their green patent announcements. I show that firms underperform after obtaining new green patents. Moreover, I provide novel evidence that the underperformance is more pronounced for firms with low R&D intensity and/or low

R&D efficiency, thereby contributing to the literature on long-run performance of R&D efficient firms (Cohen et al., 2013; Hirshleifer et al., 2013).

This thesis is of interest to companies that engage in patenting and to their investors. I provide evidence that only successful patent attorneys matter as they increase both the economic and technological value of patents. For example, hiring a patent attorney with a one standard deviation higher substantive expertise is related to a 2.24% ($=0.035\%*64$) higher market value for an average public firm with 64 patent announcements during 2003 to 2019. Therefore, innovating firms should examine the success record of patent attorneys they consider hiring and closely monitor it. In addition, the decision to use the professional services of a patent attorney firm should not be guided by the law firm's position in the Legal500 rankings, which are uncorrelated with patent value and are negatively correlated with substantive expertise of patent attorneys. I also show that firms are not rewarded for obtaining new green patents in the short run, and that green patenting companies underperform after their green patent announcements. These findings can have significant implications for new investors who may want to bet on new green technologies. I show that, on average, new green technologies do not increase shareholder wealth. Moreover, my results suggest that, in terms of firm value, an average company does not benefit from engaging in green innovation. Therefore, the money of profit-motivated firms might be better spent on projects other than environmentally friendly technologies. Moreover, this thesis can also inform the policy work of government officials and regulators with regards to addressing the global climate change problem. I show that firms are not rewarded for obtaining new green patents despite the importance of green innovation in achieving the transition to net zero carbon emissions (Nordhaus, 2021;

Stern, 2022). Therefore, it might be necessary for the government to provide additional incentives for the firms in order to facilitate the development of green innovation in the private sector. Finally, this study can inform environmentally-responsible individuals who choose to have their money invested by others. I find no evidence that an average institutional investor firm rewards its portfolio companies for developing new green technologies. This calls into question the public commitment of many institutional investors to environmentally-friendly investing.

The remainder of this thesis is structured as follows. Chapter 2 provides detailed information about patents, their purpose, and the process of obtaining new patents in the US. Chapter 3 examines the impact of patent attorney capability on the economic and technological value of patents. Chapter 4 investigates whether green patent announcements increase shareholder wealth in the short run. Chapter 5 studies the long-run performance of firms after their green patent announcements. Finally, Chapter 6 discusses the overall findings, identifies limitations of the thesis, and offers suggestions for future research.

2. What are Patents and How are They Obtained?

2.1 Overview of Patents

2.1.1 What is a Patent?

A patent is a legal right that protects an invention. In the United States (US), patents are issued by the United States Patent and Trademark Office (USPTO). A patent gives its owner a right to exclude others from practicing or commercialising an invention. Patent protection lasts for approximately 20 years from the date on which a successful patent application was initially sent to the USPTO (Bouchoux, 2013). After this period passes, an invention becomes a part of the public domain, and anyone can practice it (Durham, 2009). This is shown by Grabowski and Vernon (1992), who find that the prices of drugs decrease to 37% of the original price two years after their patent protection expires. This is caused by a market entry of generic versions of the drugs.

A patent owner can earn abnormal profits from her patented inventions. These temporary monopoly rights help inventors recover the cost of research and development of a new product, which can be substantial. For example, Bessen and Meurer (2008) report that pharmaceutical companies incur an average cost of \$403 million to develop a new drug. Governments offer patents to qualifying inventors in a bid to encourage the development of new ideas (USPTO, 2013; EUIPO, 2019). Innovation is recognized as a key contributor to economic growth. Corrado et al. (2009) show that in 1999 the total business investment in intangible and tangible assets in the US was roughly equal. Furthermore, they argue that the traditional “bricks and mortar” capital investment contributes only 8% of economic growth. Moreover, using

a panel of over 70 countries, Kim et al. (2012) find that innovation and patent activity is positively associated with economic growth in developed countries.

2.1.2 Three types of patents: Utility, Design, and Plant

The patentability requirements described in the next section apply to utility patents, which are the most popular type of a patent. In 2019, over 90% of patents issued by USPTO were utility patents (USPTO, 2021a). Utility patents cover technological inventions (Durham, 2009). An example of a utility patent is the Gillette razor patent that was issued in 1904. The second most popular type of patents are design patents, which can be used to protect new and original artistic representations (Durham, 2009). For instance, designs of clothing or furniture can be patented (Bouchoux, 2013). A famous example of a design patent, which was issued to Apple in 2012, covers the ornamental design of an iPhone. Plant patents are the last type of patents. They can be obtained on plants that are reproduced asexually and are distinctive and novel. The first plant patent that was issued covers an everblooming rose (Cook, 1932). Only 0.3% of patents granted in 2019 by the USPTO were plant patents (USPTO, 2021a).

2.2 USPTO patentability requirements

2.2.1 Subject matter eligibility

Not all inventions or discoveries qualify for patent protection. For example, abstract ideas, principles of nature, and naturally occurring substances are not patent eligible (Durham, 2009). In the US, an invention must satisfy four main conditions to be patentable. These requirements are subject matter eligibility, usefulness, novelty, and non-obviousness (Bouchoux, 2013). First of all, an invention must be a part of eligible subject matter, which includes processes, machines⁵, manufactures⁶, and compositions

⁵ An example of a machine eligible subject matter is a fork lift vehicle or a blender.

⁶ An article of manufacture category is very broad, and it covers anything built by humans (Bouchoux, 2013).

of matter⁷ (USPTO, 2020a). An example of a famous patent covering a process is the “One-Click” patent granted to Amazon.com in 1999. The patent covers a method of making online purchases without the need to provide payment and shipping details every time a new purchase is made (Brandt, 2011).

2.2.2 Usefulness

Secondly, for an invention to be patentable, it must be useful (USPTO, 2020a). An invention needs to have a specific utility and have a practical application (Durham, 2009). For example, it is not possible to patent a perpetual motion machine, because a patent can only be obtained on something that, at least in theory, does work. Furthermore, patents cannot be obtained on inventions that are fraudulent or illegal because they are fundamentally not useful (Bouchoux, 2013). Arguably, the threshold for satisfying the utility requirement is low. For example, inventions with a trivial purpose, such as toys, have enough utility to qualify for patent protection (Durham, 2009). Moreover, even a product that is inferior to existing solutions is still considered useful as long as it serves its purpose (Durham, 2009).

2.2.3 Novelty

Thirdly, only novel inventions can be patented (USPTO, 2020a). A patent cannot be obtained on something that is already publicly known or used or had been in the past⁸. Therefore, it is difficult to know whether an invention satisfies the novelty requirement. This is why a broad search for prior art, which can be described as any relevant information that pertains to an invention’s patentability, should be conducted before seeking patent protection (Hunt et al., 2007). Potential sources of prior art

⁷ The composition of matter category refers to compositions of two or more substances, an example of which is a vaccine.

⁸ There is an important exception to the novelty requirement for inventors seeking patent protection in the US. If an inventor publicly disclosed her invention, she is still eligible to obtain patent protection and she has one year to apply for it (Bouchoux, 2013). This is known as the grace period.

include other inventions and publications in writing such as academic papers, news articles, and patents (Stim, 2007).

2.2.4 Non-obviousness

The last requirement for patentability is non-obviousness. A patentable invention cannot be obvious to a person with ordinary skill in the relevant field (USPTO, 2020a). For example, if an existing patent covers a mouse trap that uses a Ping-Pong ball to trap a mouse, then trying to obtain a new patent on the same mouse trap where the Ping-Pong ball has been substituted for a rubber ball will fail, because the substitution is obvious (Durham, 2009). In other words, the invention has to include a sufficient inventive step (Reitzig, 2004). Judging whether an invention is obvious is complicated, and the prevalent method is to compare it to prior art (Bouchoux, 2013).

2.3 Patenting in the US

2.3.1 Why do companies obtain patents?

A variety of surveys find that the most important reason for patenting is protecting one's intellectual property (Holgersson and Granstrand, 2017; Blind et al. 2006; Cohen et al., 2000). Firms want to prevent their competitors from imitating their inventions and therefore eroding their revenues (Holgersson, 2013). Furthermore, firms obtain patents to block their rivals from developing technologies that would make it tougher to compete against them (Mihm et al., 2015). Torrisi et al. (2016) analyse results of a survey of 8,144 patent applications and find that 67% of the applications were filed to block others from obtaining patents on similar inventions. Similarly, patents are also used by companies to secure a freedom to operate in a technology area (Holgersson and Granstrand, 2017).

The second biggest reason for obtaining patents is to increase one's bargaining power (Cohen et al. 2002; Blind et al. 2006). Patents can be sold or licensed out to

other firms in exchange for royalties. In 2007, IBM reportedly earned almost \$1bn from its patent portfolio (Galasso and Schankerman, 2010). Companies also engage in cross-licensing of patents in order to gain access to new markets and technologies (Mihm et al., 2015), and a bigger patent portfolio increases a firm's negotiating power (Blind et al., 2009). Fragmentation of patent rights in a technology market can make negotiating patent licenses expensive, which can lead to legal conflicts between firms who failed to agree on licensing terms (Cohen et al., 2019).

Having patents can increase a firm's chances of prevailing in patent litigation (Choi, 1998; Holgersson and Granstrand, 2017). A company can use its patents to launch a legal attack on a competitor that is perceived as infringing the firm's patented technologies (Janicke and Ren, 2006). Similarly, a company whose products are patent protected might face fewer lawsuits from other businesses (Bessen and Meurer, 2005). Losing a legal battle over patents can be very costly. Hu et al. (2020) report that the median patent infringement award in the US is \$3.2m, based on 242 court decisions between 2000 and 2014. Similarly, Ansell et al. (2018), who study patent litigation in the US, report that the median damages award across 1998-2017 is \$5.9 million, based on 543 judgements. The total costs of these legal disputes to firms are understated because most patent lawsuits settle before they reach the courts (Bessen and Meurer, 2008). Moreover, patent trolls use their patents primarily in an offensive way to extract rents from other companies by accusing them of patent infringement and demanding licensing payments to avoid patent litigation (Cohen et al. 2019). Appel et al. (2019) provide evidence on the harmful impact of patent trolls by showing that the adoption of state-level anti-troll laws in the US caused the employment at high-tech start-ups to increase by 4.4%.

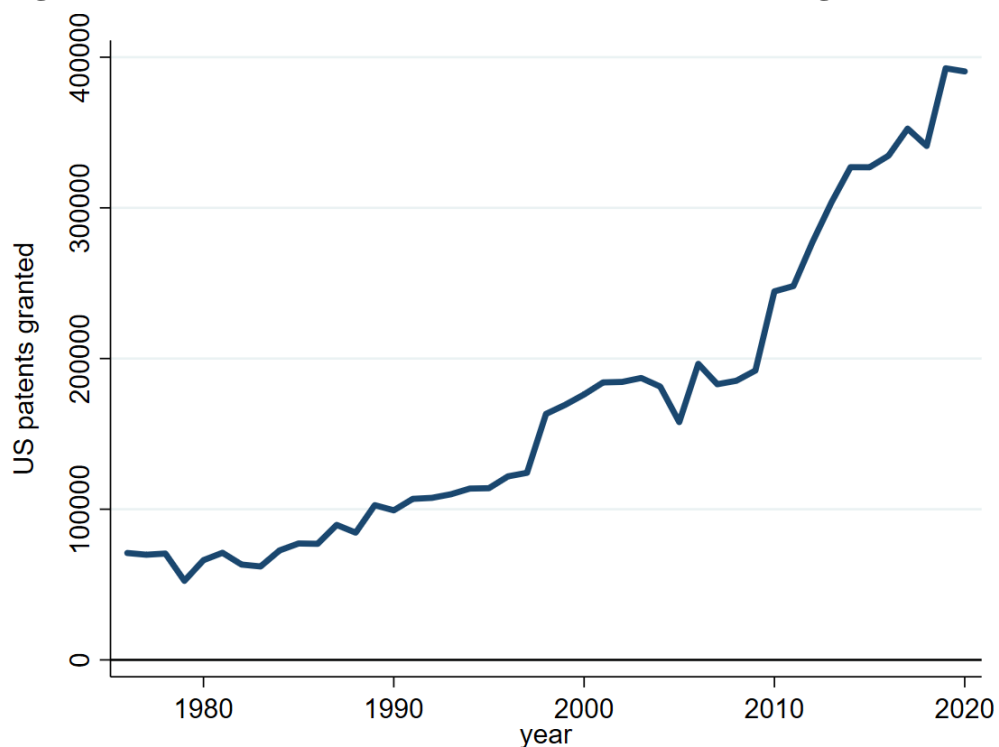
Lastly, firms seek patent protection to increase their reputation and communicate the success of their research and development efforts to the market. This is particularly important for small firms (Holgersson, 2013; Keupp et al., 2009). Hsu and Ziedonis (2008), who study 370 venture capital-backed start-ups in the semiconductor industry, find that start-ups that double the number of their patent applications receive a 28% higher valuation than an average firm in their sample. Farre-Mensa et al. (2020) show that start-ups that receive a patent by drawing a lenient patent examiner experience a 55% higher employment growth and an 80% higher sales growth five years later.

Given the benefits that patent ownership brings to companies, multiple efforts have been made to assign patents a monetary value. Kogan et al. (2017) use a sample of patents issued to public companies in the US between 1926 and 2010 and measure patent value based on the stock market reaction to patent announcements. They find that a median patent is worth \$3m, while an average patent value is \$10.3m. Similarly, Hirschey and Richardson (2001) study a sample of 256 publicly traded high-tech companies in the US across 1989-1995 and find that the marginal value of a patent lies between \$2.8m-\$3.3m. European evidence on patent value is similar. Gambardella et al. (2008) analyses a survey of over 9,000 patents granted by the European Patent Office and find a mean patent value of €3m. However, estimates of patent value are sensitive to sample choice, with some studies reporting significantly lower patent values. Fischer and Leidinger (2014) analyse the prices of 573 US patents that sold at auctions between 2006 and 2009 and find an average patent value of \$148,535. Bessen (2008) studies US patents granted in 1991 and estimates their average value to be \$78,000.

2.3.2 Number of patents granted in the US

The interest in obtaining US patents keeps increasing. Figure 2-1 shows the number of US patents granted per year during 1976-2020. In 2019, USPTO has issued 391,103 new patents, 354,430 of which were utility patents. This is more than three times as many patents as it granted in 1997 (USPTO, 2021a). Moreover, approximately 50% of patents list a foreign inventor (USPTO, 2021a). Also, patents are organised by the patent office into different technology classes based on the inventions' characteristics.⁹ USPTO (2015) count the number of patents by class during 1977 to 2015 and report that patents relating to drugs are the most widely applied for, followed by patents covering semiconductors.

Figure 2-1: Number of US Patents Granted Per Year During 1976 to 2020



⁹ The current classification system used by the USPTO is the Cooperative Patent Classification (CPC), which it adopted in January 2013. CPC has approximately 250,000 categories.

2.3.3 Patents differ in their quality

The large variance in the value of granted patents (Kogan et al. 2017) shows that there are differences in quality across patents. Arguably, the three most important indicators of patent quality are scientific merit, validity, and broadness.

First of all, inventions disclosed in patents differ in their scientific merit, which is commonly measured using patent citations¹⁰ (Trajtenberg, 1990; Harhoff et al., 1999; Hirschey and Richardson, 2004). A patent that covers a fundamental technological advancement is often more valuable than a patent that protects a modest improvement (Allison, 2019). Hall et al. (2005) study a sample of 4,864 publicly traded firms between 1976 and 1995 and estimate that an additional citation per patent is associated with a 3% increase in a firm's market value. Similarly, Bessen (2008) report that an additional citation increases patent value by 4% to 7%, while Kogan et al. (2017) report a range of 0.1% to 3.2%.

Secondly, a valid patent fulfils USPTO's patentability requirements. Hence it does not face a significant risk of being revoked in court, which, all else equal, makes it a more valuable bargaining chip or litigation weapon. Despite the fact that only legitimate patents should be granted, the USPTO has been criticised for issuing invalid patents (Farrell and Shapiro, 2008). Lemley and Shapiro (2005) point out that half of litigated patents end up being invalidated and they argue that patents should be seen as probabilistic rights. Moreover, patent offices are overwhelmed by the increasing number of patent applications they receive, which makes the examiners spend less time on each application. Frakes and Wasserman (2017) use US patent application data to

¹⁰ A patent usually cites prior art references that describe inventions that are considered closest to the invention in question (Durham, 2009). A patent citing another patent as its prior art reference is referred to as a backward citation. A patent being cited by another patent is called a forward citation.

show that the shorter examination time reduces examiners' scrutiny and makes them more likely to grant a patent. Kim and Oh (2017) analyse Korean patent application data and draw similar conclusions.

Lastly, holding all else equal, the broader the rights of a patent are, the more valuable a patent is (Bessen, 2008). A broad patent can be used to exclude others from commercialising a larger number of competing products and processes (Merges and Nelson, 1990), which increases the economic payoff from patent ownership. Lerner (1994) measures patent scope using the number of technology subclasses which were assigned to a patent by the USPTO. The author studies a sample of 173 privately held venture-backed biotechnology firms and finds that a one standard deviation increase in patent scope increases firm value by 21% (Lerner, 1994). Marco et al. (2019) argue that patent scope can also be measured by the number of independent patent claims of a patent and their length.

Increasing patent breadth carries a risk of decreasing patent validity. Patents with broad rights are more likely to be found invalid because their high scope increases the probability that they fail the novelty and non-obviousness requirements (Allison, 2019).¹¹ When drafting a patent application, a patent attorney tries to balance the risk of invalidity with the potential payoffs offered by a broader patent scope. A patent attorney considers the probability of different legal scenarios and aims to maximize the overall expected profits from a patent for their client by changing the way a patent application is written (Reitzig, 2004). This makes the attorney's level of capability critical for patent protection. For example, in order to maximize potential profits, the

¹¹ In other words, there is a larger number of potentially relevant prior art references that can deem a broad patent invalid.

patent attorney will try to maximize the scope for inventions with a high degree of novelty and non-obviousness (Reitzig, 2004).

2.4 Process of Obtaining a Patent from the USPTO

2.4.1 An overview of the process of obtaining a patent from the USPTO

Obtaining a patent from the USPTO is a complex process that takes several years.¹² It involves preparing, filing, and negotiating a patent application with the USPTO. Hiring a patent attorney¹³ is recommended by the USPTO, which inventors do 80% of the time (Bouchoux, 2013). The main steps of the process are shown in Figure 2-2. First of all, the inventor and the patent attorney discuss the invention, and, if they decide to proceed with seeking patent protection, the attorney will usually conduct a comprehensive search of prior art (Hunt et al., 2007).¹⁴ Next, if the results of the search are promising, the inventor and the patent attorney draft a patent application and submit it to the USPTO (Chitale et al., 2020). The USPTO then assigns the application to an appropriate technology centre called an art unit. Within the art unit the application is assigned to a patent examiner (Righi and Simcoe, 2019). The examiner evaluates the application against the USPTO's patentability criteria, conducts her own prior art search, and generally sends a rejection letter to the patent attorney (Lu et al., 2017). A back-and-forth negotiation begins between the patent examiner and the representative of the patent application, who in the majority of cases is a patent attorney. If the two parties come to an agreement, the examiner sends the patent applicant a Notice of Allowance and the patent is issued shortly thereafter (Gans et al.,

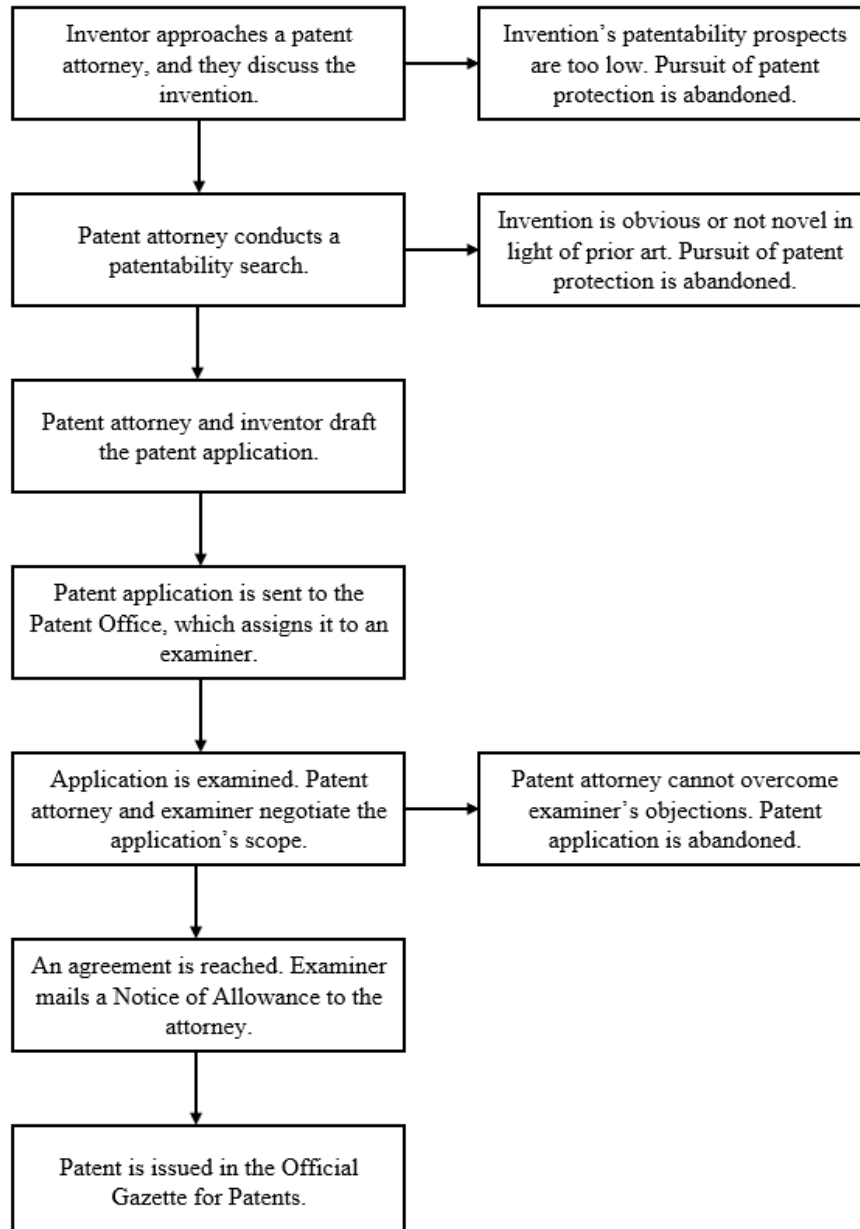
¹² It takes on average 34 months for a patent to issue from the time the patent application was initially sent to USPTO for examination (Bouchoux, 2013). This does not include the time it takes for an applicant to prepare a patent application.

¹³ Both patent attorneys and patent agents are qualified to represent a patent application before the USPTO. I use the term "patent attorney" to jointly refer to patent attorneys and patent agents.

¹⁴ The initial discussion and the prior art search steps are not mandatory, but they are recommended (Slusky, 2012; Hunt et al., 2007).

2008). However, the patent examination process can also end in an abandonment of the patent application by the applicant. Approximately 56% of patent applications lead to granted patents without the use of continuation procedures (Carley et al. 2015). In the next section, I describe every step during the process of obtaining patent protection in more detail.

Figure 2-2: Main Steps in Seeking Patent Protection in the US



2.4.2 The initial discussion

The initial discussion with the inventor helps the patent attorney understand the invention and assess its patentability prospects. An attorney that appreciates the details of how an invention is made and how it works is more effective at assisting an inventor (Slusky, 2012; Hunt et al., 2007). For example, an attorney may advise the inventor to conduct additional experiments that would help demonstrate the improvements made by the invention over prior art and increase the probability of obtaining a patent (Richard, 2007).

2.4.3 Patentability search

After the initial discussion, the patent attorney usually conducts a patentability search. The purpose of the search is to determine whether the invention is patentable in light of the prior art (Bouchoux, 2013). It can save an inventor time and money by preventing an attempt to patent something that is obvious and lacks novelty (Hunt et al., 2007). Moreover, conducting a comprehensive search prepares a patent attorney for prior art objections that could be raised by a USPTO patent examiner during the patent examination (Lu et al., 2017). Prior art searching is challenging due to the volume and variety of sources that should be checked.¹⁵ Failure to identify relevant prior art can have severe consequences. For example, in 2006, the Federal Circuit found a US patent to be invalid because of a publicly accessible Canadian patent application that the patent owner was not aware of (Hunt et al., 2007).

¹⁵ This includes any relevant publicly accessible written accounts, both technical and nontechnical, such as patents, academic articles, conference proceedings, product manuals, and newspaper articles. The most relevant sources that need to be checked depend on the invention at hand and the scope of patent protection sought by the inventor (USPTO, 2020b).

2.4.4 Patent application drafting

The results of a prior art search can help an inventor and a patent attorney draft a stronger patent application that emphasises the present invention's novelty and non-obviousness. A patent application and a granted patent largely contain the same sections (Durham, 2009). An example of a utility patent claiming a simple mousetrap is shown in Appendix 2-A. The front page of a patent includes invention's title, inventor's name, patent number, patent issue date, and an abstract briefly describing the invention. The abstract is often followed by drawings, which, in the case of the mousetrap patent, illustrate how the pivotally supported mousetrap catches a mouse through the use of a ping pong ball. Drawings help communicate how the invention works, and although they are not compulsory, almost all patents include some illustrations (Durham, 2009). The next section of a patent is the specification, which is then followed by a section listing the patent claims.

Specification is a comprehensive written description of the invention. It explains how the invention is used and made (Slusky, 2012). It often refers back to different parts of the drawings, which are labelled with referencing numbers. Specification is composed of multiple sections. The first part contains a background of the invention, and it discusses how the invention is different from prior art (Bouchoux, 2013). Next, there is a short summary of the invention and its main objectives (Durham, 2009), which in the case of the mousetrap patent is catching a mouse alive. The summary is followed by a brief description of the drawings. Finally, the last part of the specification is an exhaustive description of an invention. It has to provide enough detail to enable a person skilled in the art to make and use the invention (USPTO,

2020c).¹⁶ This is also known as the Enablement Requirement (Burk and Lemley, 2009). Furthermore, the specification has to disclose the best way of practicing the invention known to the inventor (Durham, 2009). This is known as the Best Mode Requirement. A patent application can be refused, or a patent can be deemed invalid if these requirements are not satisfied (USPTO, 2020d).

Patent claims are the last part of a patent document. There are two main types of claims: independent claims¹⁷ and dependent claims¹⁸. Claims define the scope of a patent owner's rights with relation to the invention (Slusky, 2012), and they are often at the centre of an examiner's objections during examination (Lu et al., 2017). Whether an invention is eligible for patent protection is largely determined by the contents of its claims (Durham, 2009). The patent attorney aims to write the claims in a way that maximises patent scope but at the same time still satisfies the statutory requirement of specificity (Bouchoux, 2013; Reitzig, 2004).¹⁹ In case of any doubt with regards to the claims' meaning, the claims are read in the light of the patent's specification. Courts often focus on analysing patent claims to determine whether a patent infringement has occurred (Bouchoux, 2013).

2.4.5 How a patent application reaches an examiner

After the patent application is written, it is sent to the USPTO for examination. The application is received by the Office of Patent Application Processing, which checks

¹⁶ A person skilled in the art is someone that has standard knowledge and skills in an invention's technological area. In the case of the mousetrap patent, such a person could be a professional mouse catcher.

¹⁷ Independent claims are complete sentences that stand on their own, without referring to other claims (Marco et al. 2019). Claims 1,6, and 8 of the mousetrap patent in Appendix 1 are independent claims.

¹⁸ Dependent claims refer to an independent claim and add a limitation to it (Stim, 2007). By definition, dependent claims are narrower than independent claims. Dependent claims often act as an insurance policy to hedge against a risk of losing legal rights to an invention. If an independent claim is rejected by a patent examiner or revoked by a judge, a dependent claim can still remain valid. This is referred to as a fallback feature (Slusky, 2012).

¹⁹ The USPTO requires that the language used in the claims has a definitive meaning that is clear to a person skilled in the art (Durham, 2009; USPTO, 2020e).

whether the application is complete and assigns it a technology classification based on the keywords it finds in the patent application (Righi and Simcoe, 2019). Based on this classification, the patent application is assigned to the most appropriate art unit for examination. Art units are specialised technology centres made up of a group of 8 to 15 patent examiners (Frakes and Wasserman, 2019). Within the art unit, the Supervisory Patent Examiner allocates the patent application to one of the examiners (Frakes and Wasserman, 2019; Lemley and Sampat, 2012; Sampat and Williams, 2019).

The probability that a patent application will be allowed can differ across art units. This is because art units examine different technologies and are composed of examiners with varying average allowance rates (Cockburn et al., 2002; Gaule, 2018). Vishnubhakat and Rai (2015) compare patent allowance rates between Art Unit 1631, which examines biological inventions that use data processing, and Art Unit 2123, which handles more conventional software. They find that the former art unit has a lower average allowance rate. Capable patent attorneys may be aware of the differences across art units and they can carefully select the words they use in the patent applications in order to maximise the probability of the application being assigned to a 'favourable' art unit (Law360, 2017). This practice is sometimes referred to as art unit shopping.

2.4.6 Patent examination process

After a patent application is assigned to an examiner, she conducts a prior art search and assesses whether the invention satisfies the USPTO's patentability requirements. Then the examiner can either allow a patent application or send a written notification

explaining why the application in its current form is rejected (Lu et al., 2017).²⁰ An examiner allows the patent application without any changes 13.5% of the time, and initially rejects the application 86.5% of the time (Lemley and Sampat, 2010). The first rejection is usually sent on average 28 months after the patent application was received by the USPTO (Bouchoux, 2013). An example of a first rejection is shown in Appendix 2-B.

Patent examination often focuses on a patent application's claims. Typically, an examiner lists the rejected claims while providing references to statutory and non-statutory law that justify the rejection(s). The same rejection letter can include objections based on multiple legal grounds. Lu et al. (2017) carries out a detailed analysis of the examination of 2.2 million patent applications. They find that the two most common reasons for rejecting a patent application are obviousness in the light of prior art, which appears in 77% of first rejections, and lack of novelty, which is mentioned 47% of the time (Lu et al., 2017).

After receiving a first rejection, a patent attorney has three months to send a response, but, for a fee, this period can be extended to up to six months (Bouchoux, 2013). The response sent by a patent attorney to the first rejection shown in Appendix 2-B is presented in Appendix 2-C. Typically, a patent attorney amends a number of claims to overcome an examiner's objections and/or argues against the objections and requests the claims to be allowed (Chitale et al. 2020). The patent attorney also has the option to request a telephone consultation or an in-person meeting with the examiner (Pressman and Blau, 2018). The examiner will allow the patent application if she believes that the patent attorney's response has fully addressed all objections.

²⁰ This letter is also known as the First Office Action or a Non-Final Rejection.

Otherwise, the examiner will send a second rejection, which is also known as a Final Rejection (Marco et al., 2019). A Final Rejection closes the examination, but a patent attorney has a number of options at her disposal to reinitiate the process, usually for a fee. These options include sending a response to the Final Rejection that includes a combination of claim amendments and arguments, submitting a Request for Continued Examination, appealing to the Patent Trial and Appeal Board, and filing a continuation patent application (Lu et al., 2017).²¹

2.4.7 Examination ends in allowance or abandonment

Patent examination ends in either an issuance of a patent by the Patent Office or an abandonment of the patent application by the patent applicant. The applicant may abandon an application if an examiner's objections make pursuing patent protection no longer viable and the patent attorney is not able to overcome the objections (Lemley and Sampat, 2012; Chitale et al., 2020). Abandonment can also be a result of negligence if the patent attorney does not respond to a first rejection within the required time limit or fails to pay fees in a timely manner (Marco et al. 2019).

Carley et al. (2015) study patent examination histories of 2.15 million US patent applications and find that 56% of applications become granted patents, without counting the continuation patent applications. Patents are issued in the Official Gazette for Patents, which is published by the USPTO every Tuesday (USPTO, 2021b). This is the first time that newly granted patents are announced by the Patent Office. However, it is possible for members of the public to learn about a successful patent application before it is issued as a patent through the use of the Public Patent

²¹ A continuation application is a new patent application that benefits from the priority date of the original patent application (Stim, 2007). Priority date is the date after which new prior art does not affect an invention's patentability (Bouchoux, 2013).

Application Information Retrieval system (public PAIR). Public PAIR, which was announced in 2004 (Garabedian, 2004), allows anyone with an online connection to track the examination progress of public patent applications.²²

One of the most important events that a public PAIR user can be on the lookout for is the mailing of a Notice of Allowance. A patent examiner sends a Notice of Allowance to a patent application representative once the examiner has decided that a patent application fulfils USPTO's patentability requirements. Notice of Allowance resolves the uncertainty over whether an invention will be granted patent protection (Gans et al., 2008). After a patent applicant receives the Notice of Allowance, she has three months to pay the USPTO any issue fees. Once all fees are paid and the Patent Office has finished preparing the document for publication, which takes several months, the patent applicant receives an Issue Notification (USPTO, 2020f). Issue Notification states a new patent number and a patent issue date, which is approximately 3 weeks from the date on which the Issue Notification has been mailed. This concludes the process of obtaining a patent.

²² A person has to know the patent application number and manually search for it on <https://portal.uspto.gov/pair/PublicPair> to check the status of the patent application.

3. Do Patent Attorneys Matter for the Economic and Technological Value of Patents?

3.1 Introduction

I investigate whether patent attorneys²³ impact the value of firm innovation by examining the relation between patent attorney capability and the economic and technological value of patents. Patent attorneys play a central role in drafting patent applications and negotiating the scope of patent protection with patent examiners (Reitzig, 2004). I argue that more capable patent attorneys can help firms secure more economically- and technologically- valuable patents. I distinguish between attorneys' process experience (their number of patent applications filed), and their substantive expertise (their success rate in obtaining patents).²⁴ The value implications of patent attorneys' capability remain largely unexplored. I address this gap by examining two types of value implications: *economic*, as measured by the market reaction to patent announcements during the three-day (0,+2) event window,²⁵ and *technological*, as measured by patent citations.²⁶

Patents can create a financial motivation for innovation in return for the disclosure of the innovation to the public (Hall and Harhoff, 2012). Patents are valuable because they can protect firms' inventions from being practiced or commercialised by others. The number of patents is growing, with 388,900 new patents granted in the US in 2020,

²³ I use the term 'patent attorney' to refer to both patent attorneys and patent agents. Both attorneys and agents are qualified to represent their clients before the USPTO.

²⁴ I jointly refer to process experience and substantive expertise of patent attorneys as patent attorney capability (Szmer et al., 2007; Miller et al., 2015).

²⁵ See footnote 2 on page 20 for a detailed justification for using the (0,+2) event window.

²⁶ Citations are the most widely used proxy for patent quality (Hirschey and Richardson, 2004; Trajtenberg, 1990) and are connected to firm value as Hall et al. (2005) find that one additional citation per patent is associated with a 3% higher firm value.

an increase of 103% compared with 191,927 patents granted in 2009. The market reacts positively to announcements of new patents (Kogan et al., 2017), which can boost firm growth (Farre-Mensa et al., 2020), profitability (Pandit et al., 2011), as well as survivability and access to capital (Hegde et al., 2022).

The purpose of patent attorneys is to obtain valid, broad, and both economically and technologically valuable patents for their clients. The USPTO advises inventors to hire patent attorneys to prepare and pursue patent applications on their behalf (USPTO, 2020). The work of patent attorneys requires both scientific and legal knowledge. Patent attorneys consider the probability of different legal scenarios and rely on their judgment to draft patents and negotiate with patent examiners in a way that maximises the overall expected profits for their clients (Reitzig, 2004). Therefore, patent attorneys can have a significant influence on the value of patents, as measured by the market reaction to patent announcements and the number of citations received by patents.

Despite these patent specific activities, the general work of a patent attorney is comparable to the role of a conventional attorney. Attorneys apply their knowledge of the law to construct legal arguments and negotiate on behalf of their clients. Attorneys have different levels of substantive expertise (Posner and Yoon, 2011) and process experience in representing their clients in courts (Abrams and Yoon, 2007). The *attorney capability theory* predicts that more capable attorneys produce better outcomes for their clients (Miller et al., 2015; Szmer et al., 2007). For example, more capable attorneys increase the probability of winning in the US Supreme Court (McGuire, 1995), obtain shorter sentences for the defendants they represent in felony cases (Abrams and Yoon, 2007), and secure higher monetary settlements for firms in corporate litigation (Ferrell et al., 2021). Therefore, I argue that patent attorneys'

substantive expertise and the process experience they gain in working with the USPTO should be reflected in the economic and technological value of patents they have worked on. I distinguish between substantive expertise of patent attorneys and the process experience they gain as they repeatedly pursue patent applications (Haire et al., 1999; Kritzer, 1998). I measure substantive expertise of attorneys using their rolling success rate in obtaining patents from the patent office, and I capture their process experience using the cumulative number of patent applications filed. For robustness, I also use alternative proxies of process experience and substantive expertise, as discussed in section (3.5).

The results support the importance of substantive expertise of patent attorneys. With regards to the economic value, a one standard deviation increase in substantive expertise is related to a 0.035% higher market reaction to a patent announcement. This effect accumulates to a 2.24% ($=64*0.035\%$) increase in market value for an average company in my sample with 64 patent announcements during 2003-2019. Moreover, I find that substantive expertise of patent attorneys has a positive relation with the technological value of patents. A one standard deviation (11.6%) increase in substantive expertise is associated with 3% more citations received by the patent. These results show that there is a positive correlation between patent attorney substantive expertise and the economic and technological value of patents. This suggests that successful attorneys are more skilled at pursuing patent applications.

I also test whether the process experience accumulated by patent attorneys affects the value of patents. This helps me determine whether patent attorney firms that are simply larger or more popular, in terms of the number of applications filed, are associated with patents that are more valuable. Contrary to the literature on

conventional attorney ability (Abrams and Yoon, 2007; McGuire, 1995), I find that the process experience patent attorneys gain by submitting more patent applications is not related to the economic or technological value of patents. This suggests that the value of patents cannot be explained by the different popularity or the different process experience levels of patent attorneys.

Arguably, firms may choose to hire more capable attorneys to work on obtaining patents for inventions that are more important to them (de Rassenfosse et al., 2023). I address the potential selection issues arising from a non-random matching between the patent attorneys and the inventions in two different ways. First, I investigate whether patent attorney substantive expertise has a causal effect on the economic and technological value of patents by exploiting the opening of new regional offices by the USPTO. Patent attorneys located in the states in which the new offices are opened can benefit due to an easier access to patent examiners with whom they can conduct in-person interviews to negotiate the grant of a patent (Lemley and Sampat, 2010). I find that the impact of substantive expertise of patent attorneys on the economic value of patents increased after the opening of the new USPTO offices. This only applies to patent attorneys located in the states in which new offices were opened, which suggests an existence of a causal relationship between patent attorney substantive expertise and the economic value of patents. I also find that the impact of the affected attorneys' substantive expertise on the technological value of patents did not change after the new USPTO offices were opened. This is consistent with the fact that an examiner interview occurs at a late stage of the patent examination process, when the technological aspects of an invention have already been finalised (Lemley and Sampat, 2010).

Second, I study the changes in a firm's patent attorney. I compare patents represented by different attorneys that were granted to the same company in close succession. If patent attorneys matter, I expect a positive (negative) effect of a change to a more (less) capable attorney. I find that patents of companies that switch to a patent attorney with higher (lower) substantive expertise receive more (fewer) citations and experience a higher (lower) stock market reaction at grant. The magnitude of the effect increases as the capability gap between the new and the old patent attorney widens.

In the last part of this chapter, I investigate whether more capable patent attorneys are recognised for their higher performance in the annual patent attorney law firm rankings published by the Legal500. I expect that the most successful patent attorneys are also among the highest ranked. I find that there is a simple negative (positive) correlation between top ranked patent attorney firms and their substantive (process) expertise (experience). Moreover, I find that the top patent attorney firm rankings are not statistically related to higher economic or technological value of patents. This suggests that patent attorney rankings are not effective predictors of patent value, and that they perform poorly at identifying high-capability patent attorneys.

To my knowledge, this is the first study to investigate the effect of patent attorney capability on the economic and technological value of patents. I show that the substantive expertise of patent attorneys increases the economic value of patents. Only capable patent attorneys create value for their clients. Therefore, innovating firms should closely monitor the attorneys' track record. Furthermore, I provide evidence that more capable patent attorneys are positively related to patents' technological value, as measured by patent citations. This study contributes to the literature studying the effect of patent attorneys on patents by examining their impact on the economic

and technological value of patents (de Rassenfosse et al., 2023; Gaudry, 2012; Somaya et al., 2007; Klincewicz and Szumial, 2022).²⁷ Finally, to my best knowledge, this is the first study to test the relation between patent attorney law firm rankings and the economic and technological value of patents.

3.2 Hypotheses development

Navigating the patent application process requires legal proficiency (Lee, 2020). First, applicants need to know how to write a valid patent application and what information must be disclosed with the patent office. Applicants that fail to disclose information that is material to the invention's patentability risk the patent being held unenforceable (Hricik and Meyer, 2009). Second, applicants need to know how to negotiate with patent examiners. When an examiner receives a patent application, generally they initially reject it (Lemley and Sampat, 2010).²⁸ It takes on average 3 years to obtain a patent (Farre-Mensa et al., 2020). The USPTO recommends hiring a patent attorney because "the value of a patent is largely dependent upon skilled preparation and prosecution" (USPTO, 2020, p.2).

The capability of patent attorneys may affect the value of patents. Patent attorneys often work closely with inventors, and they can recommend changes to an invention that would improve its commercial value and patentability before it is disclosed to the

²⁷ De Rassenfosse et al. (2023) is similar to this study in that they both examine the impact of patent attorney quality on patents. However, this study differs from de Rassenfosse et al. (2023) in two key ways. Firstly, I investigate how patent attorneys capability affects the economic and technological value of patents, rather than the probability of patent grant as in de Rassenfosse et al. (2023). Secondly, this study directly measures patent attorney capability, whereas de Rassenfosse et al. (2023) use high-dimensional fixed-effects models to proxy for patent attorney capability. Arguably, patent attorneys' capability can change over time as they gain more experience (McGuire, 1995; Miller et al., 2015), and my approach allows me to track this. This is not the case in the approach of de Rassenfosse et al. (2023), who estimate patent attorney fixed effects.

²⁸ After an examiner first reviews a patent application, in 86.5% of the cases they send the applicant a written notification that objects to one or more of the claims. In response, the applicant typically amends the claims and/or argues against the objections (Lu et al., 2017).

patent office (Chondrakis et al., 2021). Attorneys are often responsible for drafting patent claims, which determine the scope and validity of patent protection with relation to a technology (Yelderman, 2014). Also, attorneys often conduct prior art searches, prepare patent applications, and then negotiate the grant of patents with patent examiners (Gaudry, 2012; Lu et al., 2017).

The roles of a patent attorney and a conventional attorney are similar. Applying their knowledge of the law, constructing convincing arguments, and negotiating on behalf of their clients is required both of conventional attorneys (McGuire, 1995) and of patent attorneys (Chondrakis et al., 2021). The *attorney capability theory* posits that attorneys accrue valuable experience over time that helps them achieve better outcomes (McGuire, 1995; Miller et al., 2015). Therefore, I apply the *attorney capability theory* to test the importance of patent attorneys.

The origins of the theory can be traced back to Galanter (1974) who distinguishes between parties which only occasionally appear in courts and parties which are repeatedly engaged in litigation. The latter type, called repeat-players, accrue valuable experience over time that makes them more effective than infrequent litigators. For example, repeat-players gain procedural knowledge of the legal institutions they interact with, they develop informal relationships with decision makers, and with time they are believed to shape the law in their favour (Galanter, 1974; Miller et al., 2015). McGuire (1995) modifies the attorney capability theory of Galanter (1974) and argues that attorneys themselves are repeat-players. Over time, judges develop trust in the arguments presented by experienced legal practitioners, who are expected to communicate truthful information to maintain their good reputation (McGuire, 1995; Szmer et al., 2007). McGuire (1995) shows that attorneys who frequently litigate in

the US Supreme Court can increase their clients' probability of success by 8%. Szmer et al. (2007) study all appeals heard by the Supreme Court of Canada between 1988 and 2000. They find that attorneys' prior litigation experience and litigation team size are positively associated with the probability of winning. Haire et al. (1999) argue that the frequency of an attorney's attendance in a particular court is an incomplete measure of her capability. On top of counting the number of attorneys' appearances in court, Haire et al. (1999) also hand-collect data on each lawyer's areas of specialisation. They study product liability cases decided by the US Court of Appeals and find that inexperienced attorneys as well as attorneys not specialising in a relevant area of the law are less likely to succeed in litigation. Miller et al. (2015) test several measures of attorney capability using data on all asylum merits decisions by US immigration courts between 1990 and 2010. They find that attorneys' past general and judge-specific success rates positively predict successful outcomes, while an attorney's workload negatively affects the probability of success (Miller et al., 2015). Overall, these studies show that attorney capability matters.

Attorneys differ in their levels of process experience (McGuire, 1995); and substantive expertise (Haire et al., 1999; Posner and Yoon, 2011). Process experience is defined as the level of an attorney's familiarity with a particular court and is commonly measured by counting the number of interactions between the attorney and the said court (Szmer et al., 2007). I capture process experience by counting the number of patent applications filed by a patent attorney irrespective of whether they are successful or not. Substantive expertise refers to the attorney's specialist knowledge of law and the skill of applying relevant legal rules to situations at hand (Miller et al., 2015). Substantive expertise of patent attorneys is measured using the

percent of patent applications filed by a patent attorney that resulted in a granted patent, based on a rolling success measure.

Overall, the literature finds support for the *attorney capability theory*. Attorneys with higher substantive expertise, and attorneys with higher process experience produce superior results for their clients. Similarly, the different capability of patent attorneys may influence the value of patents that they worked on. This leads to the first hypothesis:

Hypothesis 3-1a: Patent attorney substantive expertise is positively related to the economic value of patents they represent.

Hypothesis 3-1b: Patent attorney process experience is positively related to the economic value of patents they represent.

Patent attorneys can act strategically when drafting patent claims. They need to consider the balance between breadth and validity of the claims. Patent breadth, which is also known as patent scope, is largely determined by patent claims. Patents with a broader scope protect a larger number of competing products and processes (Merges and Nelson, 1990). Broad claims are generally more valuable (Hegde et al., 2022; Lerner, 1994), but the benefit of the broader scope is limited by the risk of a claim being found invalid (Yelderman, 2014). Validity determines the probability of the patent being found invalid in court.²⁹ Therefore, patent attorneys will try to increase the scope for inventions with a high degree of novelty and non-obviousness and will aim to decrease the scope for non-original inventions (Reitzig, 2004).

Moreover, patent applicants can act strategically when deciding what information to reveal to the patent office. Sampat (2010) finds that applicants often fail to disclose

²⁹ Although the USPTO is only supposed to grant valid patents, it has been criticised for awarding patents with low validity (Lemley and Shapiro, 2005; Farrell and Shapiro, 2008).

information about their own previous patents, and that they provide more citations for inventions that are more important to them. This suggests strategic behaviour, since it is unlikely that applicants are not aware of their own patents (Sampat, 2010). Furthermore, Kuhn et al. (2020) argue that some patents deliberately include a large number of citations. Applicants can benefit by hiding relevant information in this long list of immaterial citations, as examiners facing time constraints (Frakes and Wasserman, 2017) will not be able to review all of them (Kuhn et al., 2020). Moreover, Barber and Diestre (2022), who study the patent examination history of 9,763 US patent applications between 2000 to 2006, find that patent attorneys can use patent citations to impact which examiners are assigned to patent applications. In turn, this can help them obtain patents more easily (Barber and Diestre, 2022). Overall, patent attorneys can influence how an invention is disclosed in a patent application, which can affect the number of patent citations that it ultimately receives. This leads to the second hypothesis:

Hypothesis 3-2a: Patent attorney substantive expertise is positively related to the technological value of patents they represent.

Hypothesis 3-2b: Patent attorney process experience is positively related to the technological value of patents they represent.

The impact of patent attorneys on firm value has not been previously studied in the literature. The existing studies have focused on examining the importance of patent attorneys in securing patents. For example, Gaudry (2012) tests the effect of hiring a patent attorney by comparing patent examination histories of 250 randomly selected US patent applications, where an inventor represented herself, with 250 randomly selected US patent applications represented by a patent attorney. Gaudry (2012) finds

that applications represented by the inventors themselves are abandoned 76.4% of the time, compared to 34.8% of applications represented by patent attorneys. Somaya et al. (2007) examines the determinants of firm-patenting performance, which they measure as the number of all successful US patents filed by a firm in a given year. They argue that the patenting output depends not only on a firm's research and development (R&D) investment, but also on a firm's patent-related legal expertise. Somaya et al. (2007) use the total number of US patent attorneys and agents working for a company in any given year as a proxy for patent expertise, and they find that it has a positive and statistically significant effect on patenting performance in all of their models. Frietsch and Neufausler (2019) use a sample of 1.8 million European Patent Office (EPO) patent applications to study patent representatives' impact on the patent application process. They measure the process experience of patent representatives as a rolling number of total EPO patent applications filed by an attorney. They update their measure on a yearly basis. Frietsch and Neufausler (2019) find that patent attorneys that represent individual inventors are less experienced than the ones representing large companies, and that patents represented by experienced attorneys have a lower probability of being opposed at the EPO after grant. In addition, they find no effect of patent attorney process experience on the likelihood of patent grant. This is at odds with de Rassenfosse et al. (2019) who find evidence that a one standard deviation increase in patent attorney quality is associated with a 2% increase in the probability of a grant. The different findings might be explained by the fact that de Rassenfosse et al. (2019) used a sample of 1.2 million international patent applications instead of the 1.8 million EPO patent applications. Moreover, they measured patent

attorney capability using the conditional average patent grant success rate of each representative instead of the number of patent applications filed by an attorney.

The analysis presented in this chapter differs from these studies in three main ways. First, I focus on how valuable patent attorney capability is to public companies by testing its effect on the economic and technological value of patents owned by the firms. Second, I draw on the *attorney capability theory* and I distinguish between the substantive expertise and the process experience of patent attorneys. Lastly, I measure patent attorney capability using data on millions of US patent applications represented by different attorneys (see section 3.3.2). Arguably, the larger amount of data relative to the prior literature increases the power of the analysis.

3.3. Data and descriptive statistics

3.3.1 Data selection

I use the 2020 release of the USPTO's Patent Examination Research Dataset (PatEx). The dataset includes detailed information on 9.6 million utility³⁰ patent applications filed at the USPTO until 8 April 2021. This includes information on application number, application type, application filing date, and patent grant number along with its issue date (if the patent application was successful and it led to a grant of a patent). The primary advantage of using the PatEx dataset is that it also contains data on the patent applications' examination history, which includes the names and locations of patent attorneys or patent law firms representing the applications.

This type of data is only available for patent applications that are open to public inspection, and it does not cover non-public patent applications (Graham et al., 2015).

³⁰ Utility patents cover technological inventions (Durham, 2009). Over 90% of patents issued by the USPTO in 2019 were utility patents. The two other types of patents are design and plant patents. Design patents protect new and original artistic representations (Durham, 2009). Plant patents can be obtained on plants that are reproduced asexually.

The implementation of the American Inventors Protection Act (AIPA) on 29 November 2000 largely eliminated the selection bias in the dataset by requiring all patent applications to be published by default, 18 months after they were filed (Graham et al., 2015). Therefore, I restrict my sample to applications with a non-missing filing date that were filed from 2001 onwards (Farre-Mensa et al. 2020; Hegde et al., 2020). This reduces the sample to 6.9 million patent applications. To study the market reaction, I keep applications that were successful and resulted in granted patents (4.3 million utility patents). I remove patents granted after 2019, due to the exceptional market circumstances created by the outbreak of COVID-19, which leaves me with 3.9 million patents.

The market reaction to patent grants can only be measured for patents which belong to publicly listed companies. To identify these firms, I use the patent-CRSP link created by Stoffman et al. (2021), who match companies in CRSP to patents granted by the USPTO until 31 December 2020. I successfully match 1.5 million patents to publicly listed firms. I obtain security return data from CRSP and accounting data from Compustat. I remove observations with missing stock return or accounting data, and I exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4949) (Kogan et al., 2017; Stoffman et al., 2021). This leaves 1.47 million patents.³¹ I obtain data on patent characteristics, including citations and claims from USPTO PatentsView (Stoffman et al., 2021).

For each company in the sample, I obtain earnings announcement dates from CRSP and dividend declaration dates from Compustat. In order to avoid contamination of the

³¹ The sample size is similar to prior literature using US patent data. For example, Chemmanur et al. (2021) study a sample of 0.9 million US patents granted between 2000 and 2014. Kogan et al. (2017) use 1.8m patent grants between 1926 and 2010.

patent events by other closely occurring events, I remove patent announcements which occur within two trading days of a firm's earnings or dividend announcements (Bowman, 1983; de Jong and Naumovska, 2016), resulting in 1.3 million patents granted to 3,461 firms during 2003-2019. This sample is used for conducting the event study of patent grants (section 3.4.1) and for testing the importance of patent attorney capability (sections 3.4.2-3.4.6). The sample selection process is presented in Table 3-1.

/Table 3-1 here/

3.3.2 Measures of patent attorney capability: process experience and substantive expertise

I capture substantive expertise of patent attorneys with their rolling grant success rate. The success rate is calculated as the number of successful patent applications divided by the sum of successful and abandoned applications represented by an attorney. I update this measure on a yearly rolling basis. Measuring patent attorney substantive expertise using their success rate captures how effective they are at obtaining patents for their clients. A rational individual will abandon a patent application when the costs of patent protection outweigh the potential benefits (Bessen, 2008; Lemley and Sampat, 2008). For example, a patent applicant might abandon an application when a patent examiner is only willing to allow the application if the patent applicant agrees to significantly narrow the claims (Lichtman et al., 2004). This, in turn, can deem the application as no longer worthy of being pursued.

Process experience is proxied by the cumulative number of patent applications (successful and unsuccessful) filed by patent attorneys. I use the natural logarithm of this number to account for the fact that filing of each additional patent application can have a plausibly decreasing marginal effect on process experience (Frietsch and

Neuhausler, 2019). I update this measure on a yearly rolling basis to include the filing of new patent applications.

I construct the process experience and substantive expertise measures using data on all patent applications in the PatEx dataset, which includes patents filed by individual inventors, private firms, and public companies. I use all patent applications that were filed since 1980 in order to account for the fact that some patent attorneys have been gaining experience before the implementation of AIPA. Alternatively, I construct the measures using 29 November 2000 as the starting point for robustness.

I use the name of the entity with whom the USPTO is meant to correspond about the patent application to identify the patent attorneys.³² Entities identified as patent attorneys include patent attorney firms, individual patent attorneys, and legal departments of companies. I clean the misspellings of patent attorneys' names in the PatEx dataset before constructing the measures. The steps of the cleaning process are described in Appendix 3-A. Table 3-2 presents the list of top 25 patent attorneys according to the total number of patent applications they filed between 1980 and 2019. Table 3-2 also illustrates the total success rate of each attorney during the period, and it shows that even among the most popular patent attorneys the success rate varies from 68% to 90%.

/Table 3-2 here/

3.3.3 Descriptive statistics

Table 3-3 shows the descriptive statistics, which are presented on a patent announcement day level.³³ All variables are defined in Appendix 3-B. Panel A

³² I use the "correspondence name" variable from the PatEx dataset (Graham et al., 2015).

³³ New patents are announced by the USPTO every Tuesday. The USPTO can announce a grant of multiple patents to the same company on the same day, but since I observe one market reaction per announcement day, I treat each announcement as one observation.

illustrates the characteristics of 3,461 publicly listed firms which obtained 1.3 million patents during 2003-2019. The average company has a market capitalisation of \$27.7 billion, and the median company has a market capitalisation of \$5.4 billion. With a debt to assets ratio of 0.52, the average company in the sample is highly leveraged in comparison to the average nonfinancial corporation headquartered in the US (Palazzo and Yang, 2019). The average firm in the sample has an R&D intensity of 9.3%. This is more than double the average R&D intensity of a typical US company of 4.1% (Wolfe, 2020). The characteristics of the patents granted to the companies are shown in Panel B. The average patent in the sample has a truncation adjusted amount of forward citations of 1.1.³⁴ Moreover, the average patent contains 29.6 backward citations, and 1.0 independent claims.³⁵ The descriptive statistics of the measures of patent attorney capability are presented in Panel C. The average rolling success rate is 83.8%, with a standard deviation of 11.6%.³⁶ This is similar to Gaudry (2012), who reports that 65.2% of patent applications represented by patent attorneys are successful, compared to 23.6% of applications represented by the inventors themselves. Lastly, 4.6% of patent announcements include a patent attorney firm which is ranked as a tier one firm by Legal500. Moreover, 18.9% of the announcements include a patent attorney firm that is listed in any of the five tiers in the Legal500 rankings (see section 3.4.6 for more details on the Legal 500 rankings).

/Table 3-3 here/

³⁴ When counting the number of citations, I exclude citations that originated from patent examiners and citations by other patents of the same patent owner.

³⁵ Independent claims are complete sentences that stand on their own, without referring to other claims (Marco et al. 2019). Dependent claims refer to an independent claim and add a limitation to it.

³⁶ Given that the distribution of rolling success rate is skewed, I have rerun the analysis using a log-transformed rolling success rate. The results are similar.

Appendix 3-C presents a breakdown of the sample by year of patent grant along with the number of unique companies that obtained patents that year. The yearly number of patent grants increases from 33,983 in 2003 to 106,271 in 2019. Appendix 3-D shows the top 25 firms by the number of patents obtained between 2003 and 2019. The top 25 patent owners are responsible for 42% of the patent grants.

Appendix 3-E provides the sample statistics by industry. The top 5 industries, based on the Fama French 48 industry classification, are Electronic Equipment, Computer Software, Computer Hardware, Automobiles and Trucks, and Electrical Equipment, and they collectively account for 61% of patent grants. Lemley and Sampat (2008) report that the information technology industries are responsible for half of all patent applications. Building patent portfolios is important to technology companies (Burk and Lemley, 2009), because it can take multiple patents to protect a complex invention. This leads to fragmentation of patent rights. Ziedonis (2004) shows that semiconductor firms patent aggressively to secure the right to invest in new technologies and avoid being “fenced in” by other patent owners.

3.4. Methodology, analysis, and results

3.4.1 Event study of patent grants

I begin by using a standard event study approach to measure the market valuation of patent announcements. I estimate abnormal returns (ARs) based on the difference between the security’s return and the return on the market portfolio:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{3.1}$$

where $AR_{i,t}$ is the abnormal return of a security i on day t , and $R_{i,t}$ is the actual return of a security i on day t . $R_{m,t}$ is the risk-free rate adjusted market return on day

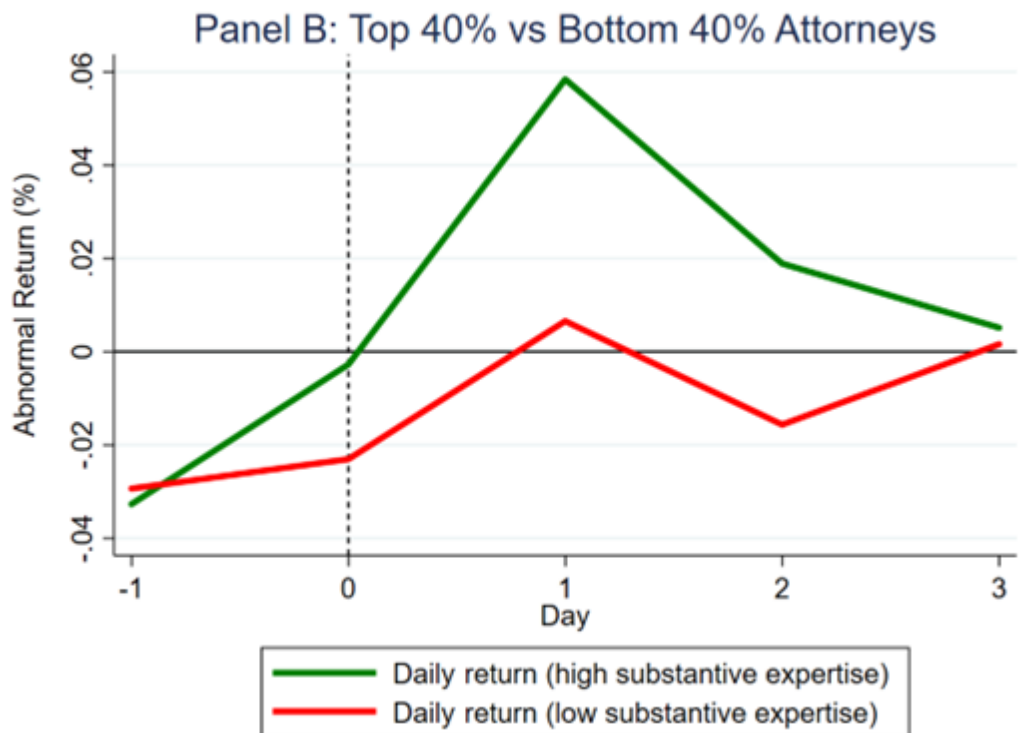
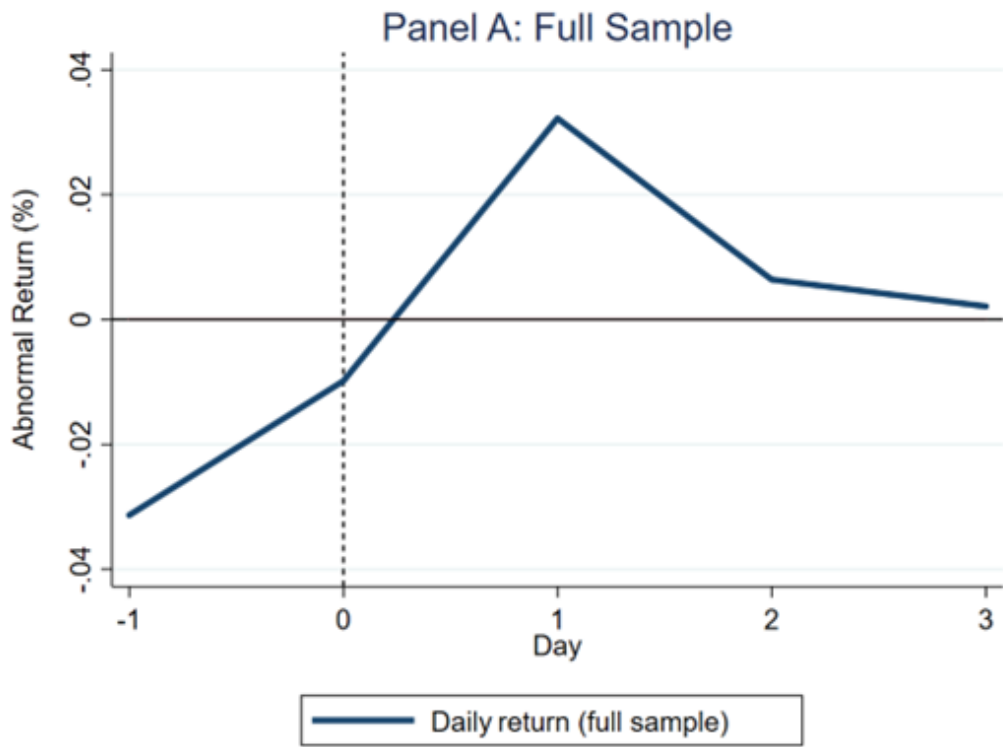
t.³⁷ As many companies in the sample obtain patents every month or even every week, I use the market adjusted model in equation (3.1), similar to Kogan et al. (2017).³⁸ This approach mitigates the potential measurement error that is introduced when estimating a company's stock market beta by using asset pricing models that rely on non-overlapping pre-event estimation periods (Brown and Warner, 1985; MacKinlay, 1997).

Panel A of Figure 3-1 illustrates the abnormal returns around the patent announcement. The daily abnormal return sharply increases on day 1, which suggests a delayed market response to patent announcements. In Panel B of Figure 3-1, I distinguish between the market reaction to patents represented by more capable versus less capable patent attorneys. I define patent attorneys as more (less) capable when their rolling success rate is in the top (bottom) 40% of the distribution. The graphs suggest that patents represented by patent attorneys with high substantive expertise experience a more favourable stock market reaction than patents represented by attorneys with low substantive expertise. When I define more (less) capable patent attorneys based on the total number of patent applications that they have filed, I see no difference in the share price reactions. This suggests that process experience of patent attorneys does not matter.

Figure 3-1: Market Reaction to Patent Announcements

³⁷ The risk-free rate adjusted market return for North America is from Kenneth French's website.

³⁸ New patents are published by the USPTO every Tuesday. This is the first time that newly granted patents are announced by the patent office (Kogan et al., 2017).



I measure the patent announcement returns over a three-day event window (0,+2) as in Kogan et al. (2017).³⁹ For robustness, I also measure the market response over alternative event windows and the results are similar. Table 3-4 shows the daily abnormal returns between day 0 and day +3 and the cumulative abnormal returns over the (0,+1), (0,+2), and (0,+3) event windows. Panel A shows that the market reacts positively to patent announcements. An average patent announcement has a CAR(0,+2) of 0.029%,⁴⁰ which is statistically significant at the 1% level. This is also economically significant. The mean market capitalisation in the sample at the time of an average patent announcement is \$27.7 billion (see Table 3-3). Given an average CAR(0,+2) of 0.029%, the mean patent announcement is associated with an increase in market value of \$8.0 million (=0.029%*\$27.7 bn).⁴¹ This is similar to Kogan et al. (2017), who find that a median patent owned by a publicly listed company is worth \$3m, and an average patent is valued at \$10.3m. The results are also similar to Gambardella et al. (2008) and Hirschey and Richardson (2001) who find a mean patent value of €3.0m and \$3.1m, respectively. The results are also quantitatively similar to those of Chemmanur et al. (2021), who report a market reaction of 0.010% based on 879,204 patent announcements.

/Table 3-4 here/

³⁹ The share turnover increases during the (0,+2) window around a patent announcement, which suggests that this is when the market reacts to the announcement (Kogan et al., 2017).

⁴⁰ It is worth noting that while the average patent announcement is valuable, the median announcement will not necessarily produce a significant market reaction. The distribution of patent values is known to be right skewed, and it is possible that a small number of valuable patents are pushing up the value of an average patent announcement (Schankerman and Pakes, 1986; Hall et al., 2005; Kogan et al., 2017). To address the risk of outliers, I use CARs(0,2) that are winsorized at the 1% and 99% levels throughout the analysis.

⁴¹ The average patent announcement value of \$8m may seem small when compared with the average market value of \$27.7bn. However, the value of patents to a firm accumulates with each additional patent announcement. For example, IBM earned almost \$1bn from licensing out its patent portfolio in 2007 alone (Galasso and Schankerman, 2010).

In panels B and C of Table 3-4, I distinguish between patent announcements associated with attorneys that have high and low substantive expertise, respectively.⁴² Panel B of Table 3-4 shows that attorneys with high substantive expertise are associated with a CAR(0,+2) of 0.074%, which is statistically significant at the 1% level. In contrast, panel C of Table 3-4 shows that announcements associated with attorneys with low substantive expertise generate a CAR(0,+2) of -0.032%, significant at the 1% level. This suggests that using the services of high-substantive-expertise patent attorneys can increase the market valuation of patent announcements.

3.4.2 The effect of patent attorney capability on the economic value of patents

Next, to explore the relationship between patent attorney capability and the value of patents in more detail, I conduct a multivariate OLS regression analysis. I estimate the following model:

$$CAR_{i,t} = \alpha + \beta_1 * patent\ attorney\ capability_{i,t} + \beta_2 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (3.2)$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2).⁴³ The independent variable of interest is *patent attorney capability*, which is a proxy for a patent attorney's level of competence. I include *patent grants volume* to control for the number of patents granted on the same day to the same firm since the market can react more positively to announcements of multiple patents. $X_{i,t-1}$ is a vector of firm specific control variables that includes *market capitalisation*, as larger firms may create more valuable innovation (Kogan et al., 2017); *firm age*, as younger firms can produce higher quality innovation (Balasubramanian and Lee, 2008), *return on assets*,

⁴² I define the substantive expertise to be high (low) when the attorneys' rolling success rate is in the top (bottom) 40% of the distribution. The results are similar if I use the top (bottom) 10% or 25% of the distribution as the cut-off point.

⁴³ In alternative specifications I use alternative event windows, and the results remain similar.

as profitability is positively associated with patent quality (Pandit et al., 2011); *leverage*, as debt levels can impact firm innovation (Geelen et al., 2021) and *R&D*, as companies that invest more in R&D can be better innovators (Chen et al., 2018).⁴⁴ γ , ξ , and ψ denote year, firm, and patent technology class fixed effects⁴⁵, respectively. I include patent technology class fixed effects because the value of patents can differ depending on the underlying technologies (Bessen, 2008), and to control for the fact that patent approval rates may vary across different technology fields (Carley et al., 2015; Hall et al., 2001).⁴⁶ The identifying assumption is that after controlling for the variables listed above, patent attorney capability is exogenous. I do not use patent attorney fixed effects, because I am interested in studying the cross-sectional patent attorney-level variation in the analysis. Moreover, patent attorney fixed effects would be collinear with the main explanatory variable, rolling success rate, which captures patent attorney capability.

First, I use the rolling success rate of a patent attorney as a proxy for their substantive expertise (see section 3.3.2 for more details). Regression results are shown in Table 3-5. In column (1), I regress $CAR(0,+2)$ solely on the rolling success rate, and I include year, firm, and patent class fixed effects. *Ceteris paribus*, the positive and statistically significant coefficient (at the 1% level) on the rolling success rate indicates that the market valuation of a patent increases by 0.30% when the rolling success rate increases by 100%. The standard deviation of the rolling success rate is 11.6% (see

⁴⁴ I replace missing R&D values with zeros as argued for by Koh and Reeb (2015). The results are similar regardless of whether or not missing R&D values are replaced with zeros.

⁴⁵ I also test different combinations of fixed effects, including industry, art unit, and examiner fixed effects. The results remain robust to the choice of fixed effects.

⁴⁶ If multiple patents are granted to the same firm on the same day, I use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way I compute the fixed effects. Moreover, the results are similar when I do not include patent class fixed effects in the model.

Table 3-3). Therefore, a one-standard deviation increase in rolling success rate increases the market valuation by 0.035% ($=11.6\%*0.30\%$). This is economically significant. The average company in the sample had 64 patent announcements between 2003-2019 (see Appendix 3-C). Hiring a competent law firm or a patent attorney to represent a firm's patent applications can increase the market value of an average company in the sample by 2.24% ($=64*0.035\%$).

/Table 3-5 here/

Columns (2) and (3) in Table 3-5 add control variables and the main result remains unchanged. The coefficients on the control variables indicate that firm size and firm age negatively predicts the market reaction to patent grants, which is consistent with the results reported in prior literature (Chemmanur et al., 2021; Chen et al., 2018). Overall, the results support the first hypothesis (*H3-1a*). Although the R^2 is low, ranging from 2.8% to 2.9%, it is consistent with the literature on patent announcements (Boscaljon et al. 2006; Chen et al., 2018; Chemmanur et al., 2021).

Second, I proxy for patent attorney process experience using the number of patent applications that they have previously represented before the USPTO (see section 3.3.2 for more details). I present the regression results in Table 3-6. The results show that across specifications, the number of applications filed to date do not have a statistically significant effect on the market valuation of patents. Similar to the results presented in Table 3-5, firm size and firm age are negatively correlated with the market reaction to patent grants. This finding suggests that patent attorneys do not gain valuable process experience by simply submitting more patent applications to the USPTO, and the busiest patent attorneys are not necessarily the most capable. Therefore, the results do not support hypothesis *H3-1b*.

3.4.3 The effect of patent attorney capability on the technological value of patents

Next, I explore whether the substantive expertise of a patent attorney, as measured by their rolling success rate, affects the number of citations that a patent receives. Patent citations are widely used as a proxy for patent quality (Hirschey and Richardson, 2004; Trajtenberg, 1990). Since patent attorneys influence the scope and validity of patents, I predict that the effect of patent attorney substantive expertise will be reflected in the number of citations received by a patent. To test this, I estimate the following model:

$$\begin{aligned}
 \text{Patent citations}_i = & \alpha + \beta_1 * \text{patent attorney expertise}_{i,t} + \beta_2 * \\
 & \ln(\text{market capitalisation})_{i,t-1} + \beta_3 * \text{backward citations}_i + \beta_4 * \\
 & \text{independent claims}_i + \gamma + \xi + \psi + u_{i,t}
 \end{aligned} \tag{3.3}$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent.⁴⁷ Using truncation-adjusted number of citations addresses the issue of older patents having had more time to accumulate citations than younger patents (Hall et al., 2001). Moreover, when counting citations, I exclude any citations that a patent receives from patent examiners and any citations it receives from the patent applicants themselves, because these citations are unlikely to reflect the technological value of a patent (Alcácer et al., 2009). The independent variable of interest is patent attorney's substantive expertise, which I first proxy for using a patent

⁴⁷ I calculate the truncation-adjusted patent citations by dividing the number of citations received by a patent by the number of citations received by an average patent granted in the same year. For example, if a patent that was granted in 2005 has received 6 citations so far, and the average patent granted in 2005 has so far received only 3 citations, the focal patent's truncation-adjusted number of citations is equal to 2 (=6/3). This indicates that the patent received twice as many citations as the average comparable patent. By eliminating the patent grant time effect, truncation-adjusted patent citations enable citation-based comparisons of patents granted at different points in time.

attorney's rolling success rate. The controls include *market capitalisation*, which is a proxy for company size (Kogan et al., 2017) and patent quality control variables, which include *backward citations* and *independent claims*.⁴⁸ Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects,⁴⁹ respectively.

First, I study the relation between the number of patent citations and patent attorney substantive expertise. The regression results are shown in Table 3-7. In column (1) of Table 3-7, I regress *patent citations* on the rolling success rate in isolation and I include year, firm, and patent class fixed effects. The results suggest that patent attorney substantive expertise is a statistically significant predictor of the technological value of patents, at the 1% level. A one standard deviation increase in the rolling success rate is associated with 0.032 (=11.6%*0.28) more truncation-adjusted patent citations. Given that the mean value of truncation adjusted citations is 1.1 (see Table 3-3), a one standard deviation higher rolling success rate increases citations by 3% (=0.032/1.1). Therefore, patent attorneys with a higher degree of substantive expertise are positively related to higher technological value of patents, which supports the second hypothesis (*H3-2a*). I add control variables in columns (2) and (3) in Table 3-7 and rolling success rate remains a positive and statistically significant predictor of patent citations, at the 1% level. The coefficients on the control variables indicate that firm size is negatively correlated with the number of citations received by patents, which is consistent with prior literature (Plehn-Dujowich, 2009).

/Table 3-7 here/

⁴⁸ *Independent claims* is a proxy for patent scope, which affects patent quality (Marco et al., 2019). Backward citations are correlated with patent importance (Jaffe and de Rassenfosse, 2019).

⁴⁹ The results remain robust to the choice of different fixed effects, including industry, art unit, and examiner fixed effects.

Second, I measure patent attorney process experience using the number of patent applications handled by a patent attorney. I present the results in Appendix 3-F, where I regress *patent citations* on the number of applications filed. The results suggest that the number of patent applications filed is statistically negatively associated with the technological value of patents, at the 5% level. A 20% increase in applications filed is associated with 0.002 (20%*0.01) lower number of truncation-adjusted citations. While the evidence of a negative correlation is surprising, the size of the effect is very close to zero. Therefore, I find no support for hypothesis *H3-2b*.

3.4.4 The effect of the openings of new USPTO offices on the economic and technological value of patents

Companies may choose to hire patent attorneys with higher capability to represent patent applications that are more valuable to them (de Rassenfosse et al., 2023). To address this potential selection issue, I exploit the effect of new openings of USPTO offices on the performance of patent attorneys. The USPTO is headquartered in the state of Virginia, which has been its only location for most of its history. This changed in July 2012, when the USPTO opened its first regional office in Detroit, Michigan. Not long after, the USPTO opened three additional regional offices. The second regional office opened in Denver, Colorado in June 2014. The third and the fourth regional offices opened in San Jose, California in October 2015, and in Dallas, Texas in November 2015 (USPTO, 2022).

I argue that the patent attorneys located in the states in which new USPTO offices have been opened should benefit from increased performance compared to patent attorneys located in other states. The opening of the new offices affects the work of patent attorneys by making it easier for them to negotiate with patent examiners (as discussed below), but the new offices do not directly impact the value of the patents.

Instead, new offices can have an indirect influence on the value of patents through their effect on the work of patent attorneys. Therefore, exploring this shock helps me to address the endogeneity concern that the effect of patent attorney substantive expertise on patents is a result of the potential non-random matching between patent attorneys and patents.

The job of a patent attorney requires negotiating the scope and the grant of patent rights with patent examiners (Gaudry, 2012; Lu et al., 2017). To facilitate the process, patent attorneys can request an in-person interview with a patent examiner at a patent office. Interviews can be an effective way to overcome examiners' objections about a patent application (Lemley and Sampat, 2010). Also, in contrast to written correspondence, the interviews are not recorded, which allows the patent attorneys to discuss the invention without creating a permanent record that could become a hinderance in any future patent litigation (Lemley and Sampat, 2010). Since negotiation is a skill, more capable patent attorneys should benefit more from the opening of the new regional offices.

First, to validate the shock, I examine whether the openings of new USPTO offices affected the performance of patent attorneys. I estimate the following model:

$$\begin{aligned}
 & \textit{rolling success rate}_{i,t} \\
 & = \alpha + \beta_1 * \textit{new offices} + \beta_2 * \textit{patent grants volume}_{i,t} + \beta_n \\
 & * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t}
 \end{aligned} \tag{3.4}$$

*Rolling success rate*_{*i,t*} is a proxy for patent attorney substantive expertise. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in

states in which the USPTO opened a new regional office, and 0 otherwise.⁵⁰ Control variables include *patent grants volume*, *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively.⁵¹

The regression results are presented in Table 3-8. In column (1) of Table 3-8 I regress the *rolling success rate* solely on *new offices*, and I include firm, year, and patent class fixed effects. The coefficient on *new offices* is 0.9%, which is statistically significant at the 5% level. Therefore, the opening of new USPTO offices increased the rolling success rate of patent attorneys located in the affected states by 0.9%. The results remain similar and significant at the 10% level after adding control variables in columns (2) and (3) of Table 3-8. In terms of the control variables, the positive and statistically significant coefficient (at the 1% level) on the market capitalisation variable suggests that patent attorneys working for larger firms are on average more successful. Similarly, the positive and statistically significant coefficient (at the 5% level) on the R&D intensity variable suggests that patent attorneys employed by firms with a higher focus on R&D are more successful. This is intuitive, as larger firms can have more resources available to hire more successful patent attorneys.

/Table 3-8 here/

Second, I test the effect of the openings of the new USPTO offices on the economic value of patents. I estimate the following model:

⁵⁰ A comparison of the descriptive statistics of the treatment and control groups is shown in Appendix 3-G. The characteristics of the two groups are similar. For instance, the average return on assets in the treatment (control) group is 8.5% (8.2%). Similarly, the average R&D intensity in the treatment (control) group is 10.2% (9.2%). Importantly, the average success rates of the patent attorneys associated with the treatment and control groups are very similar at 83.8% and 83.0%, respectively.

⁵¹ If multiple patents are granted to the same firm on the same day, I use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way I compute the fixed effects. Moreover, the results are similar when I do not include patent class fixed effects in the model.

$$\begin{aligned}
CAR_{i,t} = & \alpha + \beta_1 * \text{rolling success rate}_{i,t} + \beta_2 * \text{new offices} + \beta_3 \\
& * \text{new offices} \times \text{rolling success rate}_{i,t} + \beta_4 \\
& * \text{patent grants volume}_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t}
\end{aligned}
\tag{3.5}$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2).⁵² *Rolling success rate* is a proxy for patent attorney substantive expertise. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise. Control variables include *patent grants volume*, *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively.⁵³

The regression results are shown in Table 3-9. Column (1) of Table 3-9 includes only the rolling success rate, which has a positive and statistically significant (at the 1% level) coefficient of 0.30%, as previously shown in Table 3-5. Column (2) of Table 3-9 includes only the *new offices* dummy variable. The variable's coefficient is not statistically significant, which suggests that the opening of new offices did not have any effect on the economic value of patents represented by patent attorneys if their substantive expertise is ignored.⁵⁴ Column (3) of Table 3-9 interacts *rolling success rate* with *new offices*. The interaction term is positive and statistically significant at the 5% level. This suggests that the impact of the substantive expertise on the economic value of patents increased for patent attorneys located in the states in which

⁵² In alternative specifications I use alternative event windows and my results remain similar.

⁵³ If multiple patents are granted to the same firm on the same day, I use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way I compute the fixed effects. Moreover, the results are similar when I do not include patent class fixed effects in the model.

⁵⁴ This is beneficial because it provides support for the exogeneity assumption that the treatment (new offices) is unrelated to the outcome of interest (economic value of patents).

the USPTO opened a new office. While the openings of new offices did not impact the economic value of patents on their own (see Column (2) of Table 3-9), they increased the influence of patent attorneys' substantive expertise on patents, as evidenced by the statistically significant interaction term (Columns 3 to 5 of Table 3-9). Therefore, it is the substantive expertise of a patent attorney that determines the degree to which she benefits from the opening of the new offices. Attorneys with higher (lower) substantive expertise benefit more (less) from the opening of the new offices. The new offices made it easier for attorneys to access and negotiate with examiners. This increased the effect of substantive expertise on patents since substantive expertise is important for forming convincing legal arguments (Haire et al., 1999, Posner and Yoon, 2011).. The findings show that higher patent attorney substantive expertise increases the economic value of patents. Columns (4) and (5) add control variables, and the result remains statistically significant at the 5% level.

/Table 3-9 here/

I want to ensure that any impact of the new offices on the economic value of patents is driven by the impact of the new offices on the patent attorneys and not by its impact on firms. Therefore, I rerun model (3.5) using a dummy variable *new offices (firm location)*, which is equal to 1 for patents filed by firms located in the affected states, and 0 otherwise. This approach can help alleviate concerns that the opening of new USPTO offices may have impacted the firms located in the affected states and the patents of these firms, and have not necessarily affected the patent attorneys located in the affected states. The regression results are shown in Appendix 3-H. Column (3) of the table in Appendix 3-H interacts *new offices (firm location)* with *rolling success rate*. The interaction is not statistically significant, which suggests that patents filed by

firms located in the states with the new USPTO offices were not affected by the change. This suggests that the opening of new USPTO offices helped successful patent attorneys negotiate the grant of patents with higher economic value.

Third, I study the impact of the opening of the new offices on the technological value of patents. I estimate the following model:

$$\begin{aligned}
 \text{Patent citations}_i = & \alpha + \beta_1 * \text{rolling success rate}_{i,t} + \beta_2 * \text{new offices} + \\
 & \beta_3 * \text{new offices} \times \text{rolling success rate}_{i,t} + \beta_4 * \\
 & \text{market capitalisation}_{i,t-1} + \beta_5 * \text{backward citations}_i + \beta_6 * \\
 & \text{independent claims}_i + \gamma + \xi + \psi + u_{i,t}
 \end{aligned} \tag{3.6}$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent that excludes examiner and self-citations. The independent variable of interest is *rolling success rate*. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise. The control variables include *market capitalisation*, *backward citations* and *independent claims*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects⁵⁵, respectively.

The regression results are shown in Table 3-10. Column (3) of Table 3-10 interacts *rolling success rate* with *new offices*. The coefficient on the interaction term is not statistically significant, which suggests that the impact of patent attorney substantive expertise on the technological value of patents was not affected by the opening of new USPTO offices. This is not a surprising result. The main benefit to patent attorneys from the opening of the new offices is the fact that they have an easier access to the

⁵⁵ The results remain robust to the choice of different fixed effects, including industry, art unit, and examiner fixed effects.

patent examiners with whom they can conduct in-person interviews when negotiating the grant of a patent. These negotiations occur at an advanced stage of the patent examination process, after a patent attorney has already finished writing a patent application and sent it to the patent office. Therefore, the technological specification and the contents of a patent application have already been largely determined (Lemley and Sampat, 2012). This likely limits the extent to which a better access to an examiner affects the number of citations received by a patent.

/Table 3-10 here/

3.4.5 The impact of a patent attorney change on the economic and technological value of patents

In this section, I investigate whether a change of a company's patent attorney affects the economic and technological value of patents. Firms may decide to change their patent attorneys for a variety of reasons. First, a conflict of interest may have arisen between a company and its patent attorney if the attorney starts representing patent applications of a rival company (Becker, 1996). Second, a company may switch its patent attorney if it is not satisfied with the attorney's performance, for example if the attorney has been negligent towards the company's patents (Oddi, 2004). Third, a company may have found a different patent attorney who is believed to be more suitable for working on the firm's technology and patents (Chondrakis et al., 2021). Lastly, a firm may approach a new patent attorney because the current attorney may be simply too busy to take on additional patent applications. Insufficient time spent on a patent application can lead to lower patent quality (Frakes and Wasserman, 2017). It is challenging to know for certain why firms change their patent attorneys since patent applicants are not required to disclose this information (Graham et al., 2015).

I test whether the differences between the economic and technological value of patents that were consecutively granted to the same company can be explained by the fact that a different patent attorney or a different patent attorney law firm was employed by the company. This approach helps isolate the effect of a patent attorney on patent value, because I focus on patents obtained by the same firms in a close time proximity. These patents are likely to be more similar than patents that were secured by a company with a significant time delay. Given that the state of technology can rapidly evolve (Taub et al., 2007; Ebert, 2018), a patent granted to a computer hardware company in 2006 may protect a different technology than one granted to the same company in 2007.

First, I study the effect of patent attorney change on the economic value of patents.

I use the following model:

$$\Delta CAR_{i,t} = \alpha + \beta_1 * \text{better/worse patent attorney}_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (3.7)$$

$\Delta CAR_{i,t}$ is the difference between the market valuation of an announcement of a single patent and the market reaction to the preceding announcement of a single patent that was granted to the same company.⁵⁶ Restricting the analysis to single patent grants ensures that I am comparing similar patent announcements. Including grants of multiple patents would confound the analysis, because multiple patents granted on the same day to the same company share a single market valuation, but they can be associated with different patent attorneys. The independent variable of interest is *better/worse patent attorney*, which is a dummy variable equal to 1 if the same

⁵⁶ The sample size decreases to 102,605, because I only keep announcements of single patents to the same company.

company changed to a different patent attorney with a higher/lower rolling success rate than the previous attorney, and 0 otherwise. $X_{i,t-1}$ is a vector of firm specific control variables, which includes *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively.

The results in Table 3-11 show that the coefficient on *better patent attorney* is positive and statistically significant at the 10% level. The results suggest that the market valuation of a patent increases by 0.08% when a company switches to a more capable patent attorney. Although seemingly a small effect, it has a considerable effect since it can accumulate with each additional patent represented by the more capable patent attorney. For example, the increase in shareholder wealth can add up to 5.1% (=64*0.08%) for an average company in the sample with 64 patent announcements between 2003-2019.⁵⁷ In panel B of Table 3-11, I regress $\Delta CAR_{i,t}$ on *worse patent attorney* and I find consistent evidence. Changing to a less capable patent attorney is associated with a 0.08% lower shareholder wealth, which is significant at the 10% level. In panel C of Table 3-11, I test whether the effect is larger when the capability difference between the new and the old patent attorney widens. I calculate *difference in capability* by subtracting the rolling success rate of a new patent attorney from the rolling success rate of the previous patent attorney. I use *difference in capability* as the new independent variable of interest in equation (3.7). The coefficient on difference in capability is equal to 0.37%, which is statistically significant at the 5% level. Therefore, a 1% increase in *difference in capability* is associated with a 0.004% (0.37%

⁵⁷ While firms may not switch their patent attorney with every new patent announcement, the benefits of switching to a better patent attorney and sticking with the change will have a positive effect on any subsequent patents since they are now represented by a more capable attorney.

/ 100) higher market valuation, and a patent attorney that is one standard deviation more capable increases shareholder wealth by 0.046% (=11.6*0.004%).

/Table 3-11 here/

Next, I study the effect of patent attorney change on the technological value of patents. I use the following model:

$$\begin{aligned} \Delta \text{ patent citations}_i = & \alpha + \beta_1 * \text{ better/worse patent attorney}_{i,t} + \beta_2 * \\ & \text{ market capitalization}_{i,t-1} + \beta_3 * \text{ backward citations}_i + \beta_4 * \\ & \text{ independent claims}_i + \gamma + \xi + \psi + u_{i,t} \end{aligned} \quad (3.8)$$

$\Delta \text{ patent citations}_i$ is the difference between the truncation-adjusted number of citations received by a single patent granted to a company and the number of citations received by the previous single patent that was granted to the same company. The independent variable of interest is *better/worse patent attorney*, which is a dummy variable equal to 1 if a company changed to an attorney with a higher/lower rolling success rate, and 0 otherwise. I include *market capitalisation* to control for firm size, and *backward citations* and *independent claims* to control for patent quality. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively.

The results in Table 3-12 show that the coefficient on *better patent attorney* is positive and statistically significant at the 1% level. The results suggest that switching to a more capable patent attorney is associated with 0.09 more truncation-adjusted citations received by a patent. Given that the mean amount of truncation adjusted forward citations is 1.1 (see Table 3-3), this represents an increase of 8% (0.09/1.1). Similarly, the results in panel B of Table 3-12 suggest that the opposite is also true, with a change to a less capable patent attorney decreasing the number of truncation adjusted citations by 0.06, significant at the 5% level. Lastly, in panel C, I regress Δ

patent citations; on *difference in capability*, and I find that the strength of this effect increases depending on the difference in capabilities between the old and new patent attorney. Overall, changing to a better (worse) patent attorney is associated with both a higher (lower) economic and technological value of patents.

/Table 3-12 here/

3.4.6 The relation between patent attorney capability and patent attorney rankings

The results so far suggest that attorneys with higher substantive expertise, as measured by their rolling success rate, obtain patents with higher economic and technological value. Moreover, the process experience of patent attorneys does not matter for patents. In this section, I investigate whether successful patent attorneys are recognised in the law firm rankings for their superior performance. If successful patent attorneys are also the highest ranked, then using patent attorney ranking tables can be a quicker way of identifying more capable patent attorneys than calculating their historical success rates.

Legal500 is one of the leading providers of law firms rankings in the US across a broad range of practice areas (Ferrell et al., 2021). The company publishes the rankings based on the information provided by law firms, interviews conducted with the law firms' lawyers, and feedback provided by law firms' clients (Ferrell et al., 2021). The rankings are frequently used in the literature to identify the highest-performing law firms (Segal-Horn and Dean, 2009; Paolella and Durand, 2016; Romano and Sanga, 2017). Moreover, to my best knowledge, Legal500 is the only company that ranks

legal firms in the patent prosecution practice area in the US.⁵⁸ Therefore, I use the Legal500 rankings to identify the top patent attorney firms.

I hand-collect the Legal500 rankings data in the Patent Prosecution category by visiting the historical snapshots of the Legal500 website through the Wayback Machine. The firm started ranking law firms in this category in 2007. Hence, my ranking data covers the period from 2007 to 2019. Every year, Legal500 provides a list of the top patent prosecution firms. The list is divided into five different groups called tiers, with tier one being the highest. Moreover, within tiers, the firms are listed alphabetically. On average, each tier recognises six different law firms, for a total of 30 patent attorney firms ranked every year.

To test whether the patent attorney firms recognised in the rankings are also the most capable, I first calculate the correlation between the substantive expertise and process experience of a patent attorney firm and their Legal500 ranking. Specifically, I define a dummy variable *top tier attorney* which is equal to 1 if a patent attorney firm has been recognised as a tier one firm by the Legal500 and 0 otherwise. For robustness, I also create a dummy variable *any tier attorney*, which is equal to 1 if a patent attorney firm has been listed in any of the five tiers, and 0 otherwise. I drop in-house^{59,60} patent attorneys before calculating the correlations and conducting subsequent analysis

⁵⁸ The main competitors of Legal500 are Chambers and Partners, and The American Lawyer. However, only the Legal500 publishes rankings of patent prosecution firms.

⁵⁹ I identify in-house attorneys based on their name structure, following the literature (Moeen et al., 2013; Chondrakis et al., 2021). For example, names ending in “Associates”, “LLP”, and “Law Firm” are coded as external patent attorneys, while names ending in “Corporation”, “Technologies”, and “Laboratories” are coded as internal patent attorneys (Chondrakis et al., 2021). For robustness, I alternatively identify in-house attorneys as ones that only represented patent applications of a single company in their career, as in de Rassenfosse et al. (2023).

⁶⁰ In-house patent attorneys are likely to have lower process experience than external patent attorneys since in-house attorneys only represent a single company’s patents while external patent attorneys can represent patents for a variety of clients. Regardless, this distinction does not affect the results, which are similar irrespective of whether internal attorneys are included or excluded from the analysis.

because Legal500 only ranks external law firms, as opposed to the internal patent law departments of companies.⁶¹ Not removing the in-house patent attorneys would make it harder to detect the relation between rankings and the patent outcome variables because it is not possible for an in-house patent attorney to be ranked. Nonetheless, the results are not sensitive to how I identify in-house patent attorneys, and they are similar if I keep both in-house and external patent attorneys in the analysis.

The correlations between substantive expertise and the one- and two-year lags of the ranking variables are presented in Table 3-13.⁶² The first row of Table 3-13 shows that there is a negative correlation of -0.05 between the *rolling success rate* and *top tier attorney*, and a negative correlation of -0.08 between the *rolling success rate* and *any tier attorney*. Moreover, the second row of Table 3-13 shows that there is a positive correlation of 0.13 between *applications filed* and *top tier attorney*, and a positive correlation of 0.29 between *applications filed* and *any tier attorney*. The results suggest that the most capable patent attorneys, as measured by their success rate, are not recognised in the rankings. In contrast, the rankings more frequently consist of attorneys with higher process experience, as measured by the number of applications filed. Given that *rolling success rate (applications filed)* is (is not) positively related to the economic and technological value of patents, this suggests that the Legal500 rankings are not a reliable way of identifying the most capable patent attorneys.

/Table 3-13 here/

⁶¹ Companies may use in-house patent attorneys to prepare patent applications and negotiate their grant with patent examiners. Two example of such firms are the IBM Corporation and the Microsoft Corporation (see Table 3-2).

⁶² I lag the ranking variables by one and two years to capture the ranking of a patent attorney as of the patent examination process, which takes on average 3 years. The results are similar if I use the third lag of the ranking variable or if I use the concurrent value.

It is possible that the Legal500 rankings represent a different side of patent attorney capability which is not captured by the rolling success measure. Therefore, I test whether the top ranked patent attorney firms are associated with higher economic and technological value of patents. First, I investigate the relation between rankings and the economic value of patents, and I use the following model:

$$CAR_{i,t} = \alpha + \beta_1 * top\ tier\ attorney_{i,t-1} + \beta_2 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (3.9)$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2). *Top tier attorney* is a dummy variable equal to 1 if a patent attorney firms if a patent announcement includes a patent attorney ranked as tier one, and 0 otherwise.^{63 64} Control variables include *patent grants volume*, *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively. I drop in-house patent attorneys before running the model, but the results are similar if I keep in-house patent attorneys in the analysis.

The results are presented in Table 3-14. In column (1), I regress $CAR(0,+2)$ solely on the *top tier attorney*, and I include year, firm, and patent class fixed effects. The coefficient on the dummy variable is not statistically significant, and it remains not statistically significant after the control variables are added in columns (2) and (3). The results suggest that, compared with the lower-ranked and unranked patent attorneys, tier one patent attorneys do not obtain patents that are more valuable. Moreover, the

⁶³ I use the one year lag of the ranking variable in the model. However, the results are similar if I use a two- or a three- year lag of the variable instead. The results are also similar if I use the concurrent value of the ranking variable or its one-, two-, or three- year forward values.

⁶⁴ The results are similar if I use the dummy variable *any tier attorney* instead. Moreover, the results hold regardless of which lag or forward value of the variable I use.

results are similar if I limit the comparison group to other ranked attorneys only and remove the unranked patent attorneys from the analysis.

/Table 3-14 here/

Next, I explore whether patent attorneys that are recognised in the Legal500 rankings are associated with a higher technological value of patents. I estimate the following model:

$$\begin{aligned}
 \text{Patent citations}_i = & \alpha + \beta_1 * \text{top tier attorney}_{i,t-1} + \beta_2 * \\
 & \ln(\text{market capitalisation})_{i,t-1} + \beta_3 * \text{backward citations}_i + \beta_4 * \\
 & \text{independent claims}_i + \gamma + \xi + \psi + u_{i,t}
 \end{aligned} \tag{3.10}$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent. The independent variable of interest is *top tier attorney*, which is a dummy variable equal to 1 for tier one patent attorney firms, and 0 otherwise.⁶⁵ ⁶⁶ The controls include *market capitalisation*, *backward citations* and *independent claims*. Lastly, γ , ξ , and ψ denote year, firm, and patent technology class fixed effects, respectively. I remove in-house patent attorneys before running the model, but the results are similar if I keep in-house patent attorneys in the analysis.

The regression results are shown in Table 3-15. In column (1) of Table 3-15, I regress *patent citations* on *top tier attorney* in isolation and I include year, firm, and patent class fixed effects. The coefficients on the dummy variable are not statistically significant. This holds regardless of whether or not control variables are included, as shown in columns (2) and (3) of Table 3-15. The results suggest that the top ranked

⁶⁵ I use the one year lag of the ranking variable in the model. However, the results are similar if I use a two- or a three- year lag of the variable instead. The results are also similar if I use the concurrent value of the ranking variable or its one-, two-, or three- year forward values.

⁶⁶ The results are similar if I use the dummy variable *any tier attorney* instead. Moreover, the results hold regardless of which lag or forward value of the variable I use.

patent attorneys are not associated with higher technological value of patents. The results remain similar regardless of whether I compare top ranked attorneys with all other attorneys or if I use only the lower ranked patent attorneys as the comparison group.

/Table 3-15 here/

Overall, I find that rankings of patent attorney firms are not a good predictor of the economic or technological value of patents obtained by the attorneys. Therefore, patent attorney firm rankings do not seem to matter for patent value. The findings are consistent with Hanretty (2016) who finds that having a higher ranked legal representation does not matter for the probability of winning in conventional litigation. The author argues that law firm rankings are not a good measure of attorney skill. The findings are also similar to Griffin et al. (2014) who find that securities produced by high-ranked banks do not perform better than the structured products issued by their less reputable peers. The authors argue that high-ranked underwriters may produce securities of lower quality than other underwriters which is similar to my finding of a negative correlation between rankings and the patent attorney success rate. A higher ranking may help a patent attorney firm attract more clients, as suggested by its positive correlation with number of applications filed, but I find no evidence that higher ranking is associated with better outcomes for the clients.

3.5. Robustness checks

In order to rule out whether the results are driven by the time scale over which I constructed the rolling success measure, I formulate the measure again and this time only using patent applications filed since 2001 instead of 1980. I repeat the same

regressions from Table 3-5.⁶⁷ The results are presented Appendix 3-I. Appendix 3-I shows that the magnitude and the statistical significance of the rolling success rate remains unchanged. I further test the robustness of the measure by constructing it based on the customer id number⁶⁸ of a patent attorney instead of using the string variable containing their name. I obtain the customer id number from the PatEx dataset. I rerun the regressions and present the results in Appendix 3-J. The results remain unchanged. Furthermore, to rule out the possibility that the results are affected by potential differences in patent allowance rates across different technologies, I also construct the rolling success measure while distinguishing between the six main patent technology groups⁶⁹ (Carley et al., 2015). I rerun the regressions and present the results in Appendix 3-K. I find that the results are similar. In addition, I also construct alternative measures of patent attorneys' process experience⁷⁰ and substantive expertise⁷¹ and the results are very similar.

As an additional robustness check, I estimate the dependent variable, CAR (0,+2), using the Fama-French 5 factor model (Fama and French, 2015) instead of the market-adjusted model. I obtain data on the risk-free rate and the five factors in North America from Kenneth French's website. I estimate the α and β coefficients using a 250-day estimation window (with a minimum of 200 valid daily returns) ending 50 days before

⁶⁷ I also repeat the same regressions from Table 3-8, and I obtain similar results.

⁶⁸ Customer id number uniquely identifies the patent attorney who represents the application (Graham et al., 2015). However, the variable has a larger number of missing values than the patent representative name variable. This is reflected by the lower number of observations in the table shown in Appendix 3-J.

⁶⁹ The six main patent technology groups are Chemical, Computers and Communications, Drugs and Medical Devices, Electrical and Electronic, and Mechanical.

⁷⁰ In this study I use the number of patent applications filed by a patent attorney to measure their process experience. I obtain similar results when I use a range of alternative measures of process experience including the number of patents obtained, number of applications filed or patents obtained by patent technology class, and the number of applications filed, or patents obtained by art unit.

⁷¹ I use a patent attorney's rolling success rate to proxy for their substantive expertise. I obtain similar results when I use their total success rate calculated over 1980-2019 instead. I also arrive at similar results when I use a yearly success rate measure.

the respective patent announcement. The main regression results are statistically significant and quantitatively similar and are shown in Appendix 3-L. Similarly, I have also rerun the regression analysis using CARs (0,+2) estimated using the market model and the Fama-French 3-factor model (Fama and French, 1993) and the results remain unchanged.

3.6. Conclusion

I examine the impact of patent attorney capability on both the economic and technological value of patents. I draw on the *attorney capability theory* which distinguishes process experience and substantive expertise of attorneys. According to the *attorney capability theory*, more capable attorneys produce better outcomes. Contrary to the literature on attorney capability (Abrams and Yoon, 2007; McGuire, 1995), I find that patent attorney process experience has no effect on the economic value of patents as captured by the market valuation of patent grants. However, a patent attorney's success rate (substantive expertise) is positively associated with the economic value of patents. This suggests that only successful patent attorneys matter. I also show that higher patent attorney substantive expertise is positively related to the technological value of a patent, as captured by the number of citations received by a patent. Furthermore, the importance of substantive expertise of patent attorneys on the economic value of patents has increased for attorneys located in states in which the USPTO opened new regional offices between 2012 and 2015, which implies an existence of a causal relationship. Moreover, the change did not affect the importance of patent attorney substantive expertise for the technological value of patents. Furthermore, I find evidence suggesting that changing to a better (worse) patent attorney increases (decreases) the economic and the technological value of patents.

Lastly, I show that patent attorney law firm rankings are not positively correlated with patent attorney capability, and that they are not a good predictor of the economic and technological value of patents.

In sum, the implications of the findings are twofold. First, it is the capability of patent attorneys that matters, and not simple process experience. Second, successful patent attorneys have a positive association with both the economic and technological value of a patent. Therefore, companies should pay close attention to the track records of patent attorneys that they consider hiring and pay little attention to patent attorney law firm rankings.

Table 3-1: Sample selection process

All utility patent applications in the PatEx dataset	9,616,956	100%
Applications filed before 2001	-2,738,734	-28.5%
Applications with missing application date	-52,958	-0.6%
Not granted patent applications	-2,483,187	-25.8%
Patents granted after 2019	-442,397	-4.6%
Patents not matched to publicly listed companies	-2,408,825	-25.0%
Patents matched to financial firms	-18,119	-0.2%
Patents matched to utility firms	-622	-0.0%
Missing stock return data	-25,525	-0.3%
Confounded patent announcements	-155,259	-1.6%
Total	1,291,330	13.4%

This table presents a breakdown of the sample selection process.

Table 3-2: Top 25 patent attorney firms by number of patents (2003-2019)

#	Name	Applications filed 1980-2019	Total success 1980-2019 %
1	Oblon McClelland Maier & Neustadt LLP	163,510	79%
2	IBM Corp	101,901	90%
3	Birch Stewart Kolasch & Birch LLP	97,048	75%
4	Sughrue Mion PLLC	91,004	68%
5	Oliff PLC	88,247	81%
6	Nixon & Vanderhye PC	86,629	72%
7	Knobbe Martens Olson & Bear LLP	77,414	70%
8	Foley & Lardner LLP	76,866	74%
9	Venable LLP	76,670	88%
10	Finnegan Henderson Farabow Garrett & Dunner LLP	67,514	72%
11	Microsoft Corp	59,560	80%
12	McDermott Will & Emery LLP	50,704	76%
13	Buchanan Ingersoll & Rooney PC	46,335	77%
14	Kilpatrick Townsend & Stockton LLP West Coast	45,844	71%
15	Banner & Witcoff LTD	44,868	77%
16	Wenderoth Lind & Ponack LLP	44,226	78%
17	Philips Intellectual Property & Standards	40,852	75%
18	Staas & Halsey LLP	39,302	70%
19	Sughrue Mion Zinn Macpeak & Seas	38,076	70%
20	Pillsbury Winthrop Shaw Pittman LLP	37,823	76%
21	Cantor Colburn LLP	35,518	88%
22	Harness Dickey Troy	33,857	73%
23	Texas Instruments Inc	33,745	85%
24	Antonelli Terry Stout & Kraus LLP	33,311	85%
25	Sterne Kessler Goldstein & Fox PLLC	32,931	79%

This table lists the top 25 patent attorney firms between 1980-2019 by the total number of patent applications filed. Along with the number of patent applications, this table also shows the total success rate of the patent attorney firms during 1980-2019 which is calculated as the total number of successful patent applications divided by the sum of successful and unsuccessful (abandoned) patent applications.

Table 3-3: Descriptive statistics (patent announcement-level)

<i>Panel A: Patent owner characteristics</i>							
	Mean	Median	SD	25 th	75 th	Firms	Total events
Market cap. (\$bn)	27.7	5.4	65.7	1.2	22.0	3,184	214,307
Firm age	28.8	20.5	24.5	10.5	41.1	3,461	223,205
Return on assets (%)	8.3	12.1	22.4	7.0	17.0	3,184	214,307
Leverage (%)	51.7	51.2	27.5	33.6	66.2	3,184	214,307
R&D (%)	9.3	5.5	14.0	2.1	11.2	3,184	214,307
Tobin's Q	2.1	1.7	1.8	1.2	2.6	3,184	214,307
Institutional ownership (%)	66.3%	72.7%	23.8%	57.0%	83.4%	3,038	191,213
<i>Panel B: Patent characteristics</i>							
Forward citations (truncation adjusted)	1.1	0.3	2.0	0.0	1.0	3,461	223,205
Backward citations	29.6	14.0	43.1	7.0	30.3	3,439	218,835
Independent claims	1.0	1.0	0.1	1.0	1.0	3,461	223,205
<i>Panel C: Measures of patent attorney capability</i>							
Rolling success rate (%) (substantive expertise)	83.8%	85.2%	11.6%	75.8%	93.1%	3,459	222,964
Applications filed (process experience)	3589.8	915.5	7484.1	217.0	3407.0	3,459	222,964
Top tier attorney (%)	4.6	0.0	21.0	0.0	0.0	3,153	192,100
Any tier attorney (%)	18.9	0.0	39.1	0.0	0.0	3,153	192,100

This table reports the summary statistics for the full sample of 1,291,239 of patents issued during 2003-2019. Panel A shows patent owner characteristics. Total assets and market capitalisation are displayed in \$billion, and the rest of the firm variables are expressed in %. Panel B reports patent characteristics variables, all of which are expressed as a simple count. Lastly, Panel C shows the created measures of patent attorney capability. Rolling success rate is in %, and applications filed is a simple count. See Appendix 3-B for variable definitions.

Table 3-4: Event study results

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
All events	-0.0099**	0.0322***	0.0064	0.0021	0.0224***	0.0288***	0.0309***	223,205
<i>Panel B: Announcements with high-substantive-expertise attorneys</i>								
High-expertise events	-0.0028	0.0584***	0.0189***	0.0051	0.0556***	0.0745***	0.0796***	89,426
<i>Panel C: Announcements with low-substantive-expertise attorneys</i>								
Low-expertise events	-0.0231***	0.0065	-0.0157**	0.0016	-0.0166*	-0.0322***	-0.0306**	89,187

This table presents the event study results computed using the market-adjusted model. All results are in %. Panel A presents full sample results. Panels B and C show patent announcements that are accompanied by patent attorneys with high, and low levels of substantive expertise, respectively. I define the expertise to be high (low) when the attorneys' rolling success rate is in the top (bottom) 40% of the distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-5: Market reaction (CAR 0,+2) and attorney substantive expertise (rolling success rate)

	(1)	(2)	(3)
Rolling success rate	0.0030*** (0.0010)	0.0030*** (0.0010)	0.0034*** (0.0010)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023*** (0.0007)
Return on assets			-0.0017 (0.0020)
Leverage			-0.0010 (0.0010)
R&D			0.0031 (0.0038)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-6: Market reaction (CAR 0,+2) and attorney process experience (applications filed)

	(1)	(2)	(3)
Applications filed (*10)	-0.0001 (0.0005)	-0.0001 (0.0005)	0.0001 (0.0005)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023*** (0.0007)
Return on assets			-0.0017 (0.0020)
Leverage			-0.0010 (0.0010)
R&D			0.0034 (0.0038)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0291	0.0291	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. For ease of presentation, coefficient on the *applications filed* has been multiplied by 10. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-7: Forward citations and attorney substantive expertise (rolling success rate)

	(1)	(2)	(3)
Rolling success rate	0.2756*** (0.0678)	0.2924*** (0.0691)	0.2758*** (0.0712)
Market capitalisation		-0.0703** (0.0347)	-0.0738** (0.0345)
Independent claims			-0.0063 (0.0240)
Backward citations			0.1422*** (0.0112)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,287,963	1,256,800	1,172,856
R-squared	0.1270	0.1242	0.1310

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-8: Patent attorney substantive expertise (rolling success rate) and the openings of new USPTO offices.

	(1)	(2)	(3)
New offices	0.0093** (0.0043)	0.0089** (0.0042)	0.0080* (0.0042)
Patent grant volume		0.0064*** (0.0013)	0.0061*** (0.0012)
Market capitalisation			0.0074*** (0.0027)
Firm age			-0.0141** (0.0063)
Return on assets			0.0181 (0.0142)
Leverage			0.0066 (0.0074)
R&D			0.0722** (0.0303)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	258,770	258,770	248,687
R-squared	0.6077	0.6086	0.6100

The dependent variable is rolling success rate. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-9: Market reaction (CAR 0,+2), patent attorney substantive expertise (rolling success rate), and the opening of new USPTO offices.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.0030** (0.0010)		0.0027*** (0.0010)	0.0027*** (0.0010)	0.0031*** (0.0011)
New offices		0.0000 (0.0004)	-0.0060** (0.0028)	-0.0061** (0.0028)	-0.0054* (0.0029)
New offices x Rolling success rate			0.0073** (0.0034)	0.0073** (0.0034)	0.0069** (0.0034)
Patent grant volume				-0.0001 (0.0001)	-0.0000 (0.0001)
Market capitalisation					-0.0015** (0.0004)
Firm age					-0.0023*** (0.0007)
Return on assets					-0.0018 (0.0020)
Leverage					-0.0010 (0.0010)
R&D					0.0030 (0.0038)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	222,431	222,472	222,431	222,431	213,608
R-squared	0.0292	0.0291	0.0292	0.0292	0.0286

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-10: Forward citations and patent attorney substantive expertise (rolling success rate), and the opening of new USPTO offices.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.2756*** (0.0678)		0.2838*** (0.0713)	0.2991*** (0.0728)	0.2832*** (0.0754)
New offices		0.0221 (0.0423)	0.1106 (0.1254)	0.0947 (0.1236)	0.1127 (0.1287)
New offices x Rolling success rate			-0.1024 (0.1453)	-0.0750 (0.1444)	-0.0852 (0.1508)
Market capitalisation				-0.0710** (0.0349)	-0.0746** (0.0348)
Independent claims					-0.0063 (0.0240)
Backward citations					0.1422*** (0.0112)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	1,287,963	1,288,371	1,287,963	1,256,800	1,171,856
R-squared	0.1270	0.1269	0.1279	0.1243	0.1311

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-11: Difference in market reaction (CAR 0,+2) and the patent attorney change.

<i>Panel A: Changed to a better attorney</i>	(1)	(2)
Better patent attorney	0.0008** (0.0004)	0.0008* (0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	109,026	104,068
R-squared	0.0090	0.0087
<i>Panel B: Changed to a worse attorney</i>	(3)	(4)
Worse patent attorney	-0.0008** (0.0004)	-0.0008* (0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	109,026	104,068
R-squared	0.0126	0.0125
<i>Panel C: Difference in market reaction and the difference in patent attorney success rate</i>	(5)	(6)
Difference in capability	0.0037** (0.0017)	0.0036** (0.0017)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	48,428	46,358
R-squared	0.0301	0.0295

The dependent variable in panels A, B, and C is the difference in CARs(0,+2) of two consecutive announcements of single patents granted to the same company. I use the same control variables as in Table 3-5. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at 1% and 99% tails. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-12: Difference in forward citations and the patent attorney change.

<i>Panel A: Changed to a better attorney</i>	(1)	(2)
Better patent attorney	0.0868*** (0.0316)	0.0875*** (0.0323)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	114,796	109,975
R-squared	0.0119	0.0166
<i>Panel B: Changed to a worse attorney</i>	(3)	(4)
Worse patent attorney	-0.0713** (0.0291)	-0.0642** (0.0296)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	120,183	109,975
R-squared	0.0119	0.0165
<i>Panel C: Difference in forward citations and the difference in patent attorney success rate</i>	(5)	(6)
Difference in capability	0.5072*** (0.1491)	0.4779*** (0.1526)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	55,004	50,428
R-squared	0.0277	0.0357

The dependent variable in panels A, B, and C is the difference in the truncation-adjusted number of forward citations received by patents that were granted to the same company in two consecutive announcements of single patents. I use the same control variables as in Table 3-7. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at 1% and 99% tails. All patent quality control variables are winsorized at 1% and 99% tails. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-13: Correlations between attorney capability and Legal 500 ranking

Capability/Ranking	Top tier attorney (lag 1)	Top tier attorney (lag 2)	Any tier attorney (lag 1)	Any tier attorney (lag 2)
Rolling success rate	-0.0568	-0.0546	-0.0824	-0.0792
Applications filed	0.1324	0.1273	0.2966	0.2883

This table shows the pairwise correlations between substantive expertise (rolling success rate), process experience (applications filed) and dummy variables identifying top ranked patent attorneys.

Table 3-14: Market reaction (CAR 0,+2) and Legal 500 ranking

	(1)	(2)	(3)
Top tier attorney (lag 1)	0.0004 (0.0005)	0.0004 (0.0005)	0.0001 (0.0005)
Patent grants volume		0.0001 (0.0002)	0.0001 (0.0002)
Market capitalisation			-0.0014*** (0.0005)
Firm age			-0.0034*** (0.0010)
Return on assets			-0.0047* (0.0027)
Leverage			0.0004 (0.0012)
R&D			0.0039 (0.0049)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	127,707	127,707	121,982
R-squared	0.0403	0.0403	0.0391

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 3-15: Forward citations and Legal 500 ranking

	(1)	(2)	(3)
Top tier attorney (lag 1)	-0.0216 (0.0247)	-0.0254 (0.0251)	-0.0272 (0.0239)
Market capitalisation		-0.0937** (0.0468)	-0.0954** (0.0461)
Independent claims			-0.0058 (0.0372)
Backward citations			0.1487*** (0.0128)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	728,589	709,425	651,737
R-squared	0.1400	0.1363	0.1443

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

4. Does Green Innovation Increase Shareholder Wealth?

4.1 Introduction

Green technologies are the key to decarbonizing the economy (Nordhaus, 2021) and mitigating and adapting to climate change (United Nations, 2021). Governments rely heavily on the private sector to invest and develop many of these green technologies - a key source of innovation is the private sector. For instance, for-profit companies own 85% of patents in the US (National Science Board, 2018). Although motivated by the prospect of getting a return on their investment, green innovation can also help firms capture climate-related opportunities and lower their exposure to climate risks. Similarly, recent evidence suggests that institutional investors encourage companies to make more environmentally friendly decisions (Dyck et al., 2019). In this chapter, I investigate whether environmental (green) innovation by public firms increases shareholder wealth.

Innovation is considered crucial for the future success of a firm, and therefore one of the most important corporate decisions is how much to spend on innovation activities. Patents benefit firms as they can increase firms' employment growth, sales growth, chances of survival, and access to capital (Hegde et al., 2022). Hence, the market reacts positively to the announcements of new patents (Kogan et al., 2017).

Green innovation, which is commonly measured using the number of green patents (Aghion et al. 2016; Cohen et al., 2022), can be important to investors who care about environmental issues and want to minimize their exposure to environmental risks (Ilhan et al., 2021). Moreover, the number of green patent announcements are increasing rapidly. The annual number of green patents granted in the US increased by

301% from 2009 to 2019, compared with a 97% increase in the annual number of grey patents. Since developing green technologies is generally risky and expensive, green patents can be a credible signal of a firm's environmental commitment (Berrone et al., 2017; Spence, 1973). Therefore, I address the following question: Do green patents increase shareholder wealth?

Although prior research suggests that the market rewards innovation as indicated by the positive market reaction to patents in general, it is unclear whether the market rewards *green* innovation. The related findings on the market reaction to general sustainability-related news announcements are mixed.⁷² This study differs from this literature by focusing on the announcements of new green patents made by the USPTO. Green patents are a reliable evidence of corporate engagement with environmental issues for multiple reasons. First, green patents can be challenging to obtain for a company because innovation is path-dependent (Aghion et al., 2014). Second, innovating in green technologies requires a firm to redirect its research and development (R&D) efforts from other (potential) projects (Stern and Valero, 2021). Third, obtaining a patent is costly. Lemley (2001) shows that firms spend \$5bn every year just on the process of obtaining patents from the USPTO. Fourth, many funds have a specific focus on environmental/sustainable investments and the amount of US-domiciled assets under management following sustainable investing strategies reached \$17.1 trillion in 2020, a 42% increase from 2018 (US SIF, 2020). Therefore, green patents can help a firm attract a larger part of these funds (Cohen et al., 2022), reduce its cost of capital (Bolton and Kacperczyk, 2021; Chava, 2014), and help investors

⁷² Regarding environmental, social, and governance (ESG) issues, Krueger (2015) finds a negative stock market response to positive news, while Capelle-Blancard and Petit (2019) observe no significant reaction. In contrast, Flammer (2013) and Klassen and McLaughlin (1996) report a positive market response.

distinguish between firms that act on environmental issues and firms that only brand themselves as such. This suggests that investors may pay attention to green patents as they provide evidence of a firm's environmental progress (Amore and Bennedsen, 2016; EPO and IEA, 2021). Moreover, a patented environmental technology can benefit a company both internally and externally. A green patent can improve a company's environmental performance and reduce its emissions (Carrion-Flores and Innes, 2010). However, the advantages are not limited to the company alone. A business can also benefit from licensing out or selling the green technology to other firms which can use it to improve their own environmental sustainability (Losacker, 2022).

I identify green patents using a green patent classification scheme developed by the OECD (Hascic and Migotto, 2015), which classifies patents as protecting environmentally-friendly technologies based on their technology classification codes. For robustness, I use an alternative green patent categorization scheme created by the European Patent Office (see section 4.3).

I examine the impact of green patents on shareholder wealth by measuring the market reaction to patents granted to public firms in the US during 1976-2019. Given that green patents can improve a firm's environmental performance and can also be seen as valuable signals to investors, I expect a positive market reaction to new green patent announcements.⁷³ I find that the announcements of green patents do not increase shareholder wealth. This finding is contrary to the positive market reaction to the announcements of grey patents. Also, the results and interpretations hold regardless of whether a company is operating in a carbon-intensive industry, has a low

⁷³ In other words, in this chapter, I am investigating whether the market valuation of green patent announcements is statistically different from zero (see section 4.2).

environmental score, or has a high exposure to climate change. Lastly, to the extent that all firms which obtain green patents can be seen as environmentally responsible (Berrone et al., 2017), the findings are consistent with Pástor et al. (2021) who predict that the demand for green firms pushes up their prices and lowers their expected returns, which can lead to underperformance compared to grey firms..

I also assess whether the impact of green patents on shareholder wealth is driven by investors' environmental concerns. High levels of climate change concerns can make the climate-related risks faced by firms more important to investors and can increase investors' preference for green assets (Ardia et al., 2022). Therefore, investors may value green patents more when their climate change concerns are greater. I test if the impact of green patents on shareholder wealth depends on the amount of public attention to climate change and find no evidence that it does, even if I focus on firms in high pollution industries.

Stocks that receive low institutional investor attention are traded less frequently and less profitably (Schmidt, 2019). Also, green innovation may be particularly relevant to institutional investors, who have been putting pressure on companies to reduce their emissions (Azar et al., 2021), and improve their ESG performance (Dimson et al., 2015; Hoepner et al., 2022).⁷⁴ Institutional investors are concerned about climate risk (Krueger et al., 2020), and they avoid investing in companies with poor environmental performance (Fernando et al., 2017). Therefore, the market reaction to green patent announcements may depend on institutional investor ownership or whether

⁷⁴ As of March 2021, 575 institutional investors with a total of \$50 trillion of assets under management have joined the Climate Action 100+ initiative, which aims to engage firms on climate change issues (The Economist, 2021). One example of shareholder activism is the battle between Engine No.1 and Exxon Mobil. In June 2021, the hedge fund won a proxy battle against the oil company gaining three seats on its board (Brower and Aliaj, 2021).

institutional investors are paying attention to firms developing new green technologies. I find that neither the level of institutional investor ownership nor the amount of institutional investor attention paid to a company at the time of a patent announcement is related to the impact of green patents on shareholder wealth. Also, I assess whether the market reaction to green patents changed following the 2015 Paris Agreement. Investor attention to climate change increased after the Paris Agreement (Kruse et al., 2020), and banks started charging companies a carbon risk premium (Ehlers et al., 2022). Still, I find no evidence that the green patents granted after the adoption of the 2015 Paris Agreement have increased shareholder wealth.

Given the results, I investigate whether the changes in a company's green patenting activity are related to the changes in the firm's environmental score, level of institutional investor ownership, and firm value (Tobin's Q). I find that there is no relation between institutional investor ownership or Tobin's Q and green patenting activity. The results are consistent regardless of whether I measure green patenting activity using the number of green patents obtained, the amount of green patent applications filed, or the number of citations received by a company's green patents. Meanwhile, there is only weak evidence that green patenting activity is positively related to a firm's environmental score. The results are not consistent across different green patenting measures and they are not robust to an alternative green patent classification scheme.

Overall, the results suggest that green patent announcements do not increase shareholder wealth. The results may seem surprising in light of previous studies which find that the stock market reacts positively to evidence of firms' environmentally-friendly actions such as implementing sustainability programs and issuing green bonds

(Flammer, 2013; Flammer, 2021; Klassen and McLaughlin, 1996). However, unlike these studies, I focus on green patents which allows me to study the market response to environmentally-friendly actions over a longer period. The results also support IEA (2021) and Aghion et al. (2014) who argue that the returns to green technologies can be small compared to investments in polluting technologies, because green technologies may be in their infancy stages.

Moreover, despite institutional investors' concerns about environmental risks (Ilhan et al., 2021), I find no evidence that they reward companies for obtaining green patents. This is consistent with Michaely et al. (2021), who find that institutional investors do not support environmental and social corporate proposals when their vote matters the most. Similarly, Gianfrate et al. (2021) find no evidence that institutional investors reduce the carbon emissions of an average company. The results also complement von Schickfus (2021), who finds no evidence that firm engagement by institutional investors affects corporate green innovation.

The contribution of this chapter is threefold. First, this is the first study to my knowledge that investigates the impact of green patents on shareholder wealth. Second, I contribute to an emerging literature on the effects of investor attention to climate change (Choi et al., 2020; Huynh and Xia, 2021; Ramelli et al., 2021) by examining whether the impact of green patents on shareholder wealth depends on the level of climate change concerns. Third, I contribute to the literature on corporate green patents (Berrone et al., 2013; Cohen et al., 2022;⁷⁵ Kim et al., 2021) by

⁷⁵ Cohen et al. (2022) and this chapter both examine green patents obtained by publicly traded firms. However, the studies' approaches and the research questions differ. While Cohen et al. (2022) investigate the cross-sectional determinants of green patent production, this study examines the within-firm changes following firms' green patent announcements. Cohen et al. (2022) analyze the relationship between green patents and ESG scores across firms, while this study focuses on the shareholder wealth implications of green patent announcements. In addition, Cohen et al. (2022) focus on comparing energy

investigating how a firm's green patenting activity is related to its level of institutional investor ownership and attention. I show that despite investors' calls for climate action and green innovation (McCormick, 2021; US Chamber of Commerce, 2019), companies do not produce green innovation that increases shareholder wealth or attracts more institutional investor ownership.

4.2 Hypotheses development

The signaling theory was first introduced in the labor market context by Spence (1973). The author shows that higher education can serve as a signal of a job applicant's capability. Employers may be unaware of how capable a job candidate is. By obtaining higher education, job candidates can reduce the information asymmetry about their level of capability and distinguish themselves from their less capable peers (Connelly et al., 2011). At its core, the signaling theory focuses on how information asymmetry between two parties can be reduced.

Long (2002) builds a model of patents as a signaling mechanism and argues that patents can credibly reduce information asymmetries between a firm and its investors, which can increase a company's returns from obtaining patents. Hsu and Ziedonis (2013), who study a sample of 370 US semiconductor companies founded between 1975 and 1999, find that patents are valuable signals of a firm's quality that can help it raise more capital from investors. Therefore, patents can be valuable signals to investors.

firms with non-energy firms, while this chapter takes a broader approach and examines firms across all industries. Cohen et al. (2022) find that firms with low ESG scores obtain more patents than other firms and are less rewarded (in terms of their ESG scores) for doing so. In contrast to Cohen et al. (2022), this chapter shows that green patent announcements do not increase shareholder value, which is my primary contribution.

I apply the signaling theory to corporate green patent announcements. I argue that green patents can serve as signals that reduce the information asymmetry about a firm's environmental commitment. For a "signal" to be credible, it has to be costly to copy for firms that lack the sought-after characteristics (Riley, 1979; Spence, 1973). Green patents satisfy this condition (Berrone et al., 2017). To produce a new green technology, a company has to increase its innovative input, the R&D spending, or reallocate it from other projects.⁷⁶ Patents can represent the successful output of this investment (Lerner and Seru, 2022; Sunder et al., 2017). However, success is not guaranteed, because early-stage clean technologies are risky (Stern and Valero, 2021). Moreover, any green innovation has to pass examination at the patent office in order to be patented. This is a costly selection process that lasts on average three years (Farre-Mensa et al., 2020; Lemley, 2001), with only 56% of patent applications being successful without the use of continuation procedures (Carley et al., 2015). If the process is successful and a patent is granted, it represents robust evidence of technical progress (EPO and IEA, 2021).

Also, green patents can be valuable to firms due to their impact on firm risk and cost of capital. For instance, firms can be subject to physical climate risks. Miao and Popp (2014), who study the impact of natural disasters on green innovation in a panel of 28 countries during 1984 to 2009, argue that green technologies can help mitigate the damage suffered from future disasters. Moreover, green innovation is negatively associated with pollution. Carrion-Flores and Innes (2010) study the relation between green innovation and air pollution using a panel of 127 manufacturing industries in the

⁷⁶ A firm can also obtain patents by acquiring them from other innovative companies. However, this is not a concern in this study, because the market reaction to a patent announcement is measured only once; at the time when the patent is granted to its first owner.

US during 1989 to 2004 and find that green innovation significantly reduces toxic emissions. As investors demand higher returns for exposure to environmental regulation risk (Bolton and Kacperczyk, 2021; Chava, 2014), green patents can potentially lower a firm's cost of capital. Therefore, in addition to signaling a firm's environmental commitment, green patents can also provide other benefits to a firm. To reflect this, patents are sometimes referred to as 'productive' signals (Conti et al., 2013). This leads to the first hypothesis:

Hypothesis 4-1: Green patent announcements increase shareholder wealth.

I expect that there could be a differential market reaction to green patent announcements based on differing firm characteristics. Sautner et al. (2022) study the relation between a firm's level of climate change exposure and green innovation in a sample of 10,673 publicly-listed firms during 2002 to 2020. They find a positive correlation between a company's exposure to climate change and subsequent green patenting. Since green patents can reduce firm pollution (Carrion-Flores and Innes, 2010), the market reaction could be stronger for green patents granted to companies that are seen by investors as the highest polluters. One of the main environmental concerns is carbon dioxide emissions. Bolton and Kacperczyk (2021), who use a sample of 3,421 companies during 2005 to 2017, show that investors demand a risk premium for holding firms with high total carbon dioxide emissions. Matsumura et al. (2014) use hand-collected carbon emissions data for S&P 500 companies during 2006 to 2008 and find that the emissions are negatively related to firm value. Ehlers et al. (2022) study the impact of carbon emissions on corporate borrowing in a sample of 567 firms during 2005 to 2018 and find that lenders have started charging carbon-intensive companies a carbon risk premium since the Paris Agreement in 2015. Based

on the aforementioned studies, I expect green patents to be more valuable to carbon-intensive firms.

Fama and French (2007) study the asset pricing implications of investors' tastes and show that investor preferences for green assets can impact their price. This is a central point in the theoretical framework of Pástor et al. (2021), where green (brown) firms produce positive (negative) externalities for society. Moreover, investors care about firm sustainability and they derive utility (disutility) from holding green (brown) assets. The preference of investors for green assets drives up the value of green firms and lowers their expected returns (Pástor et al., 2021). A similar conclusion is drawn by Pedersen et al. (2021), who construct an ESG-efficient frontier to demonstrate the trade-offs between ESG score and Sharpe ratio. Guided by their theory, they find that low carbon intensity predicts low future returns, which they attribute to high valuations of green companies. Overall, the literature shows that investor preferences can impact asset prices.

Pástor et al. (2021) argue that green assets can earn higher abnormal returns than grey assets if investors' tastes for green investments increase unexpectedly. Pástor et al. (2022) test this theory in the US and find evidence that green firms have outperformed brown companies between 2012 and 2020 because of higher levels of environmental concerns. Environmental attention can shift for a variety of reasons. Ramelli et al. (2021) find that climate attention increased after the expectation-exceeding success of the first Global Climate Strike of 2019. Choi et al. (2020) find that investors' beliefs about climate change increase during periods of abnormally high local temperatures. Painter (2020) reports that the difference in the cost of bonds issued by climate and non-climate affected counties increased significantly after the 2006

release of the Stern Review: an influential report on the potential consequences of climate change. The level of concerns about climate change can proxy for the risk premium that is required by investors for bearing climate risk (Ardia et al., 2022). Higher levels of climate change concerns can increase investor preference for green assets and their demand for environmentally-friendly products (Pástor et al., 2022). Therefore, firms should be more rewarded for obtaining green patents when the levels of climate change concerns are high. This leads to the second hypothesis:

Hypothesis 4-2: The impact of green patent announcements on shareholder wealth is positively related to the level of climate change concerns.

Aghion et al. (2013) study the relation between institutional investor ownership and corporate innovation in a sample of 803 US firms during 1991 to 1999. They find that higher institutional ownership is positively associated with the number of citation-weighted patents obtained and argue that the effect is causal. Green innovation can be even more important to institutional investors than other innovation. Krueger et al. (2020) conduct a survey on the environmental risk perceptions of institutional investors and find that the investors are becoming increasingly concerned by climate risk. Dimson et al. (2015) study the impact of institutional investors' engagements on ESG issues on US companies during 1999 to 2009. They find that successful engagements on ESG issues are positively related to firms' accounting performance and corporate governance. Similarly, Hoepner et al. (2022), who use a sample of 1,712 engagements involving 573 firms during 2005 to 2018, find that successful engagements are negatively associated with firm downside risk. Moreover, Dyck et al. (2019) use the 2010 Deepwater Horizon spill to show that the effect of institutional investor ownership on firm environmental performance is causal. Meanwhile,

Fernando et al. (2017), who study the relation between institutional investor ownership, firm value, and sustainability performance for 1,449 firms during 1997 to 2007, find that institutional investors can shun firms with poor environmental performance. Overall, the literature shows that environmental risks can be important to institutional investors and that institutional investor ownership is positively associated with environmental performance.

The impact of green patent announcements on shareholder wealth can depend on the amount of attention paid by institutional investors to the announcements. Investor attention is a limited resource. Kempf et al. (2017), who study a sample of 21,872 firms held by 6,207 institutional investors during 1980 to 2010, show that paying more attention to one company in their portfolio leaves institutional investors with fewer resources for monitoring other firms. Firms that receive less investor attention announce more value-destroying acquisitions and have lower stock returns (Kempf et al., 2017). Abramova et al. (2020) study how institutional investor attention affects managers' disclosure choices. They find that when firms receive less attention, they produce fewer management forecasts and 8-K filings. Similarly, Liu et al. (2020) show that institutional investors distraction has a negative impact on board oversight. Ni et al. (2020) find that investor distraction is associated with weaker firm monitoring and higher stock price crash risk. Moreover, high institutional investor attention around earnings announcements and analyst recommendation changes leads to larger short-run abnormal returns (Ben-Rephael et al., 2017). Overall, the aforementioned studies show that institutional investor attention matters. Therefore, I argue that green patent grants accompanied by high levels of institutional investor attention should have a more positive impact on shareholder wealth. This leads to the third hypothesis:

Hypothesis 4-3: The impact of green patent announcements on shareholder wealth is positively related to the level of institutional investor attention.

4.3 Data and descriptive statistics

I obtain patent data from PatentsView, which is a publicly accessible service maintained by the USPTO. I retrieved the PatentsView data in March 2021, and it includes information on over 7.6 million patents granted in the US since 1976. I use PatentsView to obtain data on patent numbers, grant dates, citations, claims, and patent technology classes for all patents granted during 1976-2019. I do not include patents granted in 2020, because of the exceptional market circumstances created by the outbreak of COVID-19. The initial sample includes 7,236,657 patents.

I identify green patents using the classification developed by the OECD (Haščič and Migotto, 2015)⁷⁷ that is commonly used in the literature (Cohen et al., 2022; Sautner et al., 2022). Technology classification codes are assigned during the patent application process, and they depend on the inventions' technological content. The granular nature of patent classification systems allows for accurate identification of specific technologies, including "environmental" technologies (Haščič and Migotto, 2015). The green patent classification includes technologies related to climate change mitigation and adaptation, carbon capture and storage, renewable energy generation, pollution abatement, and waste management. Based on the green patent classification, the USPTO granted 7,054 green patents in 2009 and 28,320 green patents in 2019. The number of all patents granted by the USPTO was 192,052 in 2009 and 392,618 in

⁷⁷ The results are not sensitive to this particular green patent classification. The results remain unchanged if I classify green patents using the Climate Change Mitigation Technologies (CCMT) classification scheme developed by the European Patent Office (Angelucci et al., 2018). The CCMT classification focuses on patents related to climate change mitigation and adaptation. The OECD classification has a broader scope and also includes other environmentally friendly technologies (Haščič and Migotto, 2015).

2019. Overall, using patents' IPC and CPC codes, I identify 351,066 green patents in the sample that were granted between 1976 and 2019.

Next, I identify which patents in the sample are owned by public firms in the US. I use a patent-CRSP link created by Stoffman et al. (2022), who match companies in CRSP to patents granted by the USPTO until 31 December 2020. I successfully match 2,578,327 patents, out of which 110,185 are classified as green patents, to publicly listed firms.

Following standard practice in the patent literature (Appel et al., 2019; Lerner et al., 2011), I drop non-utility patents, which reduces the sample to 2,456,180 patents. I obtain firms' financial data from Compustat and their ESG scores from Refinitiv's Asset4. The share price return data comes from CRSP. The sample only includes common stocks, i.e., stocks with CRSP share code 10-12 (Cohen et al., 2013). I drop 628,102 patents with missing stock return data around the announcement date which reduces the sample to 1,828,078 patents.

For each company in the sample, I obtain earnings announcement dates from CRSP and dividend declaration dates from Compustat. To avoid contamination of the patent events by other closely occurring events (de Jong and Naumovska, 2016), I drop all patent announcements which occur within two trading days of a firm's earnings or dividend announcements (Stickel, 1986). In total I remove 192,026 patents from the sample, which reduces the sample to 1,636,052 patents. Lastly, I remove 19,118 patents owned by either financial services firms (SIC 6000-6999) or utility companies (4900-4999). Overall, the sample includes 1,616,934 patents, of which 67,310 (4.2%) are classified as green (Cohen et al. 2022 similarly report that 5.6% of the patents in their sample are green).

I obtain data on the level of climate change concerns from Ardia et al. (2022), who created a daily media index capturing negative attention about climate change. The index is based on a textual analysis of news articles published in eight major US newspapers from January 2003 to June 2018.⁷⁸ The measure counts the daily number of articles about climate change and aims to capture both the level of negativity about climate change, as well as the focus on uncertainty with regards to climate change present in each article (Ardia et al., 2022). Both the negativity and uncertainty scores are used to create a concern score for each article. Concern scores of articles published by the same newspaper are clustered together and adjusted for the heterogeneity across different news sources.⁷⁹ Next, the scores of articles published on the same day are averaged to obtain a single daily value, which is then transformed by taking a square root to arrive at the daily Media Climate Change Concerns index (MCCC).⁸⁰ Finally, to account for the fact that some daily level of climate change concerns in the media can be expected, the Unexpected Media Climate Change Concerns (UMC) index is created by subtracting the expected level of news from its actual value on a particular day.⁸¹ I use the average value of the UMC index over a three-day window (0,+2) after a patent announcement to measure the level of climate change concerns. I use alternative windows for robustness, and I obtain similar results.

⁷⁸ The eight major newspapers are the Wall Street Journal, New York Times, Washington Post, Los Angeles Times, Chicago Tribune, USA Today, New York Daily News, and New York Post (Ardia et al., 2022).

⁷⁹ Some newspapers tend to publish a larger number of negative articles about climate than others (Ardia et al., 2022).

⁸⁰ Ardia et al. (2021) aim to correct for the plausibly nonlinear impact of climate change news articles on concerns. “One concerning article about climate change may increase concerns, but 20 concerning articles are unlikely to increase concerns 20 times more.” (Ardia et al., 2022, p.9).

⁸¹ I follow Ardia et al. (2022) and compute the expected level of climate change concerns using a first-order autoregressive model calibrated on three years of MCCC data. UMC is calculated as the actual value of MCCC minus the predicted value of MCCC. Due to the fact that I use 3-years of data to calculate the UMC values, the UMC data starts in 2006.

The institutional ownership data is from Ghaly et al. (2020).⁸² The ownership data is obtained from Securities and Exchange Commission's Forms 13F that are filed by institutional investors every quarter. The forms contain information on all equity assets under the investors' management. The data covers the period from 1981 to 2018.

I measure the level of institutional investor attention using the news searching and reading activity of institutional investors on Bloomberg terminals (Ben-Rephael et al., 2017). Bloomberg creates a daily attention score for stocks, called the Bloomberg Heat Score, which is based on the number of articles related to a specific stock that are read by the terminal users.⁸³ Bloomberg compares the search activity regarding a particular firm with the search activity over the previous 30 days to identify abnormal levels of attention. Bloomberg assigns a score of 1, 2, 3, and 4 if the current level of attention is between 80%-90%, 90%-94%, 94%-96%, and 96%-100% of the distribution, respectively, and 0 otherwise. Similar to Chiu et al. (2021), I use the average value of the Bloomberg Heat Scores over a three-day window (0,+2) following a patent announcement to measure the level of institutional investor attention. I also measure institutional investor attention over alternative windows for robustness and the results remain unchanged. The institutional investor attention data covers the period from 2010 to 2019.

Lastly, I obtain firm-level climate change exposure data from Sautner et al. (2022). Sautner et al. (2022) analyze the transcripts of quarterly earnings calls of over 10,000 publicly listed companies from 34 countries during 2002-2020. The authors measure firm-level exposure to climate change as the proportion of a firm's earnings call

⁸² I am grateful to Kostas Stathopoulos for providing the updated dataset.

⁸³ Because Bloomberg terminal users can read an article without knowing that it refers to a particular stock, Bloomberg assigns a higher score to the articles that were deliberately searched for by the user (Ben-Rephael et al., 2017).

transcript that is centered around the topic of climate change. All variables are defined in Appendix 4-A.

Table 4-1 shows the descriptive statistics. I conduct the analysis and present the descriptive statistics on a patent announcement day level. Newly granted patents are announced by the USPTO on Tuesdays. The USPTO can announce a grant of multiple patents to the same company on the same day. Since I observe one market reaction per announcement day, I treat each announcement as one observation. The sample consists of 467,502 patent announcements, which include 1,616,934 patents granted during 1976-2019 to 7,263 different public companies.⁸⁴ Panel A presents firm characteristics. The average company has a market capitalization of \$19.4 billion, while the median firm has a capitalization of \$2.9 billion. With a debt to assets ratio of 0.523, the average company in the sample is more leveraged in comparison to the average nonfinancial corporation headquartered in the US (Palazzo and Yang, 2019). The average firm in the sample has an R&D intensity of 8.2%. This is double the average R&D intensity of a typical US company of 4.1% (Wolfe, 2020). Moreover, 57.2% of the equity of an average company in the sample is owned by institutional investors, which is similar to Aghion et al. (2013) and von Schickfus (2021).

/Table 4-1 here/

The characteristics of the patents granted to the firms are shown in Panel B of Table 4-1. After excluding examiner and self-citations⁸⁵, an average patent in the sample has a truncation-adjusted number of citations of 1.3.⁸⁶ Moreover, the average patent

⁸⁴ The number of patent announcements per unique company equals 64 ($=467,502/7,263$).

⁸⁵ I exclude citations added by patent examiners and self-citations made by patent owners to their own patents, because they are unlikely to be useful in capturing the true patent quality (Alcácer et al., 2009).

⁸⁶ To address the issue that older patents have had more time to accumulate citations than younger patents, I use the truncation-adjusted number of citations in the analysis (Lerner and Seru, 2022). I calculate the truncation-adjusted patent citations by dividing the number of citations received by a patent

contains 1.1 independent claims.⁸⁷ Panel C of Table 4-1 presents the characteristics of a typical patent announcement day in the sample. The average announcement includes 3.6 patents, with an average of 0.1 green patents per announcement. Lastly, panel D of Table 4-1 shows that green patents make up 3.7% of all patents granted to an average company in the sample every year.

4.4 Event study results

I use a standard event study approach to measure the impact of patent announcements on shareholder wealth. I estimate abnormal returns (ARs) based on the difference between the security's return and the return on the market portfolio:

$$AR_{i,t} = R_{i,t} - R_{m,t} \quad (4.1)$$

where $AR_{i,t}$ is the abnormal return of a security i on day t , and $R_{i,t}$ is the actual return of a security i on day t . $R_{m,t}$ is the risk-free rate adjusted market return⁸⁸ on day t . Following Kogan et al. (2017) I use the market adjusted model in equation (4.1), because many companies obtain patents every month or even every week. This approach mitigates the potential measurement error that is introduced when estimating a company's stock market beta by using asset pricing models that rely on non-overlapping pre-event estimation periods (Brown and Warner, 1985; MacKinlay, 1997).

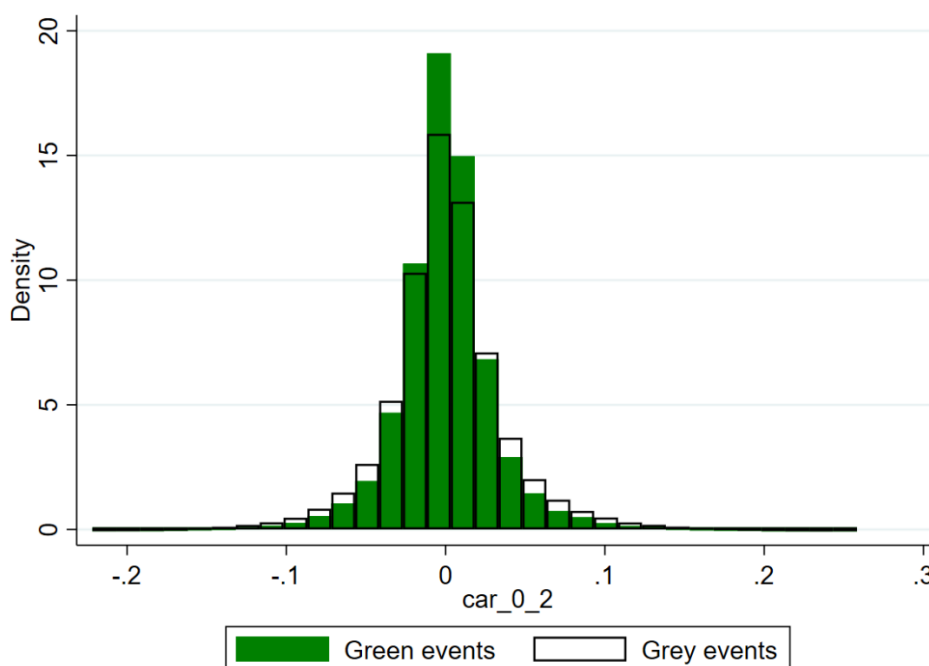
by the number of citations received by an average patent applied for in the same year. For example, if a patent that was applied for in 2005 has accumulated 6 citations, but the average patent applied for in 2005 has so far received only 3 citations, the truncation-adjusted number of patent citations is equal to 2.

⁸⁷ Claims define the scope of a patent owner's rights with relation to the invention. Independent claims are complete sentences that stand on their own, without referring to other claims (Marco et al. 2019). Dependent claims refer to an independent claim and add a limitation to it.

4.4.1 All patent announcements

I measure the cumulative abnormal returns (CAR) over a three-day event window (0,+2) (Kogan et al., 2017).⁸⁹ I do not include the abnormal returns before the event date since the patent announcements are made by the USPTO and are unlikely to be leaked (Kogan et al., 2017). The results are similar if I use alternative event windows.⁹⁰ In Table 4-2, I present the market reactions to patent announcements that do not include green patents (grey events) and patent announcements that do (green events). The CAR(0,+2) of grey and green events follow similar distributions, as shown in Figure 4-1.⁹¹

Figure 4-1: Distributions of CAR(0,+2) for green and grey events



Panel A in Table 4-2 shows that grey events have an average CAR(0,+2) of 0.033%, which is statistically significant at the 1% level. This is similar to the results reported

⁸⁹ Kogan et al. (2017) show that the share turnover increases during the first three days around a patent announcement, which suggests that this is when the patent announcement is priced in by the market.

⁹⁰ I obtain similar results when I measure the CARs over the (0,+1) and (0,+3) event windows.

⁹¹ The descriptive statistics of CAR(0,+2) of green and grey events are shown in Appendix 4-B. The CAR(0,+2) of green events are negative on average and have higher standard errors than grey events.

in the literature (Chemmanur et al., 2021). Despite being seemingly small, this is an economically significant market reaction.⁹² The average market capitalisation in the sample at the time of the patent announcement is \$19.4 billion (see Table 4-1). Given an average CAR(0,+2) of 0.033%, the average grey event is associated with an increase in market value of \$6.4 million ($=0.033\% * \19.4 bn).⁹³ This is similar to Kogan et al. (2017), who find that a median patent owned by a publicly listed company is worth \$3m, while an average patent is valued at \$10.3m. Moreover, my results are also comparable to Gambardella et al. (2008) and Hirshey and Richardson (2001) who report an average patent value of €3.0m and \$3.1m, respectively. Contrary to grey events, the average CAR(0,+2) associated with green events is not statistically significant.

/Table 4-2 here/

4.4.2 Single patent announcements

To alleviate concerns that the results are sensitive to how I define grey and green events, in panel B of Table 4-2 I restrict the sample to patent announcements that include a single patent. This should provide a clear comparison between the market reactions to green and grey patents, since the announcements of single patents are not confounded by the grants of other patents. An average announcement of a grey patent generates a CAR(0,+2) of 0.023% which is statistically significant at the 1% level, and

⁹² The benefits of patenting to a company can add up over time. Many companies obtain new patents every month or even every week (Kogan et al., 2017). The average number of patent announcements per company is 64 (see section 4.3). Therefore, the shareholder wealth increase stemming from new patent announcements can add up to 2.1% ($=64 * 0.033\%$) for an average company. Moreover, this number likely understates the total benefit from obtaining patents. Parchomovsky and Wagner (2005) find that, when it comes to patents, the combined value of a patent portfolio is greater than the sum of its parts, because it might take a group of patents to effectively protect a new technology.

⁹³ It is important to note that, given the skewness in firm size (see Table 4-1) and the fact that the sample is limited to publicly traded firms, the \$6.4 million estimate should be approached with caution. It is not necessarily representative of the 'true' value of an average patent announcement to a private firm. Moreover, Arora et al. (2023) argue that the average patent value increases with firm size because large public firms have a superior ability to commercialize and extract value from their inventions.

there is no statistically significant market reaction to an announcement of a green patent.

To further examine the market reactions to green and grey patent announcements, in panel C of Table 4-2 I limit the sample to patents granted to firms operating in polluting industries (Berrone et al., 2013).⁹⁴ Again, I find that grey patent announcements in polluting industries generate a CAR(0,+2) of 0.038% which is statistically significant at the 1% level, while there is no market reaction to green patent announcements. Next, in panel D of Table 4-2, I only include patent announcements that have a high technological value. I define technological value to be high when the truncation-adjusted number of citations associated with a patent announcement is in the top 33% of its distribution. Grey events with high technological value generate a CAR (0,+2) of 0.069%, significant at the 1% level. However, there is no statistically significant reaction to green events.

In panel E of Table 4-2 I limit the sample to patent announcements on days with a high level of climate change concerns. I define climate change concerns to be high when the value of the Unexpected Media Climate Change Concerns index measured over a three-day window (0,+2) is in the top 33% of its distribution. I find that, when climate change concerns are high, there is no statistically significant market reaction to either grey or green patent announcements.

In panel F of Table 4-2, I restrict the sample to announcements with high institutional investor ownership. I define institutional investor ownership as high when its value is in the top tercile of its distribution. I find evidence that high institutional

⁹⁴ I follow Berrone et al. (2013) and classify polluting industries as the 20 most polluting US industry sectors according to the Toxic Release Inventory (TRI), which is a US government program measuring the management and emissions of toxic chemicals. The SIC codes of the 20 polluting industry sectors are: 10, 12, 13, 20, 24, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 49, 50, 51.

investor ownership is associated with a positive market reaction to grey patent announcements, as indicated by a statistically significant $CAR(0,+2)$ of 0.093%, at the 1% level. However, I find there is no market reaction to announcements with green patents over the same event window. Finally, in panel G of Table 4-2, I restrict the sample to announcements with high institutional investor attention. I define institutional investor attention as high when its value is in the top tercile of its distribution. I find evidence that high institutional investor attention is associated with a positive market reaction to grey patent announcements, as indicated by a statistically significant $CARs(0,+2)$ of 0.126%, which is significant at the 1% level. However, there is no market reaction to announcements including green patents.

Overall, the results suggest that in contrast to grey patent announcements, green patent announcements do not have a positive effect on shareholder wealth. This holds regardless of the timing of the green patent announcements, and regardless of the type of technology protected by the patents. The results are similar if I limit the time period to 1976-1990, 1991-2005, or 2006-2019, as shown in Appendix 4-C, Appendix 4-D, and Appendix 4-E, respectively. Moreover, there is no positive effect of green patent announcements on shareholder wealth regardless of the type of green technology that the green patents protect (Haščič and Migotto, 2015).⁹⁵ The event study results broken down by green patent technology type are shown in Appendix 4-F, Appendix 4-G, Appendix 4-H, Appendix 4-I, Appendix 4-J, and Appendix 4-K.

⁹⁵ The six green technology groups are Environmental Management, Water-Related Adaptation Technologies, Energy-Related Technologies, Greenhouse Gases-Related Technologies, Transportation-Related Technologies, and Buildings-Related Technologies, as classified by Haščič and Migotto (2015).

To investigate this in more detail, and control for other factors that can affect the relationship between shareholder wealth and green patent announcements, in the next section I turn to regression analysis.

4.5 Regression analysis

Next, I test the value of green patents in a multivariate OLS regression setting. I estimate the following model:

$$CAR_{i,t} = \alpha + \beta_1 * \ln(1 + green\ patent\ volume)_{i,t} + \beta_n * X_{i,t-1} + \beta_n * Z_{i,t} + \gamma + \xi + u_{i,t} \quad (4.2)$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2) following a patent announcement.⁹⁶ *Green patent volume* is the number of green patents granted.⁹⁷ $X_{i,t-1}$ is a vector of firm specific control variables lagged by one year. In particular, I include *market capitalization*, as larger firms may produce more valuable patents (Kogan et al., 2017); *firm age*, as younger firms can produce innovation of higher technological quality (Balasubramanian and Lee, 2008), *cash*, as companies with higher cash balances can produce more competitive innovation (Atanassov and Le, 2021); *leverage*, as debt financing can influence firm innovation (Geelen et al., 2022); *R&D*, as companies that invest more in R&D can have a higher innovation capability (Chen et al., 2018),⁹⁸ and *Tobin's Q*, as growth opportunities can influence firm innovation (Jaffe, 1986). $Z_{i,t}$ is a vector of patent-related control variables. In particular, I include *patent volume*, as the market can react more

⁹⁶ In alternative specifications I use alternative dependent variables, including CAR(0,+1) and CAR(0,+3), and the results remain similar.

⁹⁷ Cohn et al. (2022) show that using the “log 1 plus” transformation may lead to biased results. Therefore, for robustness, I also identify green patent announcements in alternative ways: using a binary variable, equal to 1 when a patent announcement includes a green patent; using the proportion of green patents involved in a patent announcement. The results are similar.

⁹⁸ I replace missing R&D values with zeros as argued for by Koh and Reeb (2015). The results are similar regardless of whether or not missing R&D values are replaced with zeros.

positively to announcements of multiple patents, *patent citations*, as patents with a higher technological quality can be more valuable (Hall et al., 2005), and *patent claims*, as broader patents can be more valuable (Marco et al., 2019). Lastly, γ denotes firm fixed effects and ξ denotes year fixed effects.

4.5.1 Impact of green patents on shareholder wealth and high climate risk exposure

I expect green patents to be more valuable to firms that are more exposed to climate risks.⁹⁹ Therefore, I modify model (4.2) to include an interaction between *green patent volume* and a dummy variable that identifies firms with high exposure to climate risk.

I estimate the following model:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 * \ln(1 + \text{green patent volume})_{i,t} + \beta_2 * \text{high climate risk}_{i,t-1} \\
 & + \beta_3 * \text{high climate risk}_{i,t-1} \times \ln(1 + \text{green patent volume})_{i,t} \quad (4.3) \\
 & + \beta_n * X_{i,t-1} + \beta_n * Z_{i,t} + \gamma + \xi + u_{i,t}
 \end{aligned}$$

I identify high climate risk firms in three different ways. First, I identify high risk firms as firms operating in industries with high CO₂ emissions. I categorise carbon intensive industries using the list of heavy-emitting industries created by the Intergovernmental Panel on Climate Change (IPCC) (Choi et al., 2020; Krey et al., 2014). I match the most carbon intensive industries identified by the IPCC to the Fama-French 48 industry classification used in the sample. I create *CO₂ intensive industry*, which is a dummy variable equal to 1 if a firm is operating in a carbon intensive industry, and 0 otherwise. Second, I identify high climate risk firms as companies with a low Asset4 environmental score. I create *low environmental score*, which is a dummy variable that is equal to 1 when the firm's environmental score is in the bottom 33%

⁹⁹ Climate risk can be divided into two parts; physical risk, which refers to a firm's exposure to more extreme weather events, and transition risk that refers to the potential costs of making the company more environmentally friendly in order to comply with climate regulations (von Schickfus, 2021).

of the variable's distribution, and 0 otherwise.¹⁰⁰ Third, I identify high climate risk firms by creating a dummy variable *high climate exposure*_{*t-1*}, which is equal to 1 when the level of a firm's exposure to climate change (Sautner et al., 2022) is in the top 33% of the variable's distribution, and 0 otherwise.¹⁰¹

Regression results are shown in Table 4-3. In column (1) of Table 4-3, I regress CAR(0,+2) solely on *green patent volume*, and I include year, and firm fixed effects. The coefficient is not statistically significant, which suggests that the number of green patents contained in an announcement does not affect the market reaction. In columns (3), (6), and (9) of Table 4-3, I interact *green patent volume* with *CO₂ intensive industry*, *low environmental score*, and *high climate risk exposure*_{*t-1*}, respectively. I find that in all specifications, the interactions are not statistically significant. The results suggest that even the green patents of firms with a high exposure to climate risks do not increase shareholder wealth.

/Table 4-3 here/

Overall, the results suggest that green patents do not increase shareholder wealth. Therefore, I find no support for the first hypothesis (H4-1). This is in contrast to the positive effect on shareholder wealth of grey patent announcements shown in section 4.4. But, to the degree that all firms that secure green patents can be viewed as green (Berrone et al., 2017), the findings are consistent with Pástor et al. (2021) who argue that green assets underperform brown assets over a long period of analysis during which any changes in green preferences of investors average to zero. Moreover, since green patents are credible signals of environmental commitment (Berrone et al., 2017),

¹⁰⁰ I obtain similar results if I use the median or the bottom 25% of the distribution as the cut-off points.

¹⁰¹ I obtain similar results if I use the median or the top 25% of the distribution as the cut-off points. The firm-level measure of climate change exposure is from Sautner et al. (2022) (see: section 4.3).

the results support Avramov et al. (2021) who argue that higher ESG ratings are negatively related to returns of firms with low ESG uncertainty. Moreover, green innovation can be seen as less valuable by the market than grey innovations because innovation is path dependent and green technologies have generally fewer past innovations to build upon (Aghion et al., 2014). Nanda et al. (2015) argue that early-stage renewable energy technologies spend more time in development and require significantly more investment than grey technologies. Similarly, Gaddy et al. (2017) show that venture capital investments in clean energy technologies yield low returns compared to investments in software or medical technologies, because clean technologies require more financing, return less capital to investors, and are more likely to fail.

4.5.2 Impact of green patents on shareholder wealth and climate change concerns

The impact of green patents on shareholder wealth may depend on how concerned investors are about the climate change problem. Therefore, I explore the relation between the level of climate change concerns and the market reaction to green patent announcements. I estimate the following model:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 * climate\ concerns_{i,t} + \beta_2 * \ln(1 + green\ patent\ volume)_{i,t} \\
 & + \beta_3 * climate\ concerns_{i,t} * \ln(1 + green\ patent\ volume)_{i,t} \\
 & + \beta_n * X_{i,t-1} + \beta_n * Z_{i,t} + \gamma + \xi + u_{i,t}
 \end{aligned} \tag{4.4}$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2) following a patent announcement.¹⁰² The independent variable of interest is *climate concerns*, which measures the average level of the UMC index (Ardia et al., 2022)

¹⁰² In alternative specifications I use alternative dependent variables, including $CAR(0,+1)$ and $CAR(0,+3)$, and the results remain similar.

over a three-day window (0,+2).¹⁰³ *Green patent volume* is the number of green patents granted.¹⁰⁴ The firm specific control variables include *market capitalization, firm age, cash, leverage, R&D, and Tobin's Q*. The patent-related control variables include *patent volume, patent citations, and patent claims*. Lastly, γ denotes firm fixed effects and ξ denotes year fixed effects.

Regression results are shown in Table 4-4. First, in column 1, I regress CAR(0,+2) solely on *climate concerns*, and I include year, and firm fixed effects. I find that the level of climate change concerns is not a statistically significant predictor of the market reaction to all patent announcements. Next, in column (3), I interact *climate concerns* with the number of green patents included in the announcement. The interaction term is not statistically significant. Therefore, I find no evidence that the impact of green patents on shareholder wealth depends on the level of climate change concerns.

/Table 4-4 here/

Climate concerns may only impact the market reaction to green patents granted to polluting companies, which face higher regulatory and transition risks with regards to climate change. Therefore, I modify model (4.4) to include *CO₂ intensive industry*, which is a dummy variable equal to 1 if a firm is operating in a carbon intensive industry, and 0 otherwise. I test the effect of climate change concerns on the value of green patents in carbon intensive industries using a triple interaction term between *CO₂ intensive industry, climate concerns* and *green patent volume*. The results are shown in Appendix 4-L. Initially, in column (5) of the table in Appendix 4-L, the triple

¹⁰³ I obtain similar results if I measure the average climate change concerns over alternative windows, including (0,+1) and (-1,+1). Furthermore, the results are similar if instead of using a continuous measure I use a dummy variable that is equal to 1 when the level of climate concerns is high.

¹⁰⁴ I obtain similar results if I use a dummy variable equal to 1 when a patent announcement includes a green patent.

interaction term is positive and significant at the 5% level, but the effect disappears after I add control variables in column (6). This suggests that climate concerns do not influence the market reaction to green patents granted to carbon intensive companies.

To test the robustness of this result, I modify model (4.4) to include *high climate exposure*_{*t-1*}, which is a dummy variable equal to 1 when the level of a firm's exposure to climate change (Sautner et al., 2022) is in the top 33% of the variable's distribution, and 0 otherwise.¹⁰⁵ I test the effect of climate change concerns on the value of green patents granted to firms with high climate change exposure by using a triple interaction term between *high climate exposure*_{*t-1*}, *climate concerns* and *green patent volume*. The results are shown in Appendix 4-M. The triple interaction, which I add in the table in Appendix 4-M, is not statistically significant.

I obtain similar results if I identify high climate risk firms based on their Asset4 environmental scores. I modify model (4.4) to include *low environmental score*, which is a dummy variable that is equal to 1 when the firm's environmental score is in the bottom 33% of the variable's distribution, and 0 otherwise.¹⁰⁶ The results are shown in Appendix 4-N. In Column (5) of the table in Appendix 4-N I interact *low environmental score* with *climate concerns*, and *green patent volume*, and I find that the triple interaction is not statistically significant.

Overall, I find that the effect of green patents on shareholder wealth does not depend on the level of climate change concerns. Therefore, I find no support for the second hypothesis (H4-2). The results suggest that investors do not view green patents as

¹⁰⁵ I obtain similar results if I use the median or the top 25% of the distribution as the cut-off points. The firm-level measure of climate change exposure is from Sautner et al. (2022) (see: section 4.3).

¹⁰⁶ I obtain similar results if I use the median or the bottom 25% of the distribution as the cut-off points.

effective solutions for addressing the climate-related risks faced by companies and the broader economy.

4.5.3 Impact of green patents on shareholder wealth, and institutional investor ownership

Next, I investigate whether institutional investors reward companies for obtaining green patents. I modify model (4.4) to include institutional investor ownership as the explanatory variable of interest:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 * IO_{i,t-1} + \beta_2 * \ln(1 + \text{green patent volume})_{i,t} + \beta_3 \\
 & * IO_{i,t-1} \times \ln(1 + \text{green patent volume})_{i,t} + \beta_n * X_{i,t-1} + \beta_n \\
 & * Z_{i,t} + \gamma + \xi + u_{i,t}
 \end{aligned} \tag{4.5}$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2) following a patent announcement.¹⁰⁷ $IO_{i,t-1}$ is the proportion of a company's shares owned by institutional investors measured one quarter before a patent announcement. For example, if a patent announcement occurred in Q3 2013, I use the level of institutional investor ownership as of Q2 2013. I do this to address potential reverse causality between institutional investor ownership and patent announcements. *Green patent volume* is the number of green patents granted.¹⁰⁸ The firm specific control variables include *market capitalization, firm age, cash, leverage, R&D, and Tobin's Q*. The patent-related control variables include *patent volume, patent citations, and patent claims*. Lastly, γ denotes firm fixed effects and ξ denotes year fixed effects.

Regression results are shown in Table 4-5. First, in column (1) of Table 4-5, I regress $CAR(0,+2)$ solely on institutional ownership, and I include year, and firm fixed

¹⁰⁷ In alternative specifications I use alternative dependent variables, including $CAR(0,+1)$ and $CAR(0,+3)$, and the results remain similar.

¹⁰⁸ I obtain similar results if I use a dummy variable equal to 1 when a patent announcement includes a green patent.

effects. The coefficient on $IO_{i,t-1}$ is initially negative and statistically significant at the 5% level. However, the statistical significance disappears after I include control variables in column (4), which suggests that the level of institutional investor ownership does not affect the market reaction to all patent announcements. In column (3) of Table 4-5, I interact institutional investor ownership with the number of green patents granted. The interaction term is not statistically significant.

/Table 4-5 here/

Institutional investors differ in their investment horizons which can affect how important corporate innovation is to them (Aghion et al., 2013; Bushee, 1998). Green patents could be especially valuable to institutional investors with long investment horizons since climate change is a long-run risk factor (Bansal et al., 2016). I obtain information on institutional investor classification from Brian Bushee's website, and I differentiate between the proportion of the company owned by transient, quasi-indexer, and dedicated institutional investors. Transient institutional investors are characterized by a short investment horizon, and a high portfolio turnover. Quasi-indexer and dedicated institutional investors are characterized by a long-term investment horizon and a low portfolio turnover (Bushee, 1998).

I use model (4.5) to test whether the proportion of a company's shares owned by different types of institutional investors affects the market reaction to green patents. Regression results using the ownership by transient, quasi-indexer, and dedicated institutional investors are shown in Appendix 4-O, Appendix 4-P, and Appendix 4-Q, respectively. The interaction between the number of green patents and the ownership level by the three different types of institutional investors are all not statistically significant. I find no evidence that the level of institutional ownership is related to the

impact of green patent announcements on shareholder wealth, regardless of how the level of institutional investor ownership is classified.¹⁰⁹

4.5.4 Impact of green patents on shareholder wealth, and institutional investor attention

Institutional investors may not always be monitoring patent announcements since the amount of their attention is limited. Therefore, I test whether the impact of green patent announcements on shareholder wealth depends on the amount of institutional investor attention. I estimate the following model:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 * institutional\ attention_{i,t} + \beta_2 \\
 & * \ln(1 + green\ patent\ volume)_{i,t} + \beta_3 \\
 & * institutional\ attention_{i,t} \times \ln(1 + green\ patent\ volume)_{i,t} \\
 & + \beta_n * X_{i,t-1} + \beta_n * Z_{i,t} + \gamma + \xi + u_{i,t}
 \end{aligned} \tag{4.6}$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2) following a patent announcement.¹¹⁰ $Institutional\ attention_{i,t}$ measures the average level of institutional investor attention over a three-day window (0,+2) (Ben-Rephael et al., 2017).¹¹¹ $Green\ patent\ volume$ is the number of green patents granted.¹¹² The firm specific control variables include *market capitalization, firm age, cash, leverage, R&D, and Tobin's Q*. The patent-related control variables include *patent volume, patent citations, and patent claims*. Lastly, γ denotes firm fixed effects and ξ denotes year fixed effects.

¹⁰⁹ The results are similar if instead of using a continuous measure of institutional investor ownership I use a dummy variable that equal to 1 when the level of institutional investor ownership is high.

¹¹⁰ In alternative specifications I use alternative dependent variables, including $CAR(0,+1)$ and $CAR(0,+3)$, and the results remain similar.

¹¹¹ I use the three-day average of the Bloomberg Heat Scores (Ben-Rephael et al., 2017, Chiu et al., 2021). The results are similar if I measure institutional investor attention over alternative windows, or if I use a dummy variable to identify high levels of institutional investor attention.

¹¹² I obtain similar results if I use a dummy variable equal to 1 when a patent announcement includes a green patent.

Regression results are shown in Table 4-6. First, in column 1 of Table 4-6, I regress $CAR(0,+2)$ solely on *institutional attention*, and I include year, and firm fixed effects. Ceteris paribus, the positive and statistically significant coefficient (at the 1% level) on *institutional attention* indicates that the market reaction to a patent announcement increases by 0.09% when institutional investor attention increases by 1. The standard deviation of institutional investor attention is 1.0 (see Table 4-1). Therefore, a one-standard deviation increase in institutional investor attention increases the market reaction to a patent announcement by 0.09% ($=1.0*0.09\%$). The results are similar to Chemmanur et al. (2021), who find that investor attention is positively related to the market reaction to all patent announcements. In column 3 of Table 4-6, I interact institutional investor attention with the number of green patents announced. The interaction term in column (3) is not statistically significant. This suggests that, on average, green patent announcements do not increase shareholder wealth, even when institutional investors are paying attention to the company that is obtaining the patents.

/Table 4-6 here/

Institutional investor attention may only affect the market reaction to green patents when the level of institutional investor ownership is high. Therefore, I modify model (4.6) to include *high IO_{t-1}*, which is a dummy variable equal to 1 when the level of institutional ownership of a company is in the top 33% of the variable's distribution, and 0 otherwise.¹¹³ The results are shown in Appendix 4-R. In column (5) of the table in Appendix 4-R, I interact *high IO_{t-1}* with institutional investor attention and the number of green patents, and I find that the interaction term is not statistically

¹¹³ I obtain similar results if I use the median or the top 25% of institutional ownership's distribution as the cut-off points.

significant. This result remains unchanged if I use a high level of transient, quasi-indexer, or dedicated level of institutional ownership instead.

Institutional investor attention may affect the market reaction to green patents when the level of climate concerns is high. A high level of climate concerns can increase the perceived urgency of the climate change problem. This can make institutional investors react to green patents more positively. I test this proposition by modifying model (4.6) to include *high climate concerns*, which is a dummy variable equal to 1 when the level of climate concerns is in the top 33% of the variable's distribution, and 0 otherwise.¹¹⁴ The results are presented in Appendix 4-S. The interaction between *high climate concerns*, *institutional attention*, and the *green patent volume* is added in column (5) of the table in Appendix 4-S. The triple interaction term is not statistically significant.

Next, I investigate whether institutional investor attention affects the market reaction to green patents for firms with high climate exposure (Sautner et al., 2022). To test this, I modify model (4.6) to include *high climate exposure* $t-1$, which is a dummy variable equal to 1 when the level of a firm's exposure to climate change is in the top 33% of the variable's distribution, and 0 otherwise.¹¹⁵ The results are shown in Appendix 4-T. In column (5) of the table in Appendix 4-T, I add the triple interaction between *high climate exposure* $t-1$, *institutional attention*, and *green patent volume*. The triple interaction is not statistically significant.

Overall, I find no evidence that the impact of green patents on shareholder wealth depends on the level of institutional investors' ownership or attention, even when the

¹¹⁴ I obtain similar results if I use the median or the top 25% of institutional ownership's distribution as the cut-off points.

¹¹⁵ I obtain similar results if I use the median or the top 25% of institutional ownership's distribution as the cut-off points.

companies that obtain the green patents face a high exposure to climate change. Therefore, I find no support for the third hypothesis (H4-3). This result is consistent with Michaely et al. (2021), who study the voting behavior of institutional investors on environmental and social (ES) corporate proposals. They find that institutional investors' ES funds tend not to support ES proposals when their vote is likely to affect a voting outcome that conflicts with the broader non-ES objectives of the institutional investors. Therefore, whilst institutional investors communicate their commitment to protecting the environment (Fink, 2020), they do not necessarily act accordingly. Moreover, the results are also consistent with von Schickfus (2021), who finds that institutional investor ownership is not related to a change in the direction of firm innovation towards green technologies.

4.5.5 Impact of green patents on shareholder wealth, and the Paris Agreement

The results so far suggest that green patent announcements do not increase shareholder wealth. However, it is possible that investors have only more recently started rewarding companies for obtaining green patents as governments have increasingly highlighted the vital importance of strategies to combat climate change. To test the robustness of the results, I exploit a major shock to the importance of green technologies caused by the adoption of the Paris Agreement during the 2015 United Nations Climate Change Conference.

I examine the impact of the adoption of the Paris Agreement on the market reaction to green patents. The Paris Agreement, signed on 12 December 2015, is a legally binding international treaty which aims to tackle the problem of climate change and limit global warming to 1.5°C above pre-industrial levels (Kruse et al., 2020). The scope of the agreement and its ambitious goal of limiting the temperature increase to 1.5°C was seen as unexpected (Kruse et al., 2020). Bolton and Kacperczyk (2021)

argue that the Paris Agreement increased both the risk and the investor awareness of regulatory action aimed at limiting carbon emissions. Moreover, I observe that the number of green patents obtained by firms, as a proportion of all patents, increased from 3.7% to 5.1% after the adoption of Paris Agreement (see Table 4-7).^{116 117}

/Table 4-7 here/

Since the Paris Agreement reflected a worldwide commitment to protecting the environment, I expect the agreement to have a positive effect on the market reaction to green patents. I test this using the following model:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 * \ln(1 + \text{green patent volume})_{i,t} + \beta_2 * \text{Paris Agreement} \\
 & + \beta_3 * \text{Paris Agreement} * \ln(1 + \text{green patent volume})_{i,t} \quad (4.7) \\
 & + \beta_n * X_{i,t-1} + \beta_n * Z_{i,t} + \gamma + \xi + u_{i,t}
 \end{aligned}$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2) following a patent announcement.¹¹⁸ *Green patent volume* is the number of green patents granted.¹¹⁹ *Paris Agreement* is a dummy variable equal to 1 if a patent announcement takes place after 12 December 2015, and 0 otherwise. The firm specific control variables include *market capitalization*, *firm age*, *cash*, *leverage*, *R&D*, and *Tobin's Q*. The patent-related control variables include *patent volume*, *patent citations*, and *patent claims*. Lastly, γ denotes firm fixed effects and ξ denotes year fixed effects.

¹¹⁶ In the sample, 3.7% of all patents obtained by an average company every year are green patents (see: Table 4-1). Using the coefficient on Paris Agreement of 0.014 (column (1) of Table 4-7), I calculate the green proportion of all patents granted after the Paris Agreement at 5.1% (=3.7%+1.4%).

¹¹⁷ I use a multivariate OLS model to test this. The dependent variable is the green proportion of all patents granted to a company in a year. The independent variable of interest equals 1 for all patents granted after December 2015, and 0 otherwise. I include firm fixed effects and the same set of firm controls as in model (4.7).

¹¹⁸ In alternative specifications I use alternative dependent variables, including $CAR(0,+1)$ and $CAR(0,+3)$, and the results remain similar. For brevity I do not report these results, but they are available upon request.

¹¹⁹ I obtain similar results if I use a dummy variable equal to 1 when a patent announcement includes a green patent. I do not report these results for the sake of brevity, but they are available upon request.

The regression results are shown in Table 4-8. I interact *Paris Agreement* and *green patent volume* in column (3) of Table 4-8. The interaction term is not statistically significant, which suggests that the impact of green patents on shareholder wealth did not change after the adoption of the Paris Agreement. I add control variables in column (4) and the results remain unchanged.

/Table 4-8 here/

Next, I test whether the relation between climate concerns and the market reaction to green patents has changed after the adoption of the Paris Agreement. The agreement is considered as a historic achievement in the fight against global warming and the promise by global leaders to address the climate change problem should have a negative effect on the level of climate change concerns. I modify model (4.7) to include an interaction between *Paris Agreement*, *green patent volume*, and *climate concerns*, which measures the average level of climate change concerns over a three-day window (0,+2).¹²⁰ The regression results are presented in Appendix 4-U. The triple interaction term is not statistically significant, which suggests that the adoption of the Paris Agreement did not affect the relation between climate concerns and the market reaction to green patents.

Arguably, the adoption of the Paris Agreement has increased the risk of environmental regulations faced by companies (Degryse et al., 2022). Since green technologies can help firms mitigate these risks, companies that obtain green patents may be seen as more valuable to institutional investors after the adoption of the agreement. I test this by modifying model (4.7) to include an interaction between *Paris*

¹²⁰ I obtain similar results if I measure the average climate change concerns over alternative windows. For brevity I do not report these results, but they are available upon request.

Agreement, *green patent volume* and $IO_{i,t-1}$, which is the proportion of shares owned by institutional investors. The regression results are shown in Appendix 4-V. The triple interaction is not statistically significant.¹²¹

Lastly, I test whether the adoption of the Paris Agreement affected the relation between institutional investor attention and the market reaction to green patents. I modify model (4.7) to include an interaction between *Paris Agreement*, *green patent volume* and *institutional attention* $_{i,t}$. The regression results are shown in the table in Appendix 4-W. The triple interaction is not statistically significant, which suggests that the adoption of the agreement did not have an effect on institutional investors' reaction to green patents. Overall, I find no evidence that the impact of green patent announcements on shareholder wealth changed after the adoption of the Paris Agreement.

4.6 What happens after firms obtain green patents?

4.6.1 Measures of green patenting activity

Overall, the results suggest that green patents do not increase shareholder wealth. I investigate the possible reasons for this result by testing whether changes in green patenting activity of a firm affect a company's environmental score, level of institutional investor ownership, and Tobin's Q, respectively. In this subsection, I describe the measures of *green patenting activity*.

I use six firm-level metrics to measure *green patenting activity*. All metrics are lagged by one year. They include: (1) *green patents ratio* $_{t-1}$, which is the green proportion of all patents granted in a given year (Amore and Bennedsen, 2016; Cohen

¹²¹ I obtain similar results if I use the proportion of shares owned by transient, quasi-indexer, or dedicated institutional investors. For brevity I do not report these results, but they are available upon request.

et al., 2022), (2) *green applications ratio*_{*t-1*}, which is the green proportion of all patent applications filed in a given year that are eventually granted (Hao et al., 2022), (3) *green citations ratio*_{*t-1*}, which is the number of citations received by green patents in a year as a proportion of all patent citations received in a given year (Amore and Bennesen, 2016; Cohen et al., 2022), (4) *green patent stock ratio*_{*t-1*}, which is the green proportion of a firm's patent stock, (5) *green applications stock ratio*_{*t-1*}, which is the green proportion of a firm's patent applications stock, and (6) *green citations stock ratio*_{*t-1*}, which is the green proportion of all patent citations received by a company.

The first three measures capture a firm's green patenting behavior in a particular year. In contrast, the last three measures are calculated using a company's patent stock, which is a cumulative measure of innovation (Porter and Stern, 2000). Patent stock counts the total number of patents granted to a company until a specific point in time. It is calculated as follows:

$$patent\ stock_{i,t} = patents_{i,t} + (1 - \delta) * patent\ stock_{i,t-1} \quad (4.8)$$

Where *patents*_{*i,t*} is the number of patents granted to a firm in a given year. δ is a depreciation rate set to 15% (Balasubramanian and Sivadasan, 2011; Hall et al., 2005), which accounts for the depreciation in the value of ideas over time (Porter and Stern, 2000). For example, if a company received its first patent two years ago, received three patents last year, and obtained four patents this year, its current patent stock equals 7.27 (=1*0.85*0.85+3*0.85+4). I calculate the green proportion of a firm's patent stock by dividing a company's green patent stock by its total patent stock. I follow the same process to calculate the green proportion of the patent applications stock and the green proportion of the patent citations stock.

4.6.2 Green patenting activity, and environmental score

I start by testing whether changes in green patenting activity of a company are related to the firm's environmental score. If green patents improve environmental performance (Amore and Bennedsen, 2016), I expect to see a positive association between the two variables. I estimate the following model:

$$\begin{aligned} \text{Environmental score}_{i,t} &= \alpha + \beta_1 * \text{green patenting activity}_{i,t-1} + \beta_n * X_{i,t-1} + \gamma + \xi \\ &+ u_{i,t} \end{aligned} \quad (4.9)$$

Environmental score measures a firm's environmental performance. I measure *green patenting activity* using the six firm-level metrics described in section (4.6.1).¹²² $X_{i,t-1}$ is a vector of firm specific control variables, including *market capitalization, firm age, cash, leverage, R&D, and Tobin's Q*.¹²³ Moreover, γ denotes firm fixed effects and ξ denotes year fixed effects.

The regression results are shown in Table 4-9. In column (1) of Table 4-9, I regress *environmental score* solely on *green patents ratio*_{*t-1*}. I find that there is no statistically significant relation between green patenting activity and environmental scores. In the remaining columns of Table 4-9, I test the other measures of green patenting activity. As shown in columns (3), (5), and (11), *green applications ratio*_{*t-1*}, *green citation ratio*_{*t-1*}, and *green citation stock ratio*_{*t-1*} are positively related to *environmental score* at the 10%, 10%, and 5% level, respectively. For instance, given a coefficient of 3.85 on *green applications ratio*_{*t-1*}, a one standard deviation increase in the variable is associated with an increase in next year's *environmental score* of 0.54 (=0.14*3.85).

¹²² For robustness, in alternative model specifications I also include the second and the third lags of the green patent activity measures, and I obtain similar results.

¹²³ The results are not sensitive to the choice of firm specific control variables.

However, as shown in columns (8) and (10), there is no evidence that the other green patenting measures, *green patent stock ratio_{t-1}* and *green applications stock ratio_{t-1}*, impact *environmental score*. Moreover, when I rerun the analysis in Table 4-9 using an alternative green patent classification scheme for robustness (see section 4.7), I find no evidence that any of the green patenting activity measures are positively related to *environmental score* (see Appendix 4-AE). Overall, I do not find consistent evidence that green patenting activity affects environmental scores. The results are at odds with Cohen et al. (2022), who find a positive correlation between the number of green patents obtained and the environmental scores of firms operating outside of the energy sector. However, the difference possibly lies in the fact that Cohen et al. (2022) rely only on year fixed effects as they are interested in the cross-sectional variation across firms. Instead, I include both firm- and year-fixed effects to examine whether new green patents obtained by firms are related to changes within firms. Incorporating firm fixed effects is important in studying the impact that green patenting activity has on firms because it controls for firm characteristics which can be hard to quantify, such as a firm's culture and reputation. Holding these factors constant lets me examine whether green patenting activity leads to within-firm changes on my dependent variable(s) of interest.

/Table 4-9 here/

4.6.3 Green patenting activity, and institutional investor ownership

Next, I investigate whether the level of institutional investor ownership is related to a firm's green patenting activity. Since environmental performance can be important to institutional investors (Fernando et al., 2017; Krueger et al., 2020), I expect a positive correlation between the two variables. I use model (4.9) where all metrics of green patenting activity are lagged by one year. In alternative specifications I also

include the second and the third lags of the green patent activity measures and the results (unreported) are similar. The dependent variable is $IO_{i,t}$, which is the proportion of a company's shares owned by institutional investors in a given year. The results are presented in Table 4-10. In column (1) of Table 4-10, I regress the level of institutional investor ownership on the green proportion of all patents granted to a company in a given year. I find no statistically significant relation between the two variables. Similarly, as shown in columns (3) to (12) of Table 4-10, when I use any of the other measures of green patenting activity, I also find that they have no effect on the level of institutional investor ownership.

/Table 4-10 here/

The importance of green patents to institutional investors may also differ depending on their investment horizon. Therefore, I use model (4.9) to test whether the proportion of a company's shares owned by different types of institutional investors is related to green patenting activity. Regression results using the ownership by transient, quasi-indexer, and dedicated institutional investors are shown in Appendix 4-X, Appendix 4-Y, and Appendix 4-Z, respectively. I find that there is no relation between firms' green patenting activity and the level of ownership by the three different types of institutional investors. Overall, I find no evidence that institutional investors value green innovation, which is consistent with the previous results and the work of von Schickfus (2021).

4.6.4 Green patenting activity, and Tobin's Q

Lastly, I test whether changes in green patenting activity are related to changes in firm value, as measured by Tobin's Q. If green patents are valuable I expect to find a positive correlation between the two variables. I use model (4.9) where all metrics of green patenting activity are lagged by one year. Regression results are shown in Table

4-11. I find no statistically significant relation between any of the measures of green patenting activity and Tobin's Q.¹²⁴ Overall, I find no evidence that green patenting activity is positively associated with firm value. The results contrast with Hao et al. (2022), who find a positive correlation between green patenting and Tobin's Q. However, their study focuses on China during 2007-2018, while my sample covers the US during 1976-2019. The disparity in the results could be driven by the different regulatory environments of the two countries (Allen et al., 2005).

/Table 4-11 here/

4.7 Robustness: Climate Change Mitigation Technologies

To alleviate any concerns that the results are driven by how I classify patents on environmentally friendly technologies (see: section 4.3), in this section I focus specifically on patents covering Climate Change Mitigation Technologies (CCMTs). CCMT patents are identified by a dedicated patent classification scheme developed by the European Patent Office (Angelucci et al., 2018). CCMT patents are tagged using either an "Y02" or a "Y04" classification code. These codes are a part of the Cooperative Patent Classification (CPC) system (Grassano et al., 2020). The CCMT classification scheme includes, among others, technologies on carbon capture storage of greenhouse gases, technologies related to adaptation to climate change, and technologies that aim to reduce greenhouse gas emissions (Grassano et al., 2020).

I repeat all of the analyses using CCMT patents (Angelucci et al., 2018) instead of green patents (Haščič and Migotto, 2015) and the results remain unchanged. I find no effect of CCMT patent announcements on the shareholder wealth of firms with a high exposure to climate change risks, as shown in the table in Appendix 4-AA. Moreover,

¹²⁴ The results are similar if I use a logarithm of Tobin's Q.

there is no statistically significant relation between the level of climate change concerns and the market reaction to CCMT patents, as shown in Appendix 4-AB. Furthermore, neither the level of institutional investor ownership, nor the amount of institutional investor attention affects the market reaction to CCMT patents, as shown in Appendix 4-AC and Appendix 4-AD, respectively. I also find no relation between CCMT patenting activity and firm's environmental score, level of institutional investor ownership, or Tobin's Q, as shown in Appendix 4-AE, Appendix 4-AF, and Appendix 4-AG, respectively. I conclude that it is unlikely for the results to be driven by how I identify patents on environmentally friendly technologies.

4.8 Conclusion

Despite the urgent calls for more green innovation to fight climate change (Climate-KIC, 2021; Nordhaus, 2021; US State Department, 2021) I find no evidence that green patents increase shareholder wealth. This is true for green patents obtained by companies operating in carbon-intensive industries as well as for firms with a high exposure to climate change. I also find that the impact of green patent announcements on shareholder wealth does not depend on the level of climate concerns. Despite the increasing pressure from institutional investors on companies to reduce their carbon footprint, I find no evidence that the environment is a priority for institutional investors. The impact of green patent announcements on shareholder wealth is not related to the level of institutional investor ownership or the amount of institutional investor attention. Similarly, I find that the impact of green patent announcements on shareholder wealth has not changed after the adoption of the Paris Agreement on 12 December 2015. Moreover, I find no consistent evidence that an increase in the number of green patents obtained by companies is related to higher environmental

scores, level of institutional investor ownership, or firm value. While there is some indication that green patenting activity improves environmental scores, the results are not robust to different measures of green patenting activity or to the use of an alternative green patent classification scheme.

Overall, I find that firms are not rewarded for engaging in green innovation. At a first glance, this finding may seem surprising since green innovation is seen as the key to solving the climate change problem. However, the results can be partially explained by the argument that this may be a consequence of green tastes of investors, who can push up the prices of firms that obtain green patents and lower their expected returns (Pástor et al., 2021). Moreover, the results are consistent with green innovation being viewed as risky (Nanda et al., 2015), and potentially less advanced than grey innovation (Acemoglu et al., 2012; IEA, 2021).

Table 4-1: Descriptive statistics

<i>Panel A: Patent owner characteristics</i>							
	Mean	Median	SD	25 th	75 th	Firms	Events
Market capitalization (\$bn)	19.4	2.9	56.7	0.6	12.7	6,736	450,628
Firm age (years)	30.1	23.2	23.4	10.8	48.1	7,263	467,502
Cash (%)	11.1	6.7	13.5	1.7	15.4	6,736	450,628
Leverage (%)	52.3	51.8	40.1	37.6	64.8	6,736	450,628
R&D (%)	8.2	4.6	13.1	1.9	9.8	6,736	450,628
Tobin's Q	2.0	1.5	2.3	1.0	2.3	6,736	450,628
IO (%)	57.2	61.0	24.3	42.3	76.3	6,362	397,233
IO transient (%)	13.1	11.4	9.0	6.2	18.1	5,967	389,023
IO quasi-indexer (%)	41.3	43.4	18.9	28.9	55.5	6,315	396,619
IO dedicated (%)	3.6	1.7	5.2	0.3	4.7	4,773	328,921
Environmental score	38.4	37.5	29.3	9.4	63.7	1,310	143,952
Climate exposure (%)	8.1	3.1	18.6	0.0	8.2	2,591	206,389
<i>Panel B: Patent characteristics</i>							
Patent citations	1.3	0.5	4.0	0.1	1.2	7,101	454,741
Patent claims	1.1	1.0	0.2	1.0	1.0	7,263	467,500
<i>Panel C: Announcement day characteristics</i>							
Patent volume	3.6	1.0	7.9	1.0	3.0	7,263	467,502
Green patent volume	0.1	0.0	0.8	0.0	0.0	7,263	467,502
Climate concerns (0,+2) (%)	10.3	6.2	24.2	-6.9	23.4	2,979	171,026
Institutional attention (0,+2)	0.7	0.0	1.0	0.0	1.3	1,765	128,504
<i>Panel D: Yearly measures of green patenting activity</i>							
Green patents ratio (%)	3.7	0.0	14.2	0.0	0.0	8,030	N/A

Green applications ratio (%)	3.7	0.0	14.3	0.0	0.0	8,052	N/A
Green citations ratio (%)	4.1	0.0	15.6	0.0	0.0	7,604	N/A
Green patent stock ratio (%)	3.9	0.0	14.7	0.0	0.0	8,217	N/A
Green applications stock ratio (%)	4.0	0.0	15.0	0.0	0.0	8,234	N/A
Green citations stock ratio (%)	4.3	0.0	15.9	0.0	0.0	7,611	N/A

This table reports the descriptive statistics. Events is the number of patent announcements. Panels A, B, and C present descriptive statistics on a patent announcement-level. Panel A reports patent owner characteristics. Panel B shows patent characteristics, Panel C shows announcement day characteristics and Panel D shows descriptive statistics of green patenting activity on a yearly level. See Appendix 4-A for variable definitions.

Table 4-2: Event study results

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
All events	-0.015***	0.023***	0.020***	0.013***	0.008*	0.028***	0.042***	467,502
Grey events	-0.015***	0.025***	0.023***	0.016***	0.010**	0.033***	0.048***	428,026
Green events	-0.013	0.002	-0.010	-0.009	-0.011	-0.021	-0.030*	39,476
<i>Panel B: Announcements of single patents only</i>								
All events	-0.031***	0.019***	0.033***	0.033***	-0.012*	0.021**	0.054***	248,411
Grey events	-0.029***	0.019***	0.033***	0.033***	-0.010	0.023***	0.056***	238,412
Green events	-0.069***	0.013	0.024	0.038*	-0.056*	-0.031	0.007	9,999
<i>Panel C: All announcements in polluting industries</i>								
All events	-0.013***	0.029***	0.016***	0.008**	0.016***	0.032***	0.040***	323,916
Grey events	-0.013***	0.032***	0.019***	0.009**	0.019***	0.038***	0.047***	293,349
Green events	-0.011	0.001	-0.017	-0.003	-0.010	-0.026	-0.030	30,567
<i>Panel D: All announcements with high technological value</i>								
All events	-0.008	0.035***	0.033***	0.007	0.027***	0.060***	0.068***	149,299
Grey events	-0.009	0.038***	0.040***	0.011*	0.029***	0.069***	0.080***	136,046
Green events	0.011	0.001	-0.016	-0.028*	0.011	-0.005	-0.033	12,846

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel E: All announcements with high climate change concerns</i>								
All events	-0.029***	0.034***	-0.001	0.001	0.006	0.004	0.006	56,186
Grey events	-0.029***	0.036***	0.003	0.005	0.006	0.009	0.014	50,805
Green events	-0.020	0.019	-0.040*	-0.032	-0.001	-0.041	-0.072	5,381
<i>Panel F: All announcements with high institutional investor ownership</i>								
All events	0.016***	0.045***	0.026***	0.009*	0.061***	0.087***	0.096***	134,901
Grey events	0.018***	0.047***	0.028***	0.009*	0.065***	0.093***	0.102***	125,844
Green events	-0.003	0.007	0.008	0.008	0.004	0.012	0.019	9,057
<i>Panel G: All announcements with high institutional investor attention</i>								
All events	0.039***	0.057***	0.017*	-0.019**	0.096***	0.113***	0.095***	38,219
Grey events	0.042***	0.066***	0.017*	-0.015*	0.109***	0.126***	0.112***	31,929
Green events	0.022	0.011	0.014	-0.039**	0.033	0.047	0.008	6,290

This table presents the event study results, in %. “All events” refers to all announcements. “Green events” (“Grey events”) refers to events that do (do not) include a green patent. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value; when the truncation-adjusted number of citations is in the top 33% of its distribution. Panel E shows events with a high level of climate change concerns; when the value of the UMC index measured over a three-day window (0,+2) is in the top 33% of its distribution. Panel F shows events that include firms with a high level of institutional investor ownership; when the institutional ownership variable is in the top 33% of its distribution. Panel G shows events that are accompanied by high levels of institutional investor attention; when the value of the attention variable over a three-day window (0,+2) is in the top 33% of its distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-3: Market reaction (CAR 0,+2), green patents, and high risk firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln (1+green patent volume)	0.0002 (0.0002)		0.0001 (0.0003)	0.0001 (0.0003)		0.0003 (0.0003)	0.0004 (0.0003)		0.0001 (0.0003)	0.0002 (0.0004)
CO ₂ Intensive Industry		0.0006 (0.0007)	0.0006 (0.0007)	-0.0002 (0.0012)						
CO ₂ Intensive Industry x Ln (1+green patent volume)			0.0001 (0.0004)	-0.0000 (0.0004)						
Low env. Score _{t-1}					0.0006* (0.0004)	0.0007* (0.0004)	0.0006* (0.0003)			
Low env. Score _{t-1} x Ln (1+green patent volume)						-0.0008 (0.00013)	-0.0008 (0.0013)			
High climate exposure _{t-1} (*10)								-0.0001 (0.0020)	-0.0001 (0.0021)	-0.0002 (0.0024)
High climate exposure _{t-1} x Ln (1+green patent volume)									-0.0000 (0.0004)	-0.0001 (0.0003)
Market capitalization _{t-1}				-0.0013*** (0.0002)			-0.0028*** (0.0006)			-0.0016*** (0.0004)
Firm age _{t-1}				-0.0005* (0.0003)			0.0006 (0.0006)			-0.0005 (0.0005)
Cash _{t-1}				0.0019* (0.0010)			0.0025 (0.0016)			0.0022* (0.0004)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage _{t-1}				-0.0015** (0.0006)			-0.0014 (0.0013)			-0.0007 (0.0009)
R&D _{t-1}				-0.0001 (0.0023)			-0.0020 (0.0063)			-0.0002 (0.0033)
Tobin's Q _{t-1}				0.0000 (0.0001)			0.0001 (0.0001)			0.0001 (0.0001)
Ln (1+patent volume)				0.0002 (0.0001)			-0.0001 (0.0002)			0.0000 (0.0002)
Patent citations				0.0002* (0.0001)			0.0001 (0.0002)			0.0001 (0.0002)
Patent claims				0.0002 (0.0008)			0.0009 (0.0011)			-0.0014 (0.0010)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466,227	466,227	466,227	433,690	125,928	125,928	125,536	199,139	199,139	198,027
R-squared	0.0269	0.0269	0.0269	0.0265	0.0127	0.0127	0.0137	0.0208	0.0208	0.0211

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. For ease of presentation, the coefficient on the *high climate exposure* variable has been multiplied by 10. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-4: Market reaction (CAR 0,+2), green patents, and climate concerns

	(1)	(2)	(3)	(4)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	-0.0013 (0.0012)
Ln (1+green patent volume)		0.0002 (0.0002)	-0.0001 (0.0003)	-0.0002 (0.0003)
Climate concerns x Ln (1+green patent volume)			0.0012 (0.0010)	0.0013 (0.0010)
Market capitalization t_{-1}				-0.0022*** (0.0005)
Firm age t_{-1}				-0.0011 (0.0006)
Cash t_{-1}				0.0022 (0.0015)
Leverage t_{-1}				-0.0000 (0.0011)
R&D t_{-1}				-0.0036 (0.0039)
Tobin's Q t_{-1}				0.0001 (0.0001)
Ln (1+patent volume)				0.0002 (0.0003)
Patent citations				0.0001 (0.0002)
Patent claims				-0.0023** (0.0011)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	170,583	466,227	170,583	163,540
R-squared	0.0297	0.0269	0.0298	0.0292

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-5: Market reaction (CAR 0,+2), green patents, and inst. ownership

	(1)	(2)	(3)	(4)
IO _{t-1}	-0.0014** (0.0007)		-0.0015** (0.0007)	-0.0003 (0.0007)
Ln (1+green patent volume)		0.0002 (0.0002)	-0.0003 (0.0008)	-0.0002 (0.0008)
IO _{t-1} x Ln (1+green patent volume)			0.0007 (0.0012)	0.0004 (0.0013)
Market capitalization _{t-1}				-0.0014*** (0.0003)
Firm age _{t-1}				-0.0003 (0.0003)
Cash _{t-1}				0.0020* (0.0011)
Leverage _{t-1}				-0.0018** (0.0007)
R&D _{t-1}				-0.0007 (0.0025)
Tobin's Q _{t-1}				-0.0001 (0.0001)
Ln (1+patent volume) (*10)				0.0002 (0.0012)
Patent citations				0.0003** (0.0001)
Patent claims				0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	390,611	466,227	390,611	375,051
R-squared	0.0275	0.0269	0.0275	0.0274

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. For ease of presentation, the coefficient on the *ln (1+patent volume)* variable has been multiplied by 10. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-6: Market reaction (CAR 0,+2), green patents, and inst. Investor attention

	(1)	(2)	(3)	(4)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0010*** (0.0002)
Ln (1+green patent volume)		0.0002 (0.0002)	0.0003 (0.0003)	0.0003 (0.0003)
Institutional attention x Ln (1+green patent volume)			-0.0003 (0.0002)	-0.0003 (0.0002)
Market capitalization t_{-1}				-0.0016*** (0.0005)
Firm age t_{-1}				-0.0005 (0.0008)
Cash t_{-1}				-0.0030* (0.0017)
Leverage t_{-1}				0.0028** (0.0013)
R&D t_{-1}				0.0046 (0.0035)
Tobin's Q t_{-1}				0.0004*** (0.0001)
Ln (1+patent volume)				-0.0001 (0.0002)
Patent citations				0.0002 (0.0002)
Patent claims				-0.0005 (0.0012)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	128,305	466,227	128,305	124,326
R-squared	0.0239	0.0269	0.0239	0.0237

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-7: The Paris Agreement and the number of green patents

	(1)	(2)
Paris Agreement	0.014*** (0.003)	0.011*** (0.003)
Market capitalisation $t-1$		-0.001 (0.001)
Firm age $t-1$		0.004** (0.002)
Cash $t-1$		-0.003 (0.005)
Leverage $t-1$		-0.002 (0.004)
R&D $t-1$		-0.008 (0.006)
Tobin's Q $t-1$		0.001 (0.002)
Firm FE	YES	YES
Year FE	NO	NO
Observations	59,817	53,163
R-squared	0.507	0.506

The dependent variable is the number of green patents divided by the number of all patents obtained by a company in a year. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects. I do not include year fixed effects, because they are collinear with *Paris Agreement*. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. For ease of presentation, the coefficient on the *Tobin's Q* variable has been multiplied by 10. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-8: Market reaction (CAR 0,+2), green patents, and the Paris Agreement

	(1)	(2)	(3)	(4)
Ln (1+green patent volume)	0.0002 (0.0002)		0.0002 (0.0002)	0.0002 (0.0002)
Paris Agreement		0.0010 (0.0014)	0.0010 (0.0014)	0.0015 (0.0015)
Paris Agreement x Ln (1+green patent volume)			-0.0001 (0.0004)	-0.0004 (0.0004)
Market capitalization t_{-1}				-0.0013*** (0.0002)
Firm age t_{-1}				-0.0005 (0.0003)
Cash t_{-1}				0.0019* (0.0010)
Leverage t_{-1}				-0.0015** (0.0006)
R&D t_{-1}				0.0001 (0.0023)
Tobin's Q t_{-1}				-0.0000 (0.0001)
Patent volume				0.0002 (0.0001)
Patent citations				0.0002* (0.0001)
Patent claims				0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	466,227	466,227	466,227	433,690
R-squared	0.0269	0.0269	0.0269	0.0265

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-9: Green patenting activity and environmental score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	-1.88 (2.14)	-2.10 (2.12)										
Green applications ratio $t-1$			3.85* (1.96)	3.74* (1.86)								
Green citations ratio $t-1$					7.26* (3.67)	6.92* (3.59)						
Green patent stock ratio $t-1$							-7.51 (5.31)	-7.83 (4.95)				
Green applications stock ratio $t-1$									-3.55 (5.73)	-3.62 (5.49)		
Green citations stock ratio $t-1$											20.08** (7.67)	19.97* * (7.55)
Market capitalization $t-1$		2.59*** (0.82)		2.63*** (0.89)		2.81*** (0.83)		2.34*** (0.72)		2.26*** (0.67)		2.75** * (0.81)
Firm age $t-1$		2.12 (1.74)		2.04 (1.54)		2.48 (2.71)		2.46 (1.62)		1.89 (1.39)		2.53 (2.66)
Cash $t-1$		-1.26 (3.29)		-0.20 (3.23)		0.82 (3.98)		-0.95 (3.18)		-1.08 (2.92)		0.54 (3.82)
Leverage $t-1$		0.51 (2.87)		0.05 (2.81)		0.99 (2.61)		-0.42 (2.37)		-0.98 (2.25)		0.69 (2.57)
R&D $t-1$		2.61 (5.33)		3.36 (5.35)		4.62 (6.59)		2.69 (4.51)		2.65 (4.32)		3.79 (5.52)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tobin's Q_{t-1}		-0.12 (0.24)		-0.21 (0.23)		0.03 (0.27)		-0.00 (0.23)		-0.14 (0.23)		0.00 (0.26)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,714	7,704	7,911	7,798	8,426	8,417	10,273	10,258	10,873	10,739	9,110	9,101
R-squared	0.84	0.84	0.83	0.84	0.83	0.84	0.84	0.84	0.84	0.84	0.83	0.84

The dependent variable is environmental score (out of 100). Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-10: Green patenting activity and institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	-0.01 (0.01)	-0.01 (0.01)										
Green applications ratio $t-1$			-0.01 (0.01)	0.00 (0.01)								
Green citations ratio $t-1$					0.01 (0.01)	0.01 (0.01)						
Green patent stock ratio $t-1$							0.02 (0.02)	0.01 (0.02)				
Green applications stock ratio $t-1$									0.02 (0.02)	0.01 (0.02)		
Green citations stock ratio $t-1$											0.03 (0.03)	0.03 (0.03)
Market capitalization $t-1$		0.06*** (0.00)		0.06*** (0.00)		0.06*** (0.00)		0.07*** (0.00)		0.07*** (0.00)		0.07*** (0.00)
Firm age $t-1$		0.05*** (0.00)		0.05*** (0.00)		0.04*** (0.01)		0.04*** (0.00)		0.04*** (0.00)		0.04*** (0.01)
Cash $t-1$		0.01 (0.01)		0.00 (0.01)		0.01 (0.01)		0.00 (0.01)		-0.00 (0.01)		0.01 (0.01)
Leverage $t-1$		-0.04*** (0.01)		-0.04*** (0.01)		-0.04*** (0.01)		-0.03*** (0.01)		-0.03*** (0.01)		-0.04*** (0.01)
R&D $t-1$		-0.08*** (0.02)		-0.07*** (0.02)		-0.06*** (0.02)		-0.04** (0.02)		-0.04*** (0.01)		-0.05** (0.02)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tobin's Q_{t-1}		-0.01*** (0.00)		-0.00 (0.01)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,960	41,2539	46,746	42,548	51,377	46,978	71,674	64,983	81,597	71,428	58,214	53,048
R-squared	0.79	0.83	0.78	0.82	0.79	0.84	0.79	0.84	0.78	0.84	0.80	0.84

The dependent variable is the proportion of a company's shares owned by institutional investors. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 4-11: Green patenting activity and Tobin's Q

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	0.00 (0.06)	0.04 (0.06)										
Green applications ratio $t-1$			0.01 (0.06)	0.02 (0.05)								
Green citations ratio $t-1$					0.06 (0.08)	-0.00 (0.08)						
Green patent stock ratio $t-1$							0.18 (0.13)	0.10 (0.12)				
Green applications stock ratio $t-1$									0.17 (0.13)	0.10 (0.11)		
Green citations stock ratio $t-1$											-0.01 (0.17)	-0.11 (0.16)
Market capitalization $t-1$		0.28*** (0.02)		0.27*** (0.02)		0.27*** (0.02)		0.26*** (0.02)		0.25*** (0.02)		0.27*** (0.02)
Firm age $t-1$		-0.46*** (0.05)		-0.48*** (0.04)		-0.52*** (0.09)		-0.44*** (0.05)		-0.47*** (0.04)		-0.52*** (0.09)
Cash $t-1$		1.17*** (0.14)		1.22*** (0.13)		1.23*** (0.13)		1.20*** (0.12)		1.21*** (0.11)		1.21*** (0.13)
Leverage $t-1$		0.55*** (0.10)		0.50*** (0.10)		0.54*** (0.10)		0.52*** (0.09)		0.49*** (0.08)		0.55*** (0.09)
R&D $t-1$		3.27*** (0.34)		3.56*** (0.37)		3.61*** (0.38)		3.14*** (0.30)		3.31*** (0.29)		3.51*** (0.37)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,645	50,405	54,589	51,695	54,641	54,271	77,968	77,378	88,296	84,746	61,530	61,113
R-squared	0.55	0.58	0.53	0.58	0.54	0.57	0.54	0.57	0.53	0.57	0.54	0.57

The dependent variable is Tobin's Q. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

5. Are Investors Mispricing Green Patent Announcements?

5.1 Introduction

In the previous chapter I find that there is no statistically significant market reaction to green patent announcements in the short-run. Given that the potential benefits of green patents are predominantly long-term in nature, the market may be realizing their value with a delay. Green innovation can deliver sustainable and strong economic growth (Stern, 2022). Innovation is a central part of the transition to net zero carbon emissions and limiting the global temperature increase to 1.5°C above the pre-industrial levels (Aghion et al., 2022). Moreover, corporate green innovation can reduce the climate-related risks faced by firms including carbon transition risks (Bolton and Kacperczyk, 2022), environmental regulation risks (Bolton and Kacperczyk, 2021), and natural disaster risks (Miao and Popp, 2014). These risks are most likely to manifest in the long run (Bansal et al., 2016). Therefore, the main focus of this chapter is to investigate the long-run performance of firms following their green patent announcements.

The lack of a short-run reaction to green patent announcements may be a result of investors mispricing new green technologies. Green patents combine scientific concepts from a wider range of technological fields than the grey technologies. Studies on green innovation consistently report that green patents are on average more complex and novel than grey patents (Popp and Newell, 2012; De Marchi, 2012; Amore and Bennesen, 2016; Barbieri et al., 2020; Fusillo, 2020),¹²⁵ which can make

¹²⁵ Green patents are technologically complex because they cite inventions that belong to different technological fields more frequently than grey patents do (Popp and Newell, 2012; Amore and Bennesen, 2016). Moreover, green patents are also cited by technologically distant patents more often (Amore and Bennesen, 2016; Fusillo, 2020).

their value harder for investors to estimate (Song and Schwarz, 2010; Hirshleifer et al., 2013).

The direction of the potential mispricing is not certain ex-ante. On the one hand, green patenting firms may earn a positive alpha in the long run, since they can be better suited to tackle climate-related risks than other companies. For example, the literature finds that green technologies can help firms mitigate the damage from natural disasters (Miao and Popp, 2014), and adapt to the changing regulatory environment (Sautner et al., 2022). The initial mispricing of green patents can be amplified by the fact that investors can underestimate the risks associated with climate change (Hong et al., 2019; Stroebel and Wurlger, 2021). Therefore, the market may realize the value of green patents with a delay, for example when their benefits become salient.

On the other hand, green patenting firms may earn a negative alpha if the cost of producing green innovation exceeds the potential benefits. This is possible since developing green technologies is capital-intensive and firms may not be able to fully realize their value. Environmental technologies are characterized by the issue of environmental externalities (Hall and Helmers, 2010). The benefits of reduced pollution are shared with the society at large, which reduces the ability of firms to profit from their green innovation (Soltmann et al., 2015, Malen and Marcus, 2019). Moreover, green technologies are arguably less developed than grey technologies because they have fewer previous innovations to build upon (Acemoglu et al., 2012, Aghion et al., 2016).

To test whether investors are mispricing green patent announcements and to determine the direction of the potential mispricing, I study the long-run stock performance of companies following their green patent announcements. I apply the

calendar portfolio approach, which, arguably, is the most suitable method of estimating long-run abnormal performance since companies can obtain new patents every week (Kogan et al., 2017). The calendar time portfolio approach does not suffer from the issue of cross-sectional dependence that plagues other methods of estimating long-run returns (Sorescu et al., 2007). The issue arises as a result of economy- and/or industry-wide factors that can create contemporaneous co-movements in returns, leading to increased cross-correlation in returns (Kothari and Warner, 2007). This leads to a downward bias in the standard errors, inflating the t-statistics (Chen et al., 2014). Therefore, I apply the calendar time portfolio approach to my sample, which includes all green patent announcements involving US public companies during 1976 to 2019.

I find that firms consistently underperform after obtaining new green patents. A portfolio that is long on companies with new green patent announcements generates value- and equally-weighted alphas of -0.12% and -0.09% per week, respectively, for a 4-week portfolio holding period (significant at the 1% and 5% levels, respectively). The results across alternative portfolio holding periods are similar. This suggests that investors are mispricing green patent announcements in the short run, and that producing new green technologies can have a negative impact on the returns in the long-run. This is consistent with Soltmann et al. (2015), who find that, on an industry level, engaging in green innovation is not profitable. The results support the argument that it can be challenging for firms to capture value from producing green technologies (Hall and Helmers, 2010; Malen and Marcus, 2019).

In contrast, firms do not consistently underperform after obtaining grey patents. Alphas of all equally-weighted portfolios constructed based on grey patent announcements are not statistically significant. This suggests that firms which obtain

new grey patents do not consistently underperform in the future, and that the investors are not mispricing grey patent announcements. As shown in the previous chapter, there is a positive short-run stock market reaction to grey patents. Meanwhile, the alphas of the value weighted portfolios based on grey patent announcements are negative and predominantly weakly significant at the 10% level.

The long-run performance of green patenting firms may be affected by the amount of attention paid to environmental issues. Green technologies can be more valuable to firms when the climate-related risks become more important. Arguably, a major shift in climate attention happened in 2006 with the release of the Stern Review and the launch of Principles for Responsible Investment (Painter, 2020; Kim and Yoon, 2022). To explore whether the performance of green patenting firms changed over time, I distinguish between green patents granted during 1976 to 2005 and 2006 to 2019. I find that for the 1976 to 2005 period, the portfolio alphas are more negative than the full sample results, which are based on all green patent announcements during 1976 to 2019. In contrast, during 2006 to 2019, the alphas are not statistically different from zero. The results are consistent with investors viewing green patents as less value destroying (or being indifferent to green patents) during 2006 to 2019 because of the higher amount of attention paid to climate-related problems as evidenced by the increase in the stringency of environmental regulations (Noailly et al., 2021) and the rising levels of climate change concerns (Ardia et al., 2022). Moreover, the results are consistent with green innovation becoming more technologically advanced and therefore potentially less value-destroying to firms during the 21st century (Blanco et al., 2022). I also find that the alphas are more negative for portfolios consisting of firms operating in CO₂ intensive industries, while the alphas of firms in non-CO₂

intensive industries are not statistically significant. This is consistent with Cohen et al. (2022), who show that polluting firms are less rewarded for obtaining green patents than non-polluting firms.

It is worth noting that mispricing and the low technological maturity of green technologies during 1976 to 2005 are not the only potential explanations for the long-run underperformance of green patenting firms. The asset pricing literature on the green preferences of investors suggests that green patenting firms may have lower expected returns than other companies. Pástor et al. (2021) argue that investors can prefer holding green firms because they generate positive externalities for the environment. Arguably, this can apply to green patenting firms which can be seen as being credibly committed to addressing environmental issues (Berrone et al., 2017). Investor preference for green patenting companies may increase their valuations relative to grey companies and decrease their future returns. Consistent with this view, Pedersen et al., (2021) argue that the high market valuation of firms with a low carbon intensity leads them to earn low returns. Similarly, Avramov et al. (2022) show that firms with a low uncertainty surrounding their high ESG rating have lower expected returns, while Hong and Kacperczyk (2009) find that non-sin stocks earn lower returns than similar sin stocks.

In the last part of the chapter, I test whether firms' R&D intensity and R&D efficiency, respectively, lead to better stock price performance following the green patent announcements. I measure R&D intensity as a ratio of a company's R&D expenditures to its total assets (Hirshleifer et al., 2012), and R&D efficiency as the amount of patent citations received by a firm scaled by its R&D spending (Hirshleifer et al., 2013). Firms that are more R&D-intensive may be better at producing valuable

green innovation since green technologies are more complex than grey technologies (Barbieri et al., 2020). Moreover, high R&D efficiency can be positively related to the long-run performance of green patenting companies since green technologies require more capital than grey technologies (Gaddy et al., 2017).

I find that firms with low R&D intensity and firms with low R&D efficiency both exhibit significant underperformance after their green patent announcements. For example, the value-weighted portfolio consisting of firms in the bottom R&D efficiency quintile earns a negative alpha of -17 basis points per week (statistically significant at the 1% level), over a 52-week holding period. I also find that R&D efficiency is not related to performance of portfolios constructed based on single green patent announcements. This suggests that R&D efficiency matters more (less) for firms that obtain many (few) green patents. Overall, the results are consistent with green technologies requiring more investment and technological expertise than other technologies (De Marchi, 2012; Gaddy et al., 2017), and with green technologies being more complex and novel than other technologies (Barbieri et al., 2020). The results suggest that firms which invest more in innovation and companies that are more efficient innovators can produce green innovation that is more valuable. This view is supported by Cohen et al. (2013) and Hirshleifer et al. (2013) who show that R&D intensive and R&D efficient firms earn higher returns than other firms.

The contribution of this chapter is threefold. To my knowledge, this chapter is the first to investigate the long-run performance of firms following their green patent announcements. I show that firms that obtain new green patents underperform in the future. Second, this chapter contributes to the literature on the long-run performance of R&D efficient companies (Cohen et al., 2013; Hirshleifer et al., 2013). Prior

literature shows that high R&D efficiency companies outperform low R&D efficiency companies. I show that this relationship also applies to green patenting companies. Third, I contribute to the literature that studies the relation between green innovation and firm performance (Soltmann et al., 2015, Malen and Marcus, 2019), and the asset pricing literature on the effects of green tastes of investors (Pedersen et al. 2021; Avramov et al., 2022), and find empirical support for the theory of Pástor et al. (2021).

5.2 Hypotheses development

Information about green technologies can be difficult to process. Barbieri et al. (2020) compare patents on green technologies with patents on grey technologies using data on all patents filed at the European Patent Office during 1980-2012. The authors draw on the theory of Trajtenberg et al. (1997) and Hall et al. (2001), who argue and show that patent citation information can be used to measure the degree of a patent's complexity and novelty. Arguably, a patent that cites a broad range of technologically diverse patents can be seen as being more(less) complex (Amore and Bencedsen, 2016). Consistent with this framework, Barbieri et al. (2020) find that green technologies are more complex than grey technologies, because they draw on knowledge from a larger variety of sources (Hall et al., 2001). The authors also find that green patents are more novel because they are more likely to bring together concepts from fields that are technologically distant from one another, and they share fewer similarities with existing patents. Amore and Bencedsen (2016), who use data on 3 million US patents granted during 1976 to 1995, find that green patents are significantly more technologically complex than other patents. Similarly, Fusillo (2020), who studies European patent data, reports that green patents are more diverse than grey patents because they build on a larger variety of knowledge sources. De

Marchi (2012) studies the propensity of companies to generate green innovations using data on 6,047 manufacturing firms in Spain during 2005-2007. The author finds that firms engaging in green innovation are more likely to cooperate with other firms on R&D projects. The author argues that green technologies are more complex than other technologies and therefore require knowledge and skills that can be outside of a single firm's knowledge base. Horbach et al. (2013) study the determinants of corporate environmental innovation in France and Germany using data from the 2002-2004 Community Innovation Survey. They find that innovating in green technologies compared to other innovations often requires firms to develop new expertise and draw knowledge from previously unexplored technological fields. Overall, the studies above find that green technologies are more complex, and novel compared to grey technologies.

Song and Schwarz (2010) review the literature on information processing and find that individuals pay less attention to information that is hard to evaluate, and they understand it more poorly. Song and Schwarz (2008) conduct three experiments in which they compare the responses of individuals to information that requires different levels of effort to process. They show that the difficulty in processing information can discourage individuals from acting on that information. Similarly, Hirshleifer et al. (2013) who study how investors respond to information on new firm innovation, argue that information on new technologies that is disclosed in patents can be especially challenging for investors to process. Investors may have to adjust their views on how the firm, or an industry is transforming (Hirshleifer et al., 2013). Gaddy et al. (2017) provide supporting evidence. They compare the performance of venture capital (VC) investments in green energy technologies against similar investments in software and

medical technologies during 2006-2011. They find that the green technologies yield comparatively lower returns and are more likely to fail than grey technologies. This suggests that VC investors are less efficient at identifying successful green technologies. Similarly, Nanda et al. (2015), who study VC-backed green innovation, argue that it is difficult to assess the market potential of clean energy technologies, compared to other technologies. Moreover, clean energy investments can require more risk capital and take longer to demonstrate commercial viability (Nanda et al., 2015). Overall, the aforementioned studies suggest that it can be challenging to assess the value of green technologies and that investors may be mispricing green patent announcements in the short run.

The previous chapter shows that there is no statistically significant market reaction to green patent announcements in the short run. If investors are mispricing the announcements, then the post-announcement alphas of the green patenting firms should be statistically different from zero. This leads to the first hypothesis:

Hypothesis 5-1: Firms earn a non-zero alpha after obtaining new green patents

The literature does not offer a clear prediction on the direction of the potential mispricing. On the one hand, green patents can be a positive predictor of firm performance because they can help firms mitigate climate related risks. Carrion Flores and Innes (2010) study the relation between green innovation and air pollution using a panel of 127 manufacturing industries in the US during 1989 to 2004. They find that environmental innovation, as measured by green patents, significantly reduces toxic emissions. Miao and Popp (2014) study the impact of natural disasters on green innovation in a panel of 28 countries during 1984 to 2009. They find that countries produce more green technologies after experiencing natural disasters and that these

technologies help them reduce the damage suffered from future disasters. Sautner et al. (2022) study how firm exposure to climate change risks affects the number of green patents obtained by 10,673 firms based in 34 different countries during 2002 to 2020. The authors find that firms produce more green patents after their exposure to regulatory and physical climate risks increases, and also in response to new climate-related business opportunities. Overall, this suggests that green patents can both help firms mitigate climate risks and start new climate-related projects (Sautner et al., 2022).

On the other hand, green patenting firms may underperform if they are not able to capture enough value from their green technologies to justify the development costs. Xiang et al. (2022) study how public Chinese companies finance their green innovation during 2007 to 2014 and argue that green technologies are expensive to develop and can be challenging to profit from. Environmental technologies are characterized by environmental externalities (Hall and Helmers, 2010). This can impede firms' ability to profit from green innovation, as the benefits of addressing environmental problems are shared with the society as a whole (Hall and Helmers, 2010; Malen and Marcus, 2019). Malen and Marcus (2019) study a sample of 203 manufacturing firms in the US during 1987 and 2006 and find support for this argument. Similarly, Soltmann et al. (2015), who study green innovation at an industry level in 12 different countries during 1980 to 2009 find that green technologies are not profitable on average.

The majority of the aforementioned studies rely on data which ends during the first decade of the 21st century. Arguably, since then, the importance of green technologies has increased. A major shift happened in 2006 with the publication of Stern Review, which increased the amount of attention paid to environmental issues (Painter, 2020).

The same year saw the launch of the Principles for Responsible Investment, the largest ESG initiative in the asset management industry (Kim and Yoon, 2022). Moreover, both the stringency of environmental policies (Noailly et al., 2021) and the technological advancement of green technologies have significantly increased during the 21st century (Blanco et al., 2022). Overall, the above factors have likely increased the value of green technologies to companies. Therefore, I expect the long-term value of green patents to companies to be larger during 2006 to 2019, compared to 1976 to 2005. Similarly, since polluting companies are more at risk of being affected by climate-related regulations, I expect green patents to be more valuable to companies operating in CO₂ intensive industries.

R&D intensity of a company can proxy for the importance of innovation to a firm (Lin et al., 2006). R&D spending is frequently used to proxy for a firm's innovative input, while patents are often used to measure the successful output of this investment (Lerner and Seru, 2022; Sunder et al., 2017). Firms with high R&D intensity relative to their rivals invest in new technologies to gain competitive advantage (O'Brien, 2003). Hall et al. (2005), who study a sample of 4,864 manufacturing sector firms in the US during 1976 to 1995, find that a 1% higher research intensity is associated with 0.8% higher market value of a company. Sougiannis (1994), who studies a sample of 573 US firms during 1975-1985, estimates that a \$1m increase in R&D expenditure increases market value of a company by over \$5m. Chan et al. (2001) relate the performance of all US firms during 1975-1995 to their ratio of R&D to market value. They find that firms in the top quintile in terms of R&D intensity earn an average excess yearly return of 6.12%. Gupta et al. (2017) use a sample of 82,367 firm-year observations during 2004-2013 and find that R&D intensity has a positive effect on

firm market value in developed countries. Overall, the aforementioned studies find a positive association between R&D intensity and the market value of a company.

The efficiency with which a company utilizes its R&D may also positively affect its performance. Hirshleifer et al. (2013) studies the relationship between R&D efficiency, defined as the ratio of patents and citations to R&D, and stock returns of all non-financial firms at the intersection of the NBER patent database and the CRSP database. They sort firms into three portfolios based on their R&D efficiency and find that R&D efficiency positively predicts future returns. Similarly, Cohen et al. (2013) differentiate between firms based on their innovative efficiency, which they proxy for using the ratio of R&D to future sales. Their sample consists of all US firms in the CRSP database during 1980-2009. Cohen et al. (2013) find that portfolios consisting of firms in the top quintile in terms of both R&D intensity and R&D efficiency earn excess positive returns. Innovative efficiency could be especially important for firms that obtain green innovations, because these innovations are capital intensive (Gaddy et al., 2017; Nanda et al., 2015). This leads to the second hypothesis:

Hypothesis 5-2: R&D-intense and R&D-efficient firms earn a higher alpha after obtaining new green patents

5.3 Data and methodology

5.3.1 Data selection

The dataset includes 1,616,934 patents granted to 7,263 unique US public companies during 1976-2019. The patents were made public in 467,502 patent announcements made by the USPTO. Of these announcements, 39,476 (428,026) do (do not) include at least one green patent. I refer to these announcements as “green”

(“grey”) events. The details of the sample selection process and the summary statistics are discussed in the previous chapter.

5.3.2 The calendar-time portfolio approach

I estimate the long-run stock performance using the calendar-time portfolio approach. Under this approach, firms experiencing an event are grouped into one portfolio. Whenever a firm experiences an event, its stock is added to the portfolio, and it is held in the portfolio for a predetermined period. The abnormal returns of the portfolio are estimated while controlling for conventional risk factors known to affect stock returns:

$$R_{p,t} - R_{f,t} = \alpha + \beta_{Mkt} * (R_{m,t} - R_{f,t}) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{RMW} * RMW_t + \beta_{CMA} * CMA_t + \beta_{MOM} * MOM_t + \varepsilon_t \quad (5.1)$$

Where $R_{p,t}$ is the portfolio return, $R_{f,t}$ is the risk-free rate, and $R_{m,t}$ is the market return. SMB_t , HML_t , RMW_t , and CMA_t are the size, value, profitability, and investment factors, respectively (Fama and French, 2015). MOM_t is the momentum factor (Carhart, 1997).

The other competing method of estimating abnormal returns in the long-run are the buy and hold abnormal returns (BHAR). Under the BHAR approach, the performance of companies experiencing an event is compared with the returns earned by a reference portfolio or the returns of similar non-event firms (Mitchell and Stafford, 2000). I do not use this approach since it would produce biased estimates of the long-run performance of patenting firms for two main reasons. First, under the BHAR approach, the long-run return horizons of event firms can overlap, resulting in the issue of cross-sectional correlation. This can occur when firms have multiple events during the BHAR measurement period (Sorescu et al., 2007). The cross-sectional dependence of

returns biases the standard errors down and inflates the t-statistics (Mitchell and Stafford, 2000). Second, the BHAR results can be sensitive to the choice of a reference benchmark. Matching event firms to nonevent firms based on characteristics is a potential solution. However, the validity of this approach rests on the assumption that experiencing an event is the only difference between the event firms and the non-event firms (Kothari and Warner, 2007), which can be challenging to satisfy.

Unlike the BHAR approach, the calendar time portfolio approach does not suffer from the issue of cross-sectional dependence of returns because the stocks are grouped into one portfolio (Sorescu et al., 2007). In contrast to the BHAR method, the standard errors are computed from the time series variation of portfolio returns instead of from the cross-sectional variation of returns (Sorescu et al., 2007). Since many firms obtain patents every week (Kogan et al., 2017), the t-statistics calculated under the calendar-time portfolio approach are less likely to be biased. Therefore, I use this method to measure long-run returns, as advocated by Fama (1998) and Lyon et al. (1999).

5.4 Analysis and Results

5.4.1 Portfolio construction

In this section, I apply the calendar time portfolio approach to measure the long-run performance of firms after their new patent announcements. Every week I construct value- and equally-weighted portfolios of companies that obtain new green patents. The stock selection takes place on Tuesdays, the day when new patents are announced by the USPTO (Kogan et al., 2017).¹²⁶ I consider portfolio holding periods of 4, 12, 24, 32, 52, 104, and 156 weeks. I include a stock in a portfolio every time a new patent is

¹²⁶ The results are similar if I select the stocks every Wednesday instead.

announced, and I rebalance the portfolios every week.¹²⁷ I estimate the abnormal returns using model (5.1).

5.4.2 Portfolios based on green vs grey patent announcements

First, I measure the long-run performance of firms after they obtain new patents, and I distinguish between grey and green patent announcements. Panel A of Table 5-1 presents the alphas of both value- and equally-weighted portfolios of firms that had a green patent announcement. I find that green patent portfolios yield a negative alpha, with similar results across all holding periods. For instance, the value-weighted strategy generates a negative alpha of -11 basis points per week (significant at the 1% level) over a 12-week holding period. For robustness, in Panel B of Table 5-1 I limit the portfolio construction to companies that had a green event which consisted of a single green patent only. Similarly, the results show that across holding periods green patents yield a negative alpha. For example, the value-weighted strategy produces a negative alpha of -12 basis points per week (significant at the 1% level) over a 24-week holding period. The only exception is the 4-week holding period when the alpha is not statistically significant. The results show that firms underperform after obtaining new green patents. This suggests that investors are mispricing green patent announcements in the short-run, which provides support for hypothesis 1 (H5-1). The negative alpha earned by green patenting firms suggests that firms do not profit from green innovation in the long run. This is consistent with the argument that capturing value from green technologies can be challenging for firms due to the environmental externalities produced by the technologies (Hall and Helmers, 2010; Soltmann et al., 2015, Malen and Marcus, 2019).

¹²⁷ The results are similar if I buy the stock of the same company only once during the same portfolio holding period instead.

/Table 5-1 here/

Next, I measure the long-run performance of firms after their grey patent announcements. The alphas of both value- and equally-weighted portfolios are presented in panel A of Table 5-2. The results show that grey patent announcements do not consistently generate negative alphas. For example, the equally-weighted strategy generates an alpha of 0 basis points per week over a 12-week holding period (not statistically significant). Over the same holding period, the value weighted strategy generates a negative alpha of -6 basis points per week (significant at the 10% level). The results based on single patent announcements, which are presented in panel B of Table 5-2, are similar. The equally-weighted strategy generates an alpha of 0 basis points per week over a 12-week holding period (not statistically significant), while the value weighted strategy generates a negative alpha of -6 basis points per week (significant at the 10% level) over the same holding period. This suggests that companies do not consistently underperform after obtaining grey patents.

/Table 5-2 here/

Overall, the results suggest that firms underperform after obtaining green patents. Hence, the market is mispricing green patent announcements by not reacting to them in the short run, as shown in the previous chapter. This is consistent with hypothesis 1 (H5-1). Green patents can be more complex and arguably more difficult to analyze than grey patents (Barbieri et al., 2020; De Marchi, 2012), which can explain why investors are mispricing them. Moreover, the evidence that firms engaging in green innovation consistently underperform the market is also consistent with Gaddy et al. (2017) who show that green technologies have low average returns compared to grey technologies. Lastly, the results also support Pástor et al. (2021), who predict that

green companies have low expected returns because of their high stock market valuations. Similarly, I find support for Pedersen et al. (2021) and Avramov et al. (2022) who argue that environmentally responsible firms have low returns. Moreover, the results are consistent with Bolton and Kacperczyk (2021), who show that firms with low carbon intensity have higher valuations and lower stock performance compared to firms with high carbon intensity.

5.4.3 Portfolios based on the initial market reaction to green vs grey patent announcements

The long-run stock performance of firms after their patent announcements could be related to the initial market reaction to the announcements. For example, if the market initially underprices an announcement this could lead to higher stock returns in the future, assuming a price correction occurs (Bremer and Sweeney, 1991; Chan, 2003). To test this, I distinguish between grey and green patent announcements, and I split the portfolios into quintiles based on the market-adjusted abnormal return at the event date.

The alphas of both value- and equally-weighted portfolios based on the market reaction to new green patent announcements are presented in Table 5-3. Panels A and B of Table 5-3 show that there is no discernable pattern in the alphas earned by the different portfolios. The portfolios consisting of firms in the bottom quintile and the portfolios formed by firms in the top quintile both earn negative alphas. For example, the former portfolio earns a negative alpha of -9 basis points (significant at the 10% level), while the latter portfolio earns a negative alpha of -11 basis points (significant at the 5% level), for the 12-week horizon value-weighted strategy.

/Table 5-3 here/

I follow the same procedure to form five different portfolios based on the initial reaction to grey patent announcements. The results are shown in Table 5-4. Again, there is no pattern in alphas of the different portfolios constructed based on the initial market reaction to patent announcements. For example, as shown in Panel A of Table 5-4, the value-weighted strategy consisting of firms with the lowest (highest) initial market reaction generates a not statistically significant (significant at the 10% level) negative alpha of -4 (-7) basis points per week over a 32-week holding period. Overall, I find no evidence that the initial market reaction to green or grey patent announcements is associated with future returns.

/Table 5-4 here/

5.4.4 Portfolios based on green patent announcements during 1976-2005 vs 2006-2019

To further explore the findings of the long-run underperformance of firms after their green patent announcements, I conduct sub-sample analysis distinguishing between green patents granted before and after 2006. Arguably, this year represented a major shift in climate attention due to the release of the Stern Review (Painter, 2020) and the launch of Principles for Responsible Investment (Kim and Yoon, 2022). Furthermore, the long-run performance of green patenting firms could have changed over time because of the increasing levels of climate change concerns (Ardia et al., 2022) and the introduction of tougher regulations on pollution during the 21st century (Noailly et al., 2021). Therefore, I divide the sample into two different periods: 1976 to 2005, and 2006 to 2019.¹²⁸ First, I limit the sample to 1976 to 2005 and present the portfolios' alphas in Table 5-5. I find that over this period green patent portfolios consistently generate negative alphas that are larger in magnitude than the full sample results

¹²⁸ My results are similar if I divide the sample into 1976 to 2006 and 2007 to 2019 instead.

presented in Table 5-1. For instance, as shown in panel A of Table 5-5, the value-weighted strategy generates a negative alpha of -14 basis points per week (significant at the 1% level) over a 12-week holding period. The results are similar if I focus only on portfolios based on single green patent announcements. For example, as shown in Panel B of Table 5-5, a value-weighted strategy based on single green patent announcements generates a negative alpha of -16 basis points per week (significant at the 1% level) over a 12-week holding period.

/Table 5-5 here/

Next, I test the performance of the portfolios during 2006 to 2019. The portfolios' alphas are presented in Table 5-6. In contrast to the results during 1976 to 2005, the portfolio alphas during 2006 to 2019 are all not statistically significant. For example, as shown in Panel A of Table 5-6, the value-weighted portfolio based on all green patent announcements earns a negative alpha of -8 basis points per week, over a 12-week holding period (not statistically significant). For the 24-week holding period, the alpha equals -6 basis points per week (not statistically significant). Panel B of Table 5-6 shows the alphas of portfolios based on single green patent announcements during 2006-2019. Similarly, the strategies based on single green patent announcements yield alphas that are all not statistically significant. While green patenting firms were underperforming during 1976 to 2005, their underperformance largely disappeared during 2006 to 2019. The lack of a long-run underperformance of green patenting firms during 2006-2019 can be a result of an increased importance of green technologies to investors during 2006-2019. Green patents can lower a firm's environmental risk (Carrion-Flores and Innes, 2010; Miao and Popp, 2014) and investors became more concerned about climate risks during 2006-2019 (Ardia et al., 2022; Sautner et al.,

2022). Moreover, the results are consistent with Blanco et al. (2022), who review the evidence on the mitigating impact of green innovation on global warming. The technological progress of green innovations has significantly accelerated since the end of the 20th century (Blanco et al., 2022), and since 2010, the cost of solar and wind energy production decreased by up to 85% (Stern, 2022).

/Table 5-6 here/

Arguably, the public attention to climate change was higher during 2010 to 2019 compared to 2006 to 2009 (Ardia et al., 2022). As of January 2020, the period from 2010 to 2019 was the warmest decade ever recorded (Borunda, 2020). IPCC (2022) reports that during 2010 to 2019 the average annual global greenhouse gas emissions were at their highest ever levels. Moreover, the attention to climate change increased after the 2015 Paris Agreement (Kruse et al., 2020). Therefore, for robustness, I also test portfolio performance during 2010 to 2019. The portfolio alphas, which are shown in Table 5-7, are similar to the results from Table 5-6. The portfolios created using all and single green patent announcements have alphas that are not statistically significant.

/Table 5-7 here/

5.4.5 Portfolios based on polluting vs non-polluting firms

The long-run performance of firms after their green patent announcements could differ depending on firm characteristics. First, green patents could be more valuable to firms operating in polluting industries, which are more at risk of environmental regulations (Bolton and Kacperczyk, 2021; Chava, 2014). To test that, I differentiate between green patent announcements involving firms that operate in CO₂ intensive industries and firms that do not, as identified by the classification developed by the IPCC (Krey et al., 2014). I use the same approach described in section (5.4.1) to build the weekly portfolios.

First, I limit the sample to firms operating in CO₂ intensive industries, and I present the results in Table 5-8. I find that portfolios consisting of polluting firms earn alphas that are more negative and more statistically significant than the full-sample results presented in Table 5-1. For example, as shown in Panel A of Table 5-8, the value-weighted strategy generates a negative alpha of -17 basis points per week (significant at the 1% level) over a 12-week holding period. In Panel B of Table 5-8 I limit the construction of the portfolios to single green patent announcements and the results are similar. A value-weighted portfolio based on single announcements earns a negative alpha of -15 basis points per week, for a 24-week holding period (significant at the 1% level).

/Table 5-8 here/

Next, I limit the sample to firms operating in industries that are not classified by the IPCC as CO₂ intensive. The portfolio alphas are presented in Table 5-9. Panel A of Table 5-9 shows that the alphas of portfolios based on all green patent announcements involving non-CO₂ intensive firms are all not statistically significant. The results remain unchanged when I limit the portfolios to single green patent announcements, as shown in Panel B of Table 5-9.

/Table 5-9 here/

Overall, I find that the negative long-term performance after the announcements of new green patents is more pronounced in CO₂ intensive industries. The underperformance of the CO₂ intensive companies relative to non-CO₂ intensive firms can seem surprising since these firms stand to benefit more from developing new green technologies which can lower their exposure to climate-related risks. However, the results are consistent with Cohen et al. (2022) who study green patenting by public

firms in the US during 1980 to 2017. They find that energy companies, which are often carbon-intensive, are less rewarded for obtaining green patents than other firms, in terms of their environmental scores and investment by ESG funds. Cohen et al. (2022) suggest that investors may shun green patents produced by these firms.

5.4.6 Portfolios of firms with different R&D intensity

Green technologies often combine knowledge from a larger variety of sources than other patents do (Barbieri et al., 2020). R&D-intensive firms may be better at navigating this process since they have a higher focus on innovation. I define a firm's R&D intensity as the ratio of R&D expenditures to total assets (Hirshleifer et al., 2012). Each week, I sort firms with green patent announcements into quintiles depending on their average R&D intensity over the previous 5 years.^{129,130} The results, which are presented in Table 5-10, show that portfolios of firms in the bottom quintile in terms of R&D intensity consistently generate negative and statistically significant alphas at the 5% level. For example, as shown in Panel A of Table 5-10, the value-weighted portfolio consisting of firms in the bottom R&D intensity quintile earns a negative alpha of -13 basis points per week (statistically significant at the 5% level), over a 24-week holding period. In contrast, the alphas of portfolios of firms in the top R&D intensity quintile are not statistically significant. The same pattern exists in the alphas of portfolios based on single green patent announcements sorted on the R&D intensity measure, as shown in Panel B of Table 5-10. Overall, this suggests that firms with a relatively high R&D intensity perform better after obtaining new green patents

¹²⁹ The results are similar if I sort firms into deciles instead. The results are also similar if I use the average R&D intensity over the previous 3 years. Moreover, the results hold if I use a weighted moving average where the 1st, 2nd, 3rd, 4th, and 5th lags of R&D intensity have a weight of 1, 0.8, 0.6, 0.4, and 0.2, respectively.

¹³⁰ Before constructing the R&D intensity measure, I replace all missing R&D observations with zeros as advocated by Koh and Reeb (2015). The results are similar regardless of whether or not I make this adjustment.

than firms with a low R&D intensity. This is consistent with the argument that, in order to be successful, green innovation requires more investment and development than grey innovation (Nanda et al., 2015).

/Table 5-10 here/

5.4.7 Portfolios of firms with different R&D efficiency

Firms differ in how efficient they are in turning R&D into new technologies (Cohen et al., 2013; Hirshleifer et al., 2013). Efficiency can be especially important to the long-run performance of green patenting firms, since green technologies can be capital-intensive (Gaddy et al., 2017). Therefore, I differentiate between firms based on their R&D efficiency. Each week I sort firms with green patent announcements into quintiles depending on their previous year's R&D efficiency.^{131,132} I present the results in Table 5-11. As shown in panel A of Table 5-11, portfolios consisting of firms in the bottom R&D efficiency quintile consistently earn negative alphas. For example, a bottom quintile value-weighted portfolio with a 52-week holding period earns a negative alpha of -17 basis points per week (significant at the 1% level). In contrast, portfolios consisting of firms in the top R&D efficiency quintile largely earn alphas which are not statistically significant. In panel B of Table 5-11, I limit the portfolio construction to single green patent announcements. I find that a portfolio of firms in the bottom R&D efficiency quintile and a portfolio of firms in the top R&D efficiency quintile both earn alphas that are not statistically significant. This suggests that R&D efficiency matters more (less) for firms that obtain many (few) patents. Overall, I find

¹³¹ R&D efficiency in year t is defined as the truncation-adjusted number of citations received in year t by firm's patents that were granted in the last five years divided by the related R&D capital calculated over a five-year period (Griffin et al., 2018; Hirshleifer et al., 2013).

¹³² Before constructing the R&D efficiency measure, I replace all missing R&D observations with zeros as advocated by Koh and Reeb (2015). The results are similar regardless of whether or not I make this adjustment.

support for hypothesis 2 (*H5-2*). The results are consistent with Cohen et al. (2013) who show that US firms with low R&D intensity and low R&D efficiency underperform compared to firms with high R&D intensity and high R&D efficiency. The results are also consistent with Hirshleifer et al. (2013), who show that firms with high R&D efficiency earn higher future returns.

/Table 5-11 here/

5.5 Conclusion

This chapter applies the calendar-time portfolio approach to investigate the performance of firms following their green patent announcements. I find that green patenting firms earn negative alphas in the long run, a result that holds across different portfolio holding periods and portfolio types. The underperformance is more pronounced during 1976 to 2005 than during 2006 to 2019. Moreover, the alphas are more negative for CO₂ intensive companies, which can be shunned by investors (Cohen et al., 2022). The results suggest that firms do not profit in the long run from producing green innovation, which is consistent with Soltmann et al. (2015) and Malen and Marcus (2019). To the extent that green patenting firms are credibly committed to protecting the environment, the findings are also consistent with the theory of investors' green tastes which drive up market valuations of green companies and put a downward pressure on their expected returns (Pástor et al., 2021). I also find that portfolios consisting of firms with low R&D intensity show stronger underperformance. Similarly, portfolios of firms that are less efficient at turning R&D into new innovations earn alphas that are more negative. This supports the view that green technologies require more investment and technological expertise to be valuable

since they are more complex and novel than grey technologies (Barbieri et al., 2020; De Marchi, 2012).

Table 5-1: Green Events and Weekly Stock Returns

Panel A: Portfolios based on all green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.12***	0.04	-0.09**	0.04
12-week	-0.11***	0.04	-0.09**	0.04
24-week	-0.10**	0.04	-0.09**	0.04
32-week	-0.10**	0.04	-0.09**	0.04
52-week	-0.10**	0.04	-0.08**	0.04
104-week	-0.09**	0.04	-0.08**	0.04
156-week	-0.09**	0.04	-0.08*	0.04

Panel B: Portfolios based on single green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.09	0.06	-0.06	0.05
12-week	-0.11**	0.06	-0.08*	0.04
24-week	-0.12***	0.05	-0.08**	0.04
32-week	-0.12***	0.04	-0.07*	0.04
52-week	-0.10**	0.04	-0.06	0.04
104-week	-0.08*	0.04	-0.06	0.04
156-week	-0.09**	0.04	-0.06	0.04

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies during 1976-2019. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-2: Grey Events and Weekly Stock Returns

Panel A: Portfolios based on all grey events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.06*	0.04	-0.00	0.04
12-week	-0.06*	0.03	0.00	0.04
24-week	-0.07**	0.03	-0.00	0.04
32-week	-0.07*	0.04	-0.01	0.04
52-week	-0.06*	0.03	0.00	0.04
104-week	-0.06*	0.04	0.00	0.04
156-week	-0.06*	0.04	0.00	0.04

Panel B: Portfolios based on single grey events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.07**	0.04	-0.00	0.04
12-week	-0.06*	0.03	-0.00	0.04
24-week	-0.08**	0.03	-0.01	0.04
32-week	-0.08**	0.03	-0.00	0.04
52-week	-0.07**	0.03	0.00	0.04
104-week	-0.09**	0.03	0.00	0.04
156-week	-0.08**	0.03	0.00	0.04

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new grey patents obtained by public US companies during 1976-2019. Panel A presents alphas of portfolios constructed from all grey patent announcements, while the portfolios in Panel B are constructed using announcements of single grey patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new grey patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-3: Initial Reaction to Green Events, and Weekly Stock Returns

Panel A: Portfolios based on all green events										
	Value-weighted					Equally-weighted				
	AR _{low}	2	3	4	AR _{high}	R&D _{low}	2	3	4	AR _{high}
	4-week horizon									
α	-0.04	-0.10*	-0.13***	-0.09*	-0.14**	-0.04	-0.09*	-0.11**	-0.10**	-0.16***
	12-week horizon									
α	-0.09*	-0.10**	-0.11***	-0.13***	-0.11**	-0.08*	-0.08**	-0.08*	-0.09**	-0.12**
	24-week horizon									
α	-0.08*	-0.10**	-0.12***	-0.11***	-0.10**	-0.07*	-0.08**	-0.11***	-0.09**	-0.11***
	32-week horizon									
α	-0.07*	-0.09**	-0.11**	-0.11***	-0.10**	-0.07*	-0.08**	-0.10**	-0.09**	-0.10**
	52-week horizon									
α	-0.07*	-0.09**	-0.11***	-0.11**	-0.09**	-0.07*	-0.08**	-0.08**	-0.07*	-0.09**
	104-week horizon									
α	-0.08**	-0.10**	-0.10**	-0.11***	-0.10**	-0.07*	-0.08*	-0.08**	-0.08*	-0.08**
	156-week horizon									
α	-0.08*	-0.08**	-0.11***	-0.09**	-0.09**	-0.07*	-0.08*	-0.08**	-0.08**	-0.07*
Panel B: Portfolios based on single green events										
	Value-weighted					Equally-weighted				
	AR _{low}	2	3	4	AR _{high}	AR _{low}	2	3	4	AR _{high}
	4-week horizon									
α	0.03	-0.07	-0.02	-0.19**	-0.16	0.03	-0.03	-0.03	-0.17**	-0.24*
	12-week horizon									
α	-0.07	-0.10*	-0.06	-0.19***	-0.18**	-0.09	-0.03	-0.09*	-0.12**	-0.09
	24-week horizon									
α	-0.09	-0.12**	-0.03	-0.16***	-0.17**	-0.07	-0.08*	-0.07	-0.11**	-0.16**
	32-week horizon									
α	-0.11**	-0.13**	-0.06	-0.12**	-0.16**	-0.07	-0.06	-0.06	-0.08*	-0.12**
	52-week horizon									
α	-0.11**	-0.13**	-0.04	-0.10**	-0.16***	-0.07	-0.05	-0.05	-0.07*	-0.07
	104-week horizon									
α	-0.10*	-0.09**	-0.03	-0.07	-0.17***	-0.08*	-0.04	-0.05	-0.08*	-0.08*
	156-week horizon									
α	-0.12**	-0.11**	-0.04	-0.07	-0.11**	-0.07*	-0.04	-0.06	-0.07*	-0.09*

This table reports the weekly values of the six-factor alphas of portfolios based on new green patent announcements that are sorted on the initial market reaction to the announcement. AR_{low} (AR_{high}) contain stocks with lowest (highest) initial market reaction. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-4: Initial Reaction to Grey Events, and Weekly Stock Returns

Panel A: Portfolios based on all grey events										
Value-weighted					Equally-weighted					
AR _{low}	2	3	4	AR _{high}	R&D _{low}	2	3	4	AR _{high}	
4-week horizon										
α	0.00	-0.03	-0.08**	-0.08**	-0.08*	0.11**	0.01	-0.03	-0.05	-0.06
12-week horizon										
α	-0.02	-0.06*	-0.07**	-0.07**	-0.07*	0.05	0.01	-0.02	-0.02	-0.02
24-week horizon										
α	-0.03	-0.07**	-0.07**	-0.07**	-0.07*	0.04	-0.00	-0.02	-0.02	-0.01
32-week horizon										
α	-0.04	-0.07**	-0.08**	-0.07**	-0.07*	0.03	-0.00	-0.02	-0.02	-0.00
52-week horizon										
α	-0.04	-0.06*	-0.07**	-0.08**	-0.07**	0.03	0.00	-0.01	-0.01	0.01
104-week horizon										
α	-0.06*	-0.07**	-0.06**	-0.08**	-0.06*	0.02	0.00	-0.01	-0.01	0.01
156-week horizon										
α	-0.06*	-0.06*	-0.06*	-0.06*	-0.05	0.02	-0.00	-0.01	-0.01	0.01
Panel B: Portfolios based on single grey events										
Value-weighted					Equally-weighted					
AR _{low}	2	3	4	AR _{high}	R&D _{low}	2	3	4	AR _{high}	
4-week horizon										
α	0.00	-0.03	-0.07*	-0.10***	-0.10**	0.11**	0.01	-0.05	-0.04	-0.07*
12-week horizon										
α	-0.00	-0.06	-0.08**	-0.08**	-0.07*	0.04	0.02	-0.02	-0.02	-0.03
24-week horizon										
α	-0.05	-0.08**	-0.09***	-0.08**	-0.08**	0.02	0.00	-0.02	-0.02	-0.01
32-week horizon										
α	-0.04	-0.08**	-0.09***	-0.08**	-0.07**	0.02	0.00	-0.02	-0.02	-0.01
52-week horizon										
α	-0.05	-0.07**	-0.09***	-0.08**	-0.06*	0.02	0.00	-0.01	-0.01	-0.00
104-week horizon										
α	-0.06	-0.06*	-0.09***	-0.07**	-0.04	0.01	0.00	-0.01	-0.00	0.01
156-week horizon										
α	-0.04	-0.08**	-0.09***	-0.08**	-0.06	0.01	0.00	-0.01	-0.01	0.00

This table reports the weekly values of the six-factor alphas of portfolios based on new grey patent announcements that are sorted on the initial market reaction to the announcement. AR_{low} (AR_{high}) contain stocks with lowest (highest) initial market reaction. Panel A presents alphas of portfolios constructed from all grey patent announcements, while the portfolios in Panel B are constructed using announcements of single grey patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new grey patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-5: Green Events and Weekly Stock Returns During 1976-2005

Panel A: Portfolios based on all green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.14***	0.05	-0.12***	0.04
12-week	-0.14***	0.05	-0.12***	0.04
24-week	-0.13***	0.05	-0.12***	0.04
32-week	-0.12***	0.05	-0.12***	0.04
52-week	-0.13***	0.05	-0.12***	0.04
104-week	-0.12***	0.05	-0.11**	0.04
156-week	-0.11**	0.05	-0.11***	0.04

Panel B: Portfolios based on single green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.09	0.07	-0.04	0.06
12-week	-0.16***	0.05	-0.10**	0.04
24-week	-0.16***	0.05	-0.11***	0.04
32-week	-0.17***	0.05	-0.11***	0.04
52-week	-0.17***	0.04	-0.11***	0.04
104-week	-0.14***	0.04	-0.10**	0.04
156-week	-0.15***	0.05	-0.10**	0.04

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies during 1976-2005. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-6: Green Events and Weekly Stock Returns During 2006-2019

Panel A: Portfolios based on all green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.08	0.08	-0.06	0.09
12-week	-0.09	0.08	-0.06	0.08
24-week	-0.10	0.08	-0.07	0.08
32-week	-0.10	0.08	-0.06	0.08
52-week	-0.07	0.08	-0.04	0.08
104-week	-0.06	0.08	-0.04	0.08
156-week	-0.10	0.08	-0.04	0.08

Panel B: Portfolios based on single green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.12	0.10	-0.11	0.10
12-week	-0.08	0.09	-0.08	0.09
24-week	-0.06	0.08	-0.09	0.09
32-week	-0.05	0.08	-0.06	0.09
52-week	-0.05	0.09	-0.01	0.09
104-week	0.04	0.09	-0.02	0.09
156-week	0.06	0.10	-0.03	0.09

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies during 2006-2019. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-7: Green Events and Weekly Stock Returns During 2010-2019

Panel A: Portfolios based on all green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.06	0.07	-0.02	0.09
12-week	-0.07	0.07	-0.03	0.08
24-week	-0.05	0.07	-0.04	0.08
32-week	-0.06	0.07	-0.03	0.08
52-week	-0.02	0.07	0.01	0.08
104-week	-0.03	0.07	0.00	0.08
156-week	-0.04	0.07	0.00	0.08

Panel B: Portfolios based on single green events				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.04	0.11	-0.03	0.11
12-week	-0.08	0.09	-0.04	0.10
24-week	-0.04	0.09	-0.04	0.10
32-week	-0.02	0.09	-0.04	0.10
52-week	-0.03	0.09	0.03	0.10
104-week	0.08	0.11	0.01	0.10
156-week	0.06	0.10	0.00	0.10

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies during 2010-2019. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-8: Green Events in CO₂ Intensive Industries and Weekly Stock Returns

Panel A: Portfolios based on all green events in CO ₂ intensive industries				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.20***	0.05	-0.15***	0.04
12-week	-0.17***	0.04	-0.13***	0.04
24-week	-0.17***	0.04	-0.14***	0.04
32-week	-0.17***	0.04	-0.13***	0.04
52-week	-0.15***	0.04	-0.12***	0.04
104-week	-0.14***	0.04	-0.12***	0.04
156-week	-0.14***	0.04	-0.11***	0.04

Panel B: Portfolios based on single green events in CO ₂ intensive industries				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.12*	0.06	-0.08	0.05
12-week	-0.14***	0.05	-0.12***	0.05
24-week	-0.15***	0.05	-0.14***	0.04
32-week	-0.14***	0.05	-0.12***	0.04
52-week	-0.13***	0.05	-0.10**	0.04
104-week	-0.10**	0.05	-0.10**	0.04
156-week	-0.10**	0.05	-0.10**	0.04

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies operating in CO₂ intensive industries during 1976-2019. We categorize carbon intensive industries using the list of heavy-emitting industries created by the IPCC (Krey et al., 2014). Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-9: Green Events in non-CO₂ Intensive Industries and Weekly Stock Returns

Panel A: Portfolios based on all green events in non-CO ₂ intensive industries				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.04	0.05	-0.00	0.05
12-week	-0.06	0.05	-0.02	0.04
24-week	-0.06	0.05	-0.02	0.04
32-week	-0.05	0.05	-0.01	0.04
52-week	-0.05	0.05	-0.01	0.04
104-week	-0.05	0.05	-0.02	0.04
156-week	-0.05	0.05	-0.02	0.04

Panel B: Portfolios based on single green events in non-CO ₂ intensive industries				
Horizon	Value-weighted		Equally-weighted	
	Alpha	Robust std. error	Alpha	Robust std. error
4-week	-0.03	0.09	-0.04	0.08
12-week	-0.08	0.06	-0.01	0.06
24-week	-0.03	0.05	-0.02	0.05
32-week	-0.05	0.05	-0.02	0.05
52-week	-0.06	0.05	0.03	0.05
104-week	-0.03	0.05	0.02	0.05
156-week	-0.05	0.04	0.02	0.04

This table reports the weekly values and robust standard errors of the six-factor alphas of portfolios based on new green patents obtained by public US companies operating in non-CO₂ intensive industries during 1976-2019. We categorize carbon intensive industries using the list of heavy-emitting industries created by the IPCC (Krey et al., 2014). Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-10: Green Events, Weekly Stock Returns, and 5-year average of R&D Intensity

Panel A: Portfolios based on all green events										
	Value-weighted				Equally-weighted					
	Intensity _{low}	2	3	4	Intensity _{high}	Intensity _{low}	2	3	4	Intensity _{high}
	4-week horizon									
α	-0.14**	-0.12**	-0.08	-0.07	0.03	-0.16***	-0.12**	-0.08	-0.06	-0.02
	12-week horizon									
α	-0.14**	-0.15**	-0.09*	-0.05	-0.02	-0.14***	-0.13**	-0.08	-0.04	-0.01
	24-week horizon									
α	-0.13**	-0.15**	-0.08	-0.05	-0.00	-0.15***	-0.14***	-0.09*	-0.04	0.00
	32-week horizon									
α	-0.14**	-0.15**	-0.08	-0.05	-0.01	-0.15***	-0.13***	-0.09*	-0.04	0.00
	52-week horizon									
α	-0.13**	-0.15**	-0.08	-0.04	-0.02	-0.14***	-0.12**	-0.07	-0.04	-0.00
	104-week horizon									
α	-0.13**	-0.12**	-0.09*	-0.04	-0.02	-0.13***	-0.11**	-0.08*	-0.03	-0.00
	156-week horizon									
α	-0.13**	-0.11**	-0.08	-0.05	-0.03	-0.13***	-0.11**	-0.08*	-0.03	-0.00

Panel B: Portfolios based on single green events										
	Value-weighted				Equally-weighted					
	Intensity _{low}	2	3	4	Intensity _{high}	Intensity _{low}	2	3	4	Intensity _{high}
	4-week horizon									
α	-0.05	-0.16*	-0.05	0.10	-0.14	-0.07	-0.08	-0.06	0.07	-0.22
	12-week horizon									
α	-0.15**	-0.11	-0.11	-0.07	0.00	-0.10*	-0.09	-0.08	0.04	-0.10
	24-week horizon									
α	-0.16***	-0.13**	-0.06	-0.01	-0.01	-0.13***	-0.11**	-0.05	0.02	-0.15*
	32-week horizon									
α	-0.17***	-0.13**	-0.04	-0.03	0.01	-0.10**	-0.10**	-0.04	-0.02	-0.08
	52-week horizon									
α	-0.15***	-0.11*	-0.00	-0.01	-0.04	-0.09**	-0.07	-0.03	-0.01	-0.07
	104-week horizon									
α	-0.12**	-0.08	-0.03	0.01	-0.04	-0.09**	-0.05	-0.05	-0.02	-0.04
	156-week horizon									
α	-0.12***	-0.11**	-0.05	0.03	-0.01	-0.10**	-0.06	-0.05	-0.01	-0.01

This table reports the weekly values of the six-factor alphas of portfolios based on new green patent announcements that are sorted on R&D intensity. Every week, stocks are sorted into quintiles according to the one-year lag of the 5-year average of R&D scaled by total assets. R&D_{low} (R&D_{high}) contain stocks with lowest (highest) lag of R&D intensity. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5-11: Green Events, Weekly Stock Returns, and R&D Efficiency

Panel A: Portfolios based on all green events										
	Value-weighted				Equally-weighted					
	Efficiency _{low}	2	3	4	Efficiency _{high}	Efficiency _{low}	2	3	4	Efficiency _{high}
	4-week horizon									
α	-0.21***	-0.12**	-0.06	0.00	-0.05	-0.18***	-0.09*	-0.10*	-0.02	-0.01
	12-week horizon									
α	-0.17***	-0.12**	-0.07	-0.03	-0.13**	-0.14**	-0.09*	-0.07	-0.04	-0.07
	24-week horizon									
α	-0.16***	-0.11**	-0.07	-0.03	-0.10*	-0.14***	-0.10**	-0.07	-0.05	-0.07
	32-week horizon									
α	-0.17***	-0.12***	-0.06	-0.03	-0.09	-0.12**	-0.10**	-0.07	-0.04	-0.06
	52-week horizon									
α	-0.14***	-0.12***	-0.07	-0.04	-0.08	-0.10**	-0.10**	-0.06	-0.04	-0.06
	104-week horizon									
α	-0.15***	-0.10**	-0.06	-0.04	-0.10*	-0.12**	-0.09**	-0.05	-0.03	-0.05
	156-week horizon									
α	-0.16***	-0.10**	-0.08*	-0.04	-0.08	-0.13**	-0.09**	-0.05	-0.03	-0.05
Panel B: Portfolios based on single green events										
	Value-weighted				Equally-weighted					
	Efficiency _{low}	2	3	4	Efficiency _{high}	Efficiency _{low}	2	3	4	Efficiency _{high}
	4-week horizon									
α	-0.02	-0.13	-0.04	0.03	0.18	-0.08	-0.08	-0.02	0.05	0.13
	12-week horizon									
α	-0.07	-0.13*	-0.08	0.13*	0.07	-0.06	-0.07	-0.10	-0.06	0.01
	24-week horizon									
α	-0.06	-0.08	-0.13**	0.10*	0.01	-0.07	-0.07	-0.09*	-0.07	-0.06
	32-week horizon									
α	-0.05	-0.08	-0.14**	0.10*	-0.03	-0.07	-0.05	-0.09*	-0.06	-0.02
	52-week horizon									
α	-0.07	-0.07	-0.12**	-0.07	-0.00	-0.04	-0.05	-0.06	-0.05	-0.03
	104-week horizon									
α	-0.05	-0.06	-0.09*	-0.07	0.00	-0.06	-0.06	-0.05	-0.05	0.01
	156-week horizon									
α	-0.05	-0.07	-0.09*	-0.06	0.00	-0.07*	-0.06	-0.05	-0.04	-0.00

This table reports the weekly values of the six-factor alphas of portfolios based on new green patent announcements that are sorted on R&D efficiency. Every week, stocks with non-missing one-year lag of R&D efficiency are sorted into quintiles. Efficiency_{low} (Efficiency_{high}) contain stocks with lowest (highest) lag of R&D efficiency. Panel A presents alphas of portfolios constructed from all green patent announcements, while the portfolios in Panel B are constructed using announcements of single green patents only. All portfolios are constructed weekly, with stock selection on Tuesdays. A stock is added to a portfolio whenever a new green patent is announced. We rebalance the portfolios every week and evaluate portfolio performance over 4,12,24,32,52,104, and 156-week long portfolio holding periods. All factor returns are from Kenneth French's website. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

6. Conclusion

6.1 The importance of patents

This PhD thesis consists of four essays that explore the value of patents to companies and what affects it. The purpose of patents is to incentivise and reward the creation of new knowledge. New inventions that fulfil the requirements relating to subject matter eligibility, usefulness, novelty, and non-obviousness are eligible for patent protection that lasts for approximately 20 years from the filing date of a patent application. A patent can be valuable, because it gives its owner an exclusive right to try to exclude others from practicing the invention disclosed in the patent. Kogan et al. (2017) estimate the median value of a patent owned by a publicly listed company at \$3.2m, while Gambardella et al. (2008) report a mean patent value of €3.0m. The main reasons why firms obtain patents is to prevent the imitation of their intellectual property, to protect their revenue streams, and to gain competitive advantage over competitors (Blind et al., 2006; Holgersson and Granstrand, 2017). Patents also increase a firm's negotiating power since they can be sold or licensed to others (Blind et al., 2009). Companies can also engage in cross-licensing of patent rights to access new markets and technologies (Mihm et al., 2015). Moreover, patents can be used by a firm as a basis for launching a legal attack on a firm or on an individual who is perceived to be violating a plaintiff's patent rights (Janicke and Ren, 2006). Patents can differ in their scientific merit, the breadth of the exclusive rights to a technological field they grant, and in their validity. These patent characteristics determine how effective patents are at protecting the underlying invention, and they are largely determined during the process of pursuing patent protection at a patent office (Reitzig, 2004).

The process of pursuing patent protection from the patent office requires expert legal and scientific knowledge, and the USPTO advises inventors to hire patent attorneys (USPTO, 2020). Their services are used by over 80% of inventors (Bouchoux, 2013). Before a patent application is filed, a patent attorney can recommend a scientist to make changes to an invention to increase its chances of obtaining patent protection (Richard, 2007). Furthermore, a patent attorney often conducts a comprehensive search of prior art to determine how novel an invention is and to prepare for any possible future objections that a patent examiner might have about an invention's patentability (Hunt et al., 2007). Moreover, a patent attorney frequently drafts the patent application document, which is submitted to the patent office for examination (Reitzig, 2004). A patent application is initially rejected by an examiner 86.5% of the time (Lemley and Sampat, 2010). Therefore, effectively responding to and addressing the examiner's objections is an important part of a patent attorney's work (Lu et al., 2017). The central role that patent attorneys play in the process of pursuing patent protection motivates Chapter 3.

6.2 Do Patent Attorneys Matter for the Economic and Technological Value of Patents?

Despite the influence that patent attorneys can have on patents, the topic has been underexplored in the academic literature. A handful of studies focus on the importance of patent attorneys for obtaining patents (Somaya et al., 2007; Gaudry, 2012; Frietsch and Neufausler, 2019), but they do not explore how patent attorneys affect patent value. Chapter 3 aims to fill this gap by investigating whether the capability of patent attorneys affects the economic and technological value of patents that they have worked on. Similar to Kogan et al. (2017), I measure the economic value of patents

using the market reaction to patent announcements. I capture technological value using the number of patent citations received (Hall et al., 2005). Based on the *attorney capability theory* from the legal literature (Szmer et al., 2007; Miller et al., 2015), I distinguish between process experience (patent applications filed to date) and substantive expertise (success rate in obtaining patents) of patent attorneys.

I find that substantive expertise of patent attorneys positively affects both the technological and the economic value of patents. A one standard deviation increase in patent attorney substantive expertise (success rate) is related to a 0.035% higher market reaction to a patent announcement and a 3% higher number of citations received by patents. Moreover, I provide evidence suggesting that the relationship is causal. I find that the importance of patent attorney substantive expertise for the economic value of patents increased after the USPTO opened new regional offices in the US. This only affected the work of patent attorneys located in the states with the new offices. This change helped the affected patent attorneys by giving them an easier access to patent examiners with whom they negotiate the fate of a patent application during the patent examination process (Lemley and Sampat, 2010). I also explore how patent attorney switching by the same firm is related to the value of the company's patents. I show that firms that switch to patent attorneys with higher (lower) substantive expertise, obtain patents with higher (lower) economic and technological value. Overall, the results presented in Chapter 3 show that patent attorney substantive expertise (success rate) positively affects patent value. Contrary to the literature on attorney capability (Abrams and Yoon, 2007; McGuire, 1995), this result does not apply to process experience (applications filed) which I find does not matter for the economic or technological value of patents. Lastly, I show that the importance of

patent attorney substantive expertise is not recognized in the annual Legal 500 patent attorney firm rankings. The rankings are negatively correlated with substantive expertise and are positively related to process experience of patent attorneys. Moreover, there is no statistically significant association between the top ranked patent attorney firms and the economic or technological value of patents that they help obtain. The results support Hanretty (2016), who finds that law firm rankings do not matter for conventional litigation outcomes. I show that this also applies to the rankings of patent attorney firms.

6.3 Does Green Innovation Increase Shareholder Wealth?

The fourth chapter is motivated by the importance of green technologies in lowering the cost of transitioning away from fossil fuels and decarbonizing the economy (Nordhaus, 2021). Green innovation facilitates mitigation and adaptation to climate change (United Nations, 2021). Investors are concerned about the risk that climate change poses to companies and they can push firms to make more environmentally friendly decisions (Krueger et al., 2020; Azar et al., 2021; Ilhan et al., 2021). Green patents, which are commonly used as a measure of corporate environmental innovation (Hascic and Migotto, 2015; Cohen et al., 2022), could be valuable to investors, because they represent evidence of a firms' environmental progress (Berrone et al., 2017). Green patents are credible signals of firms' environmental commitment (Spence, 1973; Berrone et al., 2013), which can help investors distinguish between firms that are environmentally-responsible and firms that only brand themselves as such. Moreover, green patents can lower the physical and regulatory climate risks faced by companies (Carrion-Flores and Innes, 2010; Miao and Popp, 2014). Therefore, I expect that the market reacts positively to the announcements of new green patents.

I find no evidence that green patent announcements increase shareholder wealth in the short run. This result holds regardless of whether the green patents are obtained by companies operating in carbon-intensive industries or by firms with a high exposure to climate change. Similarly, the level of climate concerns does not impact the market reaction to green patent announcements. Moreover, despite the evidence that institutional investors are concerned by environmental risks (Ilhan et al., 2021) and that they pressure firms to reduce their carbon emissions (Dimson et al., 2015; Hoepner et al., 2022), I find no evidence that green innovation matters to institutional investors. The impact of green patent announcements on shareholder wealth does not depend on the level of institutional investor ownership or on the amount of attention that institutional investors pay to the announcements. Furthermore, the 2015 Paris Agreement, which increased the amount of climate attention (Kruse et al., 2020; Bolton and Kacperczyk, 2021), did not affect how the market reacts to new green patent announcements. Overall, I find that new green patent announcements do not increase shareholder wealth, which contrasts with the positive market reaction to the announcements of new grey patents. This is broadly consistent with Pastor et al. (2021), who argue that the preference of investors for holding green stocks can push up the valuations of green firms and lower their expected returns. Moreover, the results support the argument that green technologies are on average less developed and therefore potentially less valuable than other technologies (Aghion et al., 2014; Nanda et al., 2015; IEA, 2021). Since I find no evidence that green patents increase shareholder wealth in the short run, I also investigate whether obtaining more green patents benefits firms in other ways. I explore whether the number of green patents obtained by a company increases its environmental score, level of institutional investor

ownership, and Tobin's Q , respectively. I find no robust evidence that higher green patenting activity improves these outcomes.

6.4 Are Investors Mispricing Green Patent Announcements?

Investors may be mispricing new green patent announcements or reacting to them with a delay. This possibility is the primary motivation for Chapter 5. Green technologies are more complex than grey technologies, because they utilize and combine knowledge from a wider range of sources (De Marchi, 2021; Barbieri et al., 2020). Since complex information can be challenging for investors to process (Song and Schwarz, 2010; Hirshleifer, 2013), investors may be mispricing newly announced green patents in the short run. I explore this question using the calendar time portfolio approach to study the long run stock price performance of firms after their green patent announcements.

I find that firms earn negative alphas after obtaining new green patents. This result does not depend on the portfolio holding period or on how the stocks in a portfolio are weighted. I also find that firms do not consistently underperform after their grey patent announcements. The results suggest that investors are mispricing the green patent announcements in the short run and that corporate green patenting is negatively related to long-run stock performance. Moreover, I find that the underperformance of green patenting firms decreased after that the 2006 release of the Stern Review and the launch of Principles for Responsible Investment, which arguably increased climate attention (Painter, 2020; Kim and Yoon, 2022). I also investigate whether the underperformance of firms after their green patent announcements is different for firms operating in CO₂ intensive industries. I find that the alphas earned by CO₂

polluting firms are more negative, which is consistent with Cohen et al. (2022) who find that green innovation produced by polluting firms can be shunned by investors. Lastly, I explore the relation between the long-run stock performance of firms and their R&D intensity and R&D efficiency, respectively. Since green innovation is complex (Barbieri et al., 2020), I argue that R&D intensive firms, which are focused on innovation, may produce green innovation that is more valuable. Moreover, since producing green technologies is capital-intensive (Gaddy et al., 2017), R&D efficiency may positively affect the long-run performance of green patenting firms. I find support for both arguments. I find that firms in the bottom quintiles in terms of R&D intensity or R&D efficiency earn alphas that are more negative than other firms. Overall, the evidence in Chapter 5 shows that producing new green technologies can have a negative impact on the long-run returns of firms. This supports the argument that generating value from green innovation can be challenging for firms, because of environmental externalities (Hall and Helmers, 2010), high development costs (Nanda et al., 2015; Gaddy et al., 2017), and technological infancy (Aghion et al., 2014; IEA, 2021) of green innovation.

6.5 Thesis contribution and implications

This thesis makes several contributions to the existing literature. To my knowledge, Chapter 3 is the first study to investigate the effect of the capability of patent attorneys on the economic and technological value of patents that they have worked on. Based on the *attorney capability theory*, I distinguish between process experience and substantive expertise of patent attorneys, and I show that only substantive expertise matters for patent value. Patent attorney substantive expertise (success rate) positively affects both the economic and technological value of patents, while process experience

(applications filed) does not affect these outcomes. The results support and contribute to the literature which argues that patent attorneys play an important role in the process of obtaining new patents (Gaudry, 2012; Frietsch and Neufausler, 2019; Klincewicz and Szumial, 2022). Second, I provide novel evidence that patent attorney rankings are not useful in identifying the most capable patent attorneys. I show that the Legal 500 rankings are negatively (positively) associated with substantive (process) expertise (experience) and are statistically unrelated to the economic and technological value of patents. Third, Chapter 4 is the first study to investigate the impact of green patent announcements on shareholder wealth. I show that, in contrast to grey patents, new green patents do not increase shareholder wealth in the short run. I further find that this result holds irrespective of a firm's climate change exposure, the level of climate concerns, or the institutional investor ownership or attention. The last empirical chapter explores the long run stock performance of firms following their green patent announcements. It provides new evidence that firms underperform after obtaining new green patents. Lastly, I contribute to the literature on the stock price performance of innovation-focused firms (Cohen et al., 2013; Hirshleifer et al., 2013) by showing that firms with low R&D intensity and firms with low R&D efficiency experience larger underperformance after their green patent announcements.

This thesis has several implications. First, this study provides new insights on the positive effect of patent attorney substantive expertise (success rate) on patent value, which can be of interest to firms that obtain patents and to their investors. Companies should pay attention to success track record of patent attorneys they consider hiring. Second, the results show that the Legal500 patent attorney firm rankings are not useful at capturing patent attorney capability. Therefore, firms should not pay too much

attention to rankings of patent attorneys. Third, I show that green patent announcements do not increase shareholder wealth in the short run, and that firms underperform after obtaining new green patents. This result can be of interest to shareholders, patenting firms, and government regulators. The results suggest that, on average, investors do not reward companies for engaging in green innovation. Since firms are not recognized for obtaining green patents, this may be impeding the technological advancement of green technologies in the private sector.

6.6 Thesis limitations

This thesis suffers from three main limitations. The first two limitations are common in studies using patent data. First, not every technology or innovation is eligible for patent protection. Any technology that does not fulfil the USPTO patenting requirements described in Chapter 2 section (2.2) is not included in the patent datasets that were used in this study. Furthermore, not all eligible inventions are patented. For example, Coca Cola has famously never patented their recipe for the popular soda (Moser, 2012). Therefore, the applicability of the main result from Chapter 4 that green innovation does not increase shareholder wealth is limited to green technologies that were patented by firms. The second main limitation stems from the fact that the market reaction to a patent announcement can only be measured for patents obtained by publicly listed firms (Kogan et al., 2017). As a consequence, the implication of the result from Chapter 3 that patent attorney substantive expertise increases the economic value of patents is limited to patents obtained by US public firms. Third, the ranking analysis in Chapter 3 is limited to the ranking data published by the Legal500, which is the only major provider of patent attorney firm rankings in the US. Relying on a single provider's rankings does not necessarily provide irrefutable evidence that patent

attorney rankings in general do not matter. However, when combined with the other results from Chapter 3, the ranking-related findings are robust, and they complement the main results and interpretations in the chapter.

6.7 Suggestions for future research

It would be interesting for a future research project to explore what affects the fees that patent attorneys charge for their services. It is estimated that it costs on average \$20,000 to hire a patent attorney to obtain a patent from the USPTO (Lemley, 2001; Masur, 2010). However, to my knowledge, granular invention-level patent attorney fee data is not publicly available. Therefore, obtaining the information by surveying companies or patent attorneys directly would represent an important contribution to the body of knowledge. Moreover, it would be interesting to explore how the patent attorney fees relate to patent attorney capability. It is possible that high-capability attorneys are aware of their skills and charge their customers a higher fee (Kao, 2004; Ferrell, 2021). It would be interesting to examine which patent attorneys provide the best return on investment, given their fees and the effect their work has on the economic and technological value of patents.

Since the analysis in this thesis is limited to publicly listed firms, an interesting avenue for future research would be to explore how important patent attorney capability is for patents obtained by start-ups. Intellectual property assets can be especially important to start-ups, who often have few tangible assets (Federal Trade Commission, 2010; Farre-Mensa et al., 2020). For example, Farre-Mensa et al. (2020) show that obtaining a first patent can increase a start-up's sales and employment growth five years later by 80% and 55%, respectively. Moreover, it would be interesting to explore whether the capability of a patent attorney employed by a start-

up increases a patent's technological value and whether it affects the probability of raising capital from VC investors.

Lastly, it would be interesting for a future research project to investigate how general (industry-wide) law firm rankings relate to the attorneys' success rates in obtaining patents and the economic and technological value of patents they work on. It would be interesting to test whether these different rankings have predictive power with regards to patent value.

Appendix

Appendix 2-A – Utility Patent No. 5,502,918 (The Mousetrap Patent)



US005502918A

United States Patent [19]

[11] **Patent Number:** **5,502,918**

Oviatt

[45] **Date of Patent:** **Apr. 2, 1996**

[54] **MOUSETRAP FOR CATCHING MICE LIVE**

1,226,641 5/1917 Cushing 43/60
4,768,305 9/1988 Sackett 43/61

[76] **Inventor:** **Bill Oviatt**, 1375 Highway 71 North,
Springdale, Ark. 72764

Primary Examiner—Kurt Rowan
Attorney, Agent, or Firm—Rick Martin

[21] **Appl. No.:** **347,890**

[57] **ABSTRACT**

[22] **Filed:** **Dec. 1, 1994**

[51] **Int. Cl.⁶** **A01M 23/02**

A "Y" shaped mousetrap lures a mouse into an open end of the "Y" by means of smelly bait located at a closed end of the bottom of the "Y". The "Y" is pivotally supported horizontally by a stand. As the mouse walks past the pivot point, a ping pong ball rolls from the opposite short "Y" tube member and down to the entrance of the open ended tube member. The mouse is trapped alive and can be drowned by immersing the mousetrap.

[52] **U.S. Cl.** **43/61; 43/60; 43/66**

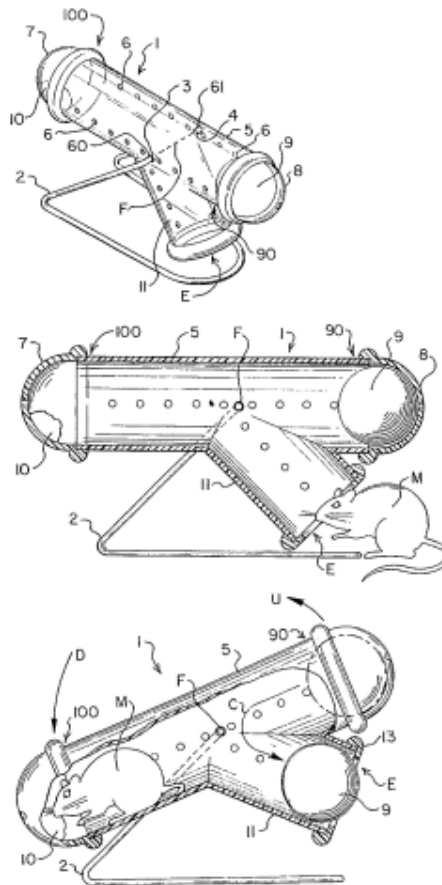
[58] **Field of Search** **43/66, 67, 61, 43/60, 58, 75**

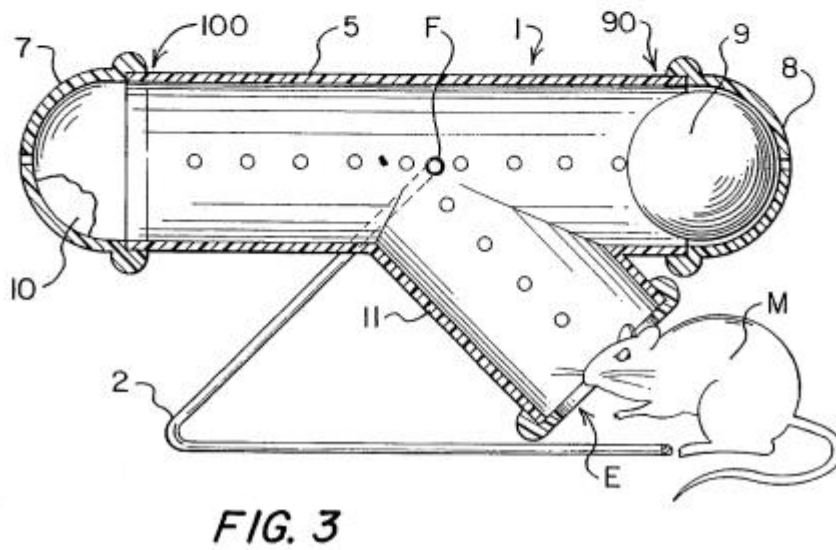
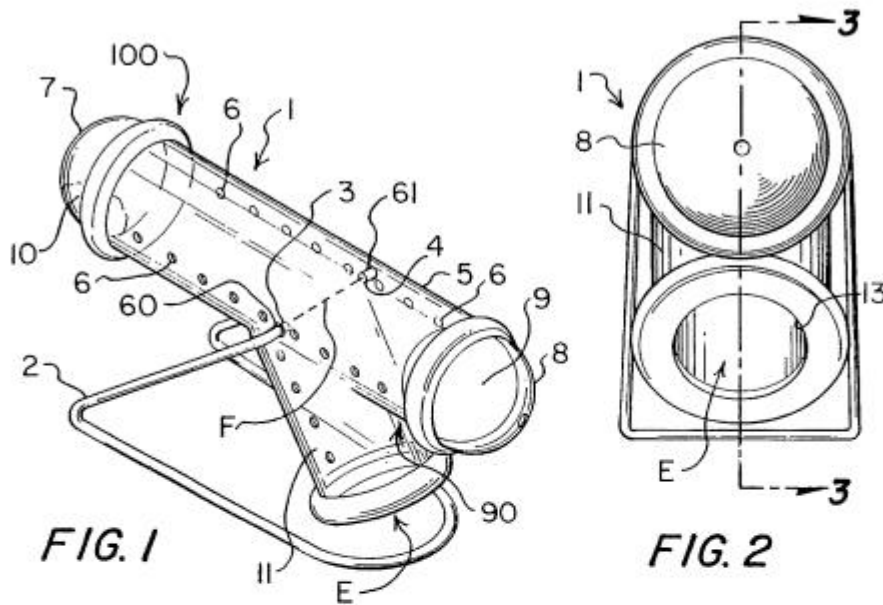
[56] **References Cited**

U.S. PATENT DOCUMENTS

944,926 12/1909 Turbo 43/66

8 Claims, 3 Drawing Sheets





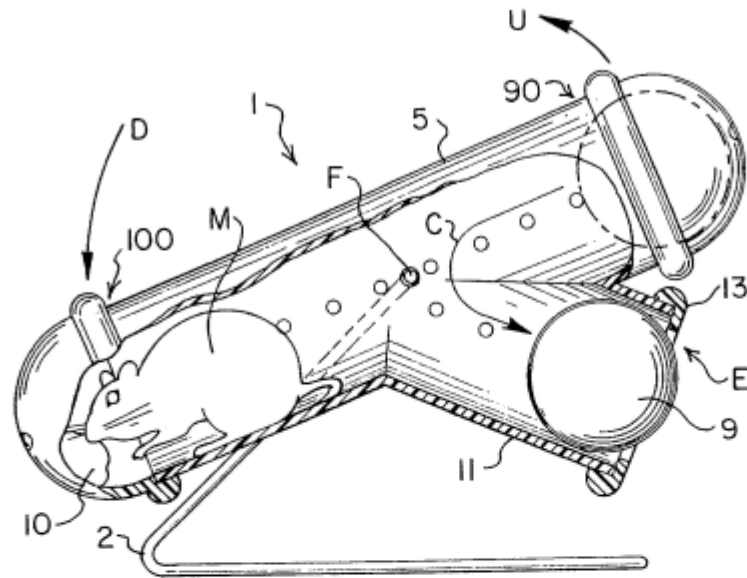


FIG. 4

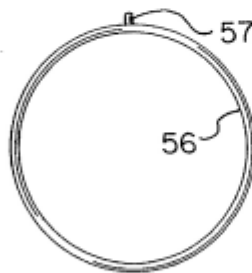


FIG. 6

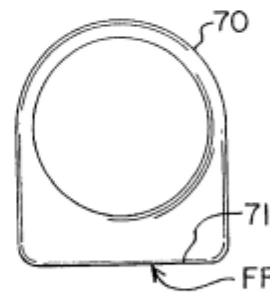


FIG. 7

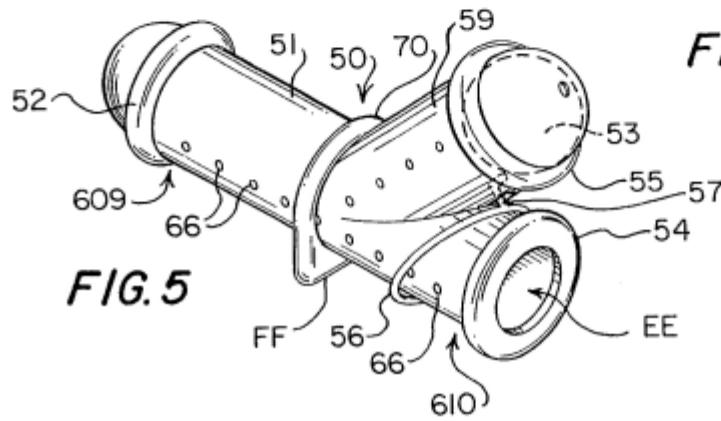


FIG. 5

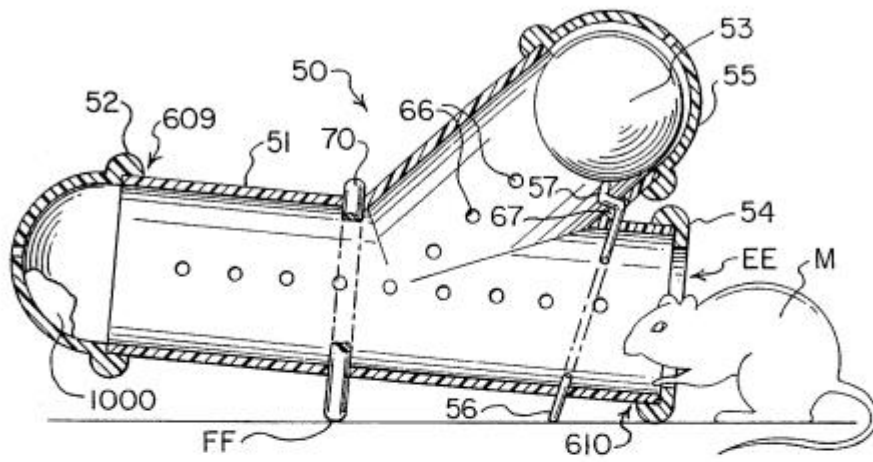


FIG. 8

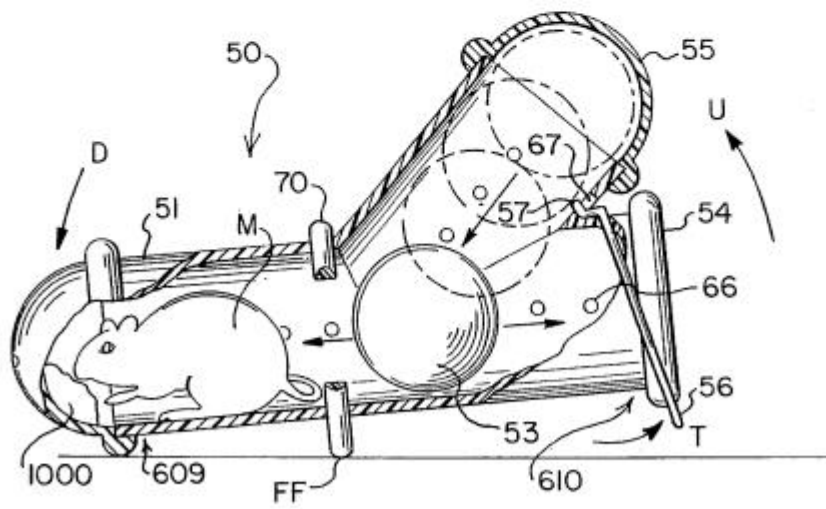


FIG. 9

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MOUSETRAP FOR CATCHING MICE LIVE**FIELD OF INVENTION**

The present invention relates to a better mousetrap. 5

BACKGROUND OF THE INVENTION

Mice can be a nuisance and/or a health menace. Traditional mousetraps are comprised of either a mechanical or chemical killing means. When a mouse is killed in a household, many health problems can arise. These health problems include the release of body fluids containing viruses inside the household. Parasites including worms or lice can be released. Decomposition bacteria will cause odors and cause injury to pets or children who ingest them.

The present invention eliminates these hazards by catching the mouse alive. A simple, cylindrical, teeter-totter contains bait at a closed end of the cylinder. The mouse enters the open end of the cylinder and walks toward the bait. As the mouse passes a fulcrum the cylinder tilts the bait end of the cylinder downward. The mouse becomes trapped by a downward rolling ping pong ball. The trap containing the trapped mouse can be brought outside where the entire trap can be thrown in a bucket to drown the mouse.

SUMMARY OF THE INVENTION

The main object of the present invention is to trap a mouse alive.

Another object of the present invention is to provide an inexpensive trap.

Yet another object of the present invention is to allow the trap to be easily dropped into a bucket of water to drown the mouse.

Still yet another object of the present invention is to reuse the trap.

Other objects of this invention will appear from the following description and appended claims, reference being had to the accompanying drawings forming a part of this specification wherein like reference characters designate corresponding parts in the several views.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a top perspective view of the preferred embodiment.

FIG. 2 is a front plan view of the preferred embodiment shown in FIG. 1.

FIG. 3 is a longitudinal sectional view taken along line 3—3 of FIG. 2.

FIG. 4 is a side plan view with a partial cut-away showing the mouse of FIG. 3 trapped.

FIG. 5 is a top perspective view of an alternate embodiment.

FIG. 6 is a front plan view of the retaining ring of FIG. 5.

FIG. 7 is a front plan view of the pivot stand of FIG. 5.

FIG. 8 is a longitudinal partial sectional view of the embodiment of FIG. 5 in the process of trapping a mouse.

FIG. 9 is a partial cut-away of the embodiment shown in FIG. 8 having caught the mouse.

Before explaining the disclosed embodiment of the present invention in detail, it is to be understood that the invention is not limited in its application to the details of the particular arrangement shown, since the invention is capable

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of other embodiments. Also, the terminology used herein is for the purpose of description and not of limitation.

DESCRIPTION OF THE PREFERRED EMBODIMENT

Referring first to FIG. 1 the trap 1 is comprised of a support stand 2 preferably made of wire. Support stand 2 has wire ends 3, 4 which form a fulcrum for the main tube 5. Main tube 5 preferably is a plastic cylinder having holes 6, 60, 61. Holes 60, 61 removably attach to the wire ends 3, 4 thereby permitting the main tube 5 to teeter-totter around the fulcrum F. Holes 6 also provide an entrance for water when the trap 1 is immersed to kill a mouse.

A pair of removable end caps 7, 8 seal the ends of main tube 5. Before the end caps 7, 8 are secured to main tube 5, the bait 10 and the ping pong ball 9 are inserted as shown at bait end 100 and ball end 90.

An entrance tube 11 forms a "Y" with the main tube 5. Entrance tube 11 depends downward from main tube 5 and points away from the bait end 100.

FIG. 2 shows a mouse eye view of the trap 1. The lure of the bait 10 emanates from entrance E. In FIG. 3 the mouse M is entering entrance E of entrance tube 11. The main tube 5 is in the loaded position which is horizontal. Thus, the ping pong ball 9 rests at ball end 90.

Referring next to FIG. 4 the mouse M has had it. He's eating the bait 10. But as he walked past the fulcrum F his weight caused the main tube 5 to pivot around fulcrum F so that the bait end 100 fell down in direction D and the ball end 90 rose up in direction U. The ping pong ball 9 urged by gravity rolled in path C to close the entrance E. A rim 13 prevents the ping pong ball 9 from rolling past the entrance E.

When finished eating mouse M will turn around and walk past fulcrum F. Main tube 5 will teeter back to a horizontal position. However, ping pong ball 9 will prevent the egress of mouse M out of entrance E. All mouse M can do is travel back and forth in main tube 5 and entrance tube 11, thereby causing the trap 1 to teeter-totter around fulcrum F. Trap 1 can then be immersed in water to drown mouse M or opened at end caps 7, 8 to release mouse M. Of course, in an alternate use one could kill mouse M with poison bait and trap him in the same manner.

Referring next to FIGS. 5, 6, 7a trap 50 is shown. FIG. 5 shows the trap 50 in the horizontal loaded position. In this alternate embodiment a main tube 51 teeter-totters around fulcrum FF. Preferably a plastic ring 70 has a flat base 71 which acts as fulcrum FF. The entrance EE is at the entrance end 610 of the main tube 51. A removable cap 52 seals the bait end 609 of the main tube 51. Holes 66 can allow water to enter main tube 51 during immersion.

The trapping mechanism is comprised of a retaining tube 59 forming a "Y" with the main tube 51. Retaining tube 59 rises obliquely from main tube 51 away from the bait end 609 of the main tube 51. The ping pong ball 53 is held up in the load position by retaining prong 57 of swivel ring 56.

Referring last to FIGS. 8, 9 mouse M is first entering in FIG. 8 entrance EE. The swivel ring 56 is resting on the ground in the cocked position. The retaining prong 57 is pivotally supported in hole 67. Retaining prong 57 is holding up the ping pong ball 53.

When the mouse M passes the fulcrum FF he becomes trapped. The main tube 51 teeters so that the bait end 609 falls in direction D, and the entrance end 610 rises in

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direction U. The swivel ring 56 pivots in direction T because the prong 57 is urged downward by ping pong ball 53. Hole 67 acts as a fulcrum. The ping pong ball 53 is restrained from exiting entrance EE by rim 54. End caps 52, 55 prevent the mouse's egress.

Although the present invention has been described with reference to preferred embodiments, numerous modifications and variations can be made and still the result will come within the scope of the invention. No limitation with respect to the specific embodiments disclosed herein is intended or should be inferred.

I claim:

1. A mousetrap comprising:

- a main tube having a central fulcrum means, a bait end, and a ball end;
- a base stand having a means to support the main tube at the fulcrum;
- said bait end further comprising mouse bait and a main tube closure;
- said ball end further comprising a ball and a main tube closure;
- an entrance tube depending down from the main tube at the central fulcrum means, and angled toward the ball end;
- said entrance tube having a mouse entrance adjacent a supporting surface for the base stand; and
- said main tube having a horizontal load position wherein said ball rests at the ball end, wherein a mouse enters the mouse entrance, walks toward the bait up the entrance tube, and passes the fulcrum means, thereby causing the main tube to teeter down at the bait end, and cause the ball to roll down the main tube then down the entrance tube, functioning to block an egress of the mouse out the mouse entrance.

2. The mousetrap of claim 1 wherein said central fulcrum means further comprise holes in the main tube.

3. The mousetrap of claim 2 wherein said means to support further comprises a pair of prong ends fittingly engaged in the holes in the main tube.

4. The mousetrap of claim 1 wherein the ball further comprises a ping pong ball.

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5. The mousetrap of claim 3 wherein said central fulcrum means further comprises a support stand depending from the main tube.

6. A mousetrap comprising:

- a main tube having a closed bait end, a mouse entrance end, and a central fulcrum means supporting the main tube on a support surface;
- a ball tube angularly rising from the main tube;
- said ball tube further comprising a closure, a ball, and a ball support means, functioning to hold the ball against the closure when the main tube is teetered in a cocked position;
- a bait in the bait end, functioning to lure a mouse into the mouse entrance, past the central fulcrum means, thereby causing the main tube to teeter downward at the bait end, and causing the ball support means to release the ball to roll into the main tube and thereby block an egress of the mouse out the mouse entrance.

7. The mousetrap of claim 5 wherein said ball support means further comprises a swivel ring suspended from a hole in the ball tube by a prong, wherein said prong swings away from the ball, thereby releasing it when the main tube is teetered downward at the bait end.

8. A mousetrap comprising:

- a "Y" shaped tube pivotally supported at a center point by a stand;
- said "Y" shaped tube having a straight tube closed at both ends, and having bait at one end, and a ball at an opposing ball end, said ball end being adjacent to an open tube member;
- said open tube member depending from the straight tube so as to form a mouse entrance when the straight tube is suspended horizontally, whereby a mouse attracted by a bait at the bait end passes the center point and causes the straight tube to teeter with the bait end down, thereby causing the ball to travel to the open tube member, thus trapping the mouse.

* * * * *

Appendix 2-B – First Office Action of Application No. 13/287,731

Office Action Summary	Application No. 13/287,731	Applicant(s) CAI, ZHIJUN	
	Examiner Bunjoo Jaroenchonwanit	Art Unit 2466	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1) Responsive to communication(s) filed on 11/28/11.

2a) This action is **FINAL**. 2b) This action is non-final.

3) Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4) Claim(s) 1-21 is/are pending in the application.

 4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5) Claim(s) _____ is/are allowed.

6) Claim(s) 1-21 is/are rejected.

7) Claim(s) _____ is/are objected to.

8) Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9) The specification is objected to by the Examiner.

10) The drawing(s) filed on _____ is/are: a) accepted or b) objected to by the Examiner.
 Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).
 Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11) The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12) Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

 a) All b) Some * c) None of:

 1. Certified copies of the priority documents have been received.

 2. Certified copies of the priority documents have been received in Application No. _____.

 3. Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

 * See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) <input checked="" type="checkbox"/> Notice of References Cited (PTO-892)	4) <input type="checkbox"/> Interview Summary (PTO-413)
2) <input type="checkbox"/> Notice of Draftsperson's Patent Drawing Review (PTO-948)	Paper No(s)/Mail Date: _____
3) <input type="checkbox"/> Information Disclosure Statement(s) (PTO/SB/08)	5) <input type="checkbox"/> Notice of Informal Patent Application
Paper No(s)/Mail Date: _____	6) <input type="checkbox"/> Other: _____

DETAILED ACTION

Claim Rejections

1. Applicant is advised that during the prosecution, a recitation of the intended use of the claimed invention must result in a structural difference between the claimed invention and the prior art in order to patentably distinguish the claimed invention from the prior art. If the prior art structure is capable of performing the intended use, and then it meets the claim. Furthermore, a preamble is generally not accorded any patentable weight where it merely recites the purpose of a process or the intended use of a structure, and where the body of the claim does not depend on the preamble for completeness but, instead, the process steps or structural limitations are able to stand alone. See *In re Hirao*, 535 F.2d 67, 190 USPQ 15 (CCPA 1976) and *Kropa v. Robie*, 187 F.2d 150, 152, 88 USPQ 478, 481 (CCPA 1951). As such, the amendment to the preamble of claim 1 and 21 does not give life and vitality to the claims 1-2, 4-8, 21 and 22.

Double Patenting

2. The nonstatutory double patenting rejection is based on a judicially created doctrine grounded in public policy (a policy reflected in the statute) so as to prevent the unjustified or improper timewise extension of the "right to exclude" granted by a patent and to prevent possible harassment by multiple assignees. A nonstatutory obviousness-type double patenting rejection is appropriate where the conflicting claims are not identical, but at least one examined application claim is not patentably distinct from the reference

claim(s) because the examined application claim is either anticipated by, or would have been obvious over, the reference claim(s). See, e.g., *In re Berg*, 140 F.3d 1428, 46 USPQ2d 1226 (Fed. Cir. 1998); *In re Goodman*, 11 F.3d 1046, 29 USPQ2d 2010 (Fed. Cir. 1993); *In re Longi*, 759 F.2d 887, 225 USPQ 645 (Fed. Cir. 1985); *In re Van Ornum*, 686 F.2d 937, 214 USPQ 761 (CCPA 1982); *In re Vogel*, 422 F.2d 438, 164 USPQ 619 (CCPA 1970); and *In re Thorington*, 418 F.2d 528, 163 USPQ 644 (CCPA 1969).

A timely filed terminal disclaimer in compliance with 37 CFR 1.321(c) or 1.321(d) may be used to overcome an actual or provisional rejection based on a nonstatutory double patenting ground provided the conflicting application or patent either is shown to be commonly owned with this application, or claims an invention made as a result of activities undertaken within the scope of a joint research agreement.

Effective January 1, 1994, a registered attorney or agent of record may sign a terminal disclaimer. A terminal disclaimer signed by the assignee must fully comply with 37 CFR 3.73(b).

3. Claims 1-21 provisionally rejected on the ground of nonstatutory obviousness-type double patenting as being unpatentable over claims 1, 2, 4-8, 11, 12, 14-18, 21, 22, and 24-32 of copending Application No.11/957624. Although the conflicting claims are not identical, they are not patentably distinct from each other because they direct to the same inventions but differ in word arrangement and the claims of the instant application are broader than the claims in the earlier filed copending application.

This is a provisional obviousness-type double patenting rejection because the conflicting claims have not in fact been patented.

Claim Rejections - 35 USC § 102

4. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless -

(e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

5. Claims 1-3, 5-9, 11-14, 16-18, 20, and 21 are rejected under 35 U.S.C. 102(e) as being anticipated by US 2008/0101268, hereinafter "Sammour."

6. Claims 1, 7, 13 and 18, Sammour discloses and idea of a method and apparatus for operating a base station to provide wireless communications to a mobile device configured to operate in a discontinuous reception (DRX) mode, the DRX mode including sleep periods during which the mobile device does not monitor downlink control channel elements (CCE's), and awake periods during which the mobile device monitors downlink CCE's, and a reciprocal process on a mobile device, the idea comprising:

determining, by the base station, awake periods during which the mobile device will monitor downlink control channel elements (CCE's) (¶¶ 0014, 0037, 0040-0043, 0049, 0051, 0053-0055, 0057; WTRU monitor control channel element at an active period, active period is DRX awake periods); and

transmitting by the network signaling a DRX control parameter that indicate the first of said awake periods (§§ 0037, 0040-0043, 0050).

7. As to claims 2, 8, and 14, Sammour discloses the system that includes both absolute and relative active time (Sammour- §§0047-0048) that is able to extend an active period as needed, e.g., dynamic active schedule allocation, (Sammour-§ 0051).

8. As to claims 3 and 9, Sammour discloses transmitting signaling to the mobile device to indicate the first of said periods thus comprises of transmitting signaling that indicates the first of said periods in relative terms (Sammour-§ 0048, 0052).

9. As to claims 5, 11, 16, and 20, Sammour discloses using Layer 1 sub-frame index (Sammour-§ 0053).

10. As to claims 6, 12, 17, and 21, Sammour discloses the base station is part of a Long Term Evolution (LTE) network, and wherein the mobile device is configured to be associated with the LTE network (§ 0003).

11. As to claims 11 and 24, Sammour discloses monitoring channel control element in an active period or awake DRX period (Sammour-§§ 0014, 0049).

Claim Rejections - 35 USC § 103

12. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

(a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention

was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negated by the manner in which the invention was made.

13. Claims 4, 10, 15, and 19 are rejected under 35 U.S.C. 103(a) as being unpatentable over US 2008/0101268, hereinafter "Sammour" in view of US 2008/0232284, hereinafter "Dalsgaard."

14. As to claims 4, 10, 15, and 19, Sammour discloses wherein transmitting signaling to the mobile device to indicate the first of said periods thus comprises of transmitting signals that indicates the first of said periods in absolute terms (Sammour-¶¶0047-0048, 0053). Sammour does not explicitly disclose that its networking device transmits a plurality of CCE's consecutively to a mobile device during an awake period.

However, in the same field of endeavor, Dalsgaard discloses the same. For instance, Dalsgaard teaches a network device transmits CCE's such as PDCCH and PDCH consecutively to a mobile device during awake period (See fig.2, ¶¶ 0070), in order to accommodate a large amount of users in VoIP communications (¶¶ 0032-0041).

Thus, it would have been obvious to an ordinary skilled in the art at the time of the invention was made to incorporate the idea and advantage of Dalsgaard with Sammour to improve efficiency and expand an application as suggested in Sammour.

Conclusion

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Bunjob Jaroenchonwanit whose telephone number is (571)272-3913. The examiner can normally be reached on Monday to Thursday from 0800 -1800 EST. If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Daniel J. Ryman can be reached on (571)272-3152. The fax phone number for the organization where this application or proceeding is assigned is (571)273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see <http://pair-direct.uspto.gov>. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at (866)217-9197 (toll-free). If you would like assistance from a USPTO Customer Service Representative or access to the automated information system, call (800)786-9199 (IN USA OR CANADA) or (571)-272-1000.

/Bunjob Jaroenchonwanit/
Primary Examiner, Art Unit 2466

/bj/
12/7/2011

Amendments to the Claims:

This listing of claims replaces all prior versions and listings of claims in the application:

Listing of Claims:

1. **(Currently Amended)** A method for operating a base station in a wireless network to provide wireless communications to a mobile device configured to operate in a discontinuous reception (DRX) mode, the DRX mode including sleep periods during which the mobile device does not monitor downlink control channel elements (CCE's), and awake periods during which the mobile device monitors downlink CCE's, the method comprising:

determining, by the base station configured to provide wireless communications to a mobile device configured to operate in a discontinuous reception (DRX) mode, awake periods during which the mobile device will monitor consecutive downlink layer 1 control channel elements (CCE's), wherein the DRX mode includes sleep periods during which the mobile device does not monitor consecutive downlink layer 1 CCE's, and awake periods during which the mobile device monitors consecutive downlink layer 1 CCE's, the downlink layer 1 CCE's providing signaling of a dynamically allocated resource for the mobile device to communicate data; and

transmitting, by the base station, signaling comprising a DRX control parameter that indicates a first of said awake periods.

2. **(Currently Amended)** The method of claim 1, further comprising:
transmitting, by the base station, signaling comprising a DRX control parameter that indicates an extension period during which the mobile device will continue to monitor downlink layer 1 CCE's following one of said awake periods for a dynamic scheduling allocation.

3. **(Original)** The method of claim 1, wherein transmitting the signaling comprises transmitting signaling that indicates the first of said awake periods in relative terms.

4. **(Currently Amended)** The method of claim 1, further comprising transmitting, by the base station, a plurality of downlink layer 1 CCE's consecutively to the mobile device during at least one of the awake periods.

5. **(Cancelled)**

6. **(Original)** The method of claim 1, wherein the base station is part of a Long Term Evolution (LTE) network, and wherein the mobile device is configured to be associated with the LTE network.

7. **(Currently Amended)** A method for operating a mobile device to receive wireless communications from a base station, the method comprising:

operating the mobile device in a discontinuous reception (DRX) mode, the DRX mode including sleep periods during which the mobile device does not monitor consecutive downlink layer 1 control channel elements (CCE's) and awake periods during which the mobile device monitors consecutive downlink layer 1 CCE's; and

receiving, by the mobile device, signaling comprising a DRX control parameter that indicates a first of said awake periods.

8. **(Currently Amended)** The method of claim 7, further comprising:

receiving, by the mobile device, a DRX control parameter that indicates an extension period during which the mobile device will continue to monitor downlink layer 1 CCE's following one of said awake periods for a dynamic scheduling allocation.

9. **(Original)** The method of claim 7, wherein receiving the signaling comprises receiving signaling that indicates the first of said awake periods in relative terms.

10. **(Currently Amended)** The method of claim 7, further comprising receiving, by the mobile device, a plurality of downlink layer 1 CCE's transmitted consecutively during at least one of the awake periods.

11. **(Cancelled)**

12. (Original) The method of claim 7, wherein the base station is part of a Long Term Evolution (LTE) network, and wherein the mobile device is configured to be associated with the LTE network.

13. **(Currently Amended)** A base station device for communicating with a mobile device ~~in a wireless network configured to operate in a discontinuous reception (DRX) mode, the DRX mode including sleep periods during which the mobile device does not monitor downlink control channel elements (CCE's) and awake periods during which the mobile device monitors downlink CCE's~~, the device comprising:

a discontinuous reception (DRX) controller configured to determine a DRX control parameter for a mobile device, the DRX control parameter indicating awake periods during which the mobile device will monitor consecutive downlink layer 1 control channel elements (CCE's), the DRX controller being further configured to determine a first of said awake periods; **[[and]]**

wherein the mobile device is configured to operate in a DRX mode, which includes sleep periods during which the mobile device does not monitor consecutive downlink layer 1 CCE's and awake periods during which the mobile device monitors consecutive downlink layer 1 CCE's, the downlink layer 1 CCE's providing signaling of a dynamically allocated resource for the mobile device to communicate data; and

a transceiver and at least one antenna configured to establish a wireless link with the mobile device;

wherein the device is configured to transmit signaling to the mobile device to indicate the first of said awake periods.

14. **(Currently Amended)** The device of claim 13, wherein the device is further configured to generate a DRX control parameter that indicates an extension period during which the mobile device will continue to monitor downlink layer 1 CCE's following one of said awake periods for a dynamic scheduling allocation.

15. **(Currently Amended)** The device of claim 13, wherein the device is further configured to transmit a plurality of downlink layer 1 CCE's consecutively during at least one of the awake periods.

16. **(Cancelled)**

17. **(Original)** The device of claim 13, wherein the base station device is part of a Long Term Evolution (LTE) network, and wherein the mobile device is configured to be associated with the LTE network.

18. **(Currently Amended)** A mobile device comprising:
a radio manager configured to operate in accordance with one or more discontinuous reception (DRX) parameters received from a base station,
wherein the one or more DRX parameters indicate awake periods during which the mobile device monitors consecutive downlink layer 1 control channel elements (CCE's), and indicate a first of said awake periods,
wherein the mobile device is configured to operate in a DRX mode including sleep periods during which the mobile device does not monitor consecutive downlink layer 1 CCE's and awake periods during which the mobile device monitors consecutive downlink layer 1 CCE's, starting with the first of said awake periods.

19. **(Currently Amended)** The device of claim 18, wherein the mobile device is configured to receive a plurality of downlink layer 1 CCE's consecutively transmitted during at least one of the awake periods.

20. **(Cancelled)**

21. **(Original)** The device of claim 18, wherein the base station is part of a Long Term Evolution (LTE) network, and wherein the mobile device is configured to be associated with the LTE network.

REMARKS

Applicant has reviewed the application in view of the December 12, 2011 Office Action ("Office Action"). Claims 1, 2, 4, 7, 8, 10, 13, 14, 15, 18, and 19 have been amended. Claims 5, 11, 16, and 20 are cancelled. For at least the reasons presented below, Applicant submits that the pending claims are allowable over the cited references. Applicant therefore requests reconsideration and allowance of the claims.

Interview Summary

The Applicant thanks the examiner for the courtesy of the telephonic interview held on January 25, 2012. The claims and the referenced art were discussed. The argument that the references, if combined, would be rendered inoperable was also discussed. No agreement was reached as to the allowability of the claims. The parties agreed, however, that the Applicant will identify sections of the MPEP that support the argument and provide such in a formal response.

Double Patenting

Claims 1–21 have been provisionally rejected on the ground of nonstatutory double patenting as being unpatentable over Claims 1, 2, 4–8, 11, 12, 14–18, 21, 22, and 24–32 of co-pending Application No. 11/957,624. Applicant respectfully traverses the rejection, and the assertions and holdings therein, and further notes that the application forming the basis of the double patenting rejection has not been issued, and thus, the double patenting rejection is not ripe. Applicants understand that the substantive examination of the claims can continue without the filing of a terminal disclaimer. Applicant will consider filing a terminal disclaimer provided that other rejections to the claims are resolved and the claims allowed.

Section 102 Rejections

Claims 1–3, 5–9, 11–14, 16–18, 20, and 21 have been rejected under 35 U.S.C. § 102(e) as being anticipated by *Sammour* (U.S. Publication No. 2008/0101268) ("*Sammour*"). Applicant respectfully traverses these rejections and the assertions and holdings therein because the claims, as amended, are not anticipated by *Sammour*.

Applicant respectfully submits that amended Claim 1 is allowable over the cited reference, because the cited reference fails to teach or suggest the method of determining awake periods of the DRX mode, “**during which the mobile device will monitor consecutive downlink layer 1 control channel elements (CCE’s)**,” as recited in the first element of amended Claim 1 (emphasis added). *Sammour* at best describes that the mobile device “may monitor an L1/L2 control channel during a predefined interval to see whether there is incoming data.” See *Sammour* ¶ [0014] (emphasis added).

Furthermore, *Sammour* fails to teach or suggest, “**the downlink layer 1 CCE’s providing signaling of a dynamically allocated resource for the mobile device to communicate data,**” as recited in Claim 1 (emphasis added). At best, *Sammour* discusses that the “WTRU may dynamically apply the DRX parameter information in a particular DRX profile using MAC signaling that makes reference to the DRX profile ID” *Sammour* ¶ [0046]. On its face, the feature does not give rise to the claims of the present application, but going further, the MAC signaling described in *Sammour* is not a layer 1 feature; rather, it is a data link layer feature (layer 2). Therefore, *Sammour* fails to teach or suggest the “downlink layer 1 CCE’s providing signaling of a dynamically allocated resource for the mobile device to communicate data,” as in Claim 1.

Based on the forgoing, *Sammour* does not teach each and every element of amended Claim 1. Accordingly, amended Claim 1, along with its dependent claims, are allowable. Applicant respectfully requests reconsideration and allowance of the claims.

For similar reasons as above, Applicant respectfully submits that amended Claims 7, 13 and 18 are allowable over the cited reference. Amended Claims 7, 13 and 18 include certain aspects analogous to amended Claim 1. The Office Action applies the same reasoning to Claims 1, 7, 13 and 18. As such, Applicant respectfully submits that the remarks above for Claim 1 would apply to Claims 7, 13 and 18. Accordingly, Applicant respectfully requests reconsideration and allowance of amended Claims 7, 13, 18 and all claims depending therefrom.

Section 103 Rejections

Claims 4, 10, 15, and 19 have been rejected under 35 U.S.C. § 103(a) in view of *Sammour* and in view of *Dalsgaard* (U.S. Publication No. 2008/0232284) (“*Dalsgaard*”).

Applicant respectfully traverses these rejections and the assertions and holdings therein. Applicant respectfully submits that Claims 1, 7, 13, and 18 are patentable over *Sammour* in view of *Dalsgaard* as set forth below, and that Claims 4, 10, 15, and 19 are patentable over the references as they depend from the allowable base claims and recite further distinguishing features. Accordingly, Applicant respectfully requests reconsideration and allowance of Claims 4, 10, 15, and 19, and all claims depending therefrom.

Legal Standard for Obviousness

The Patent and Trademark Office has the burden under section 103 to establish a *prima facie* case of obviousness. *In re Piasecki*, 745 F.2d 1468, 1471-72, 223 USPQ 785, 787-87 (Fed. Cir. 1984). The U.S. Supreme Court in *KSR International Co. v. Teleflex Inc.*, 127 S. Ct. 1727, 1740 (2007) stated that it will often “be necessary for a court to look to interrelated teachings of multiple patents; the effects of demands known to the design community or present in the market place; and the background knowledge possessed by a person having ordinary skill in the art, all in order to determine whether there was an apparent reason to combine the known elements in the fashion claimed by the patent at issue” (emphasis added). However, *the need to demonstrate the presence of all claim limitations in the prior art (when the legal theory is based upon obviousness due to the combination of prior art teachings) has not been obviated by KSR.* *Abbott Labs. v. Sandoz, Inc.*, 500 F. Supp. 2d 846, 851 (N.D. Ill. May 24, 2007).

1) The References fail to meet the need to demonstrate the presence of all claim limitations

As discussed above with respect to the 102 rejection, *Sammour* fails to teach the method of determining awake periods of the DRX mode, “**during which the mobile device will monitor consecutive downlink layer 1 control channel elements (CCE’s), the downlink layer 1 CCE’s providing signaling of a dynamically allocated resource for the mobile device to communicate data,**” as recited in Claim 1 (emphasis added). *Dalsgaard also fails to teach the above features. Therefore, the references fail to meet the need to demonstrate the presence of all claim limitations in the prior art.* See *Abbott Labs. v. Sandoz, Inc.*, 500 F. Supp. 2d 846, 851 (N.D. Ill. May 24, 2007).

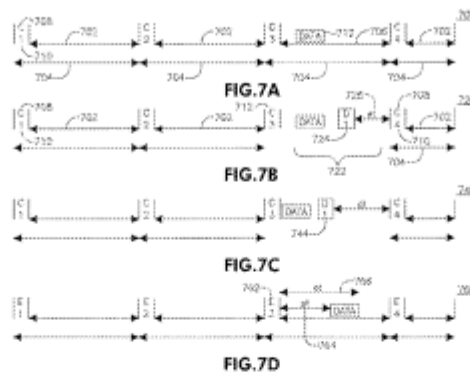
As such, Claims 1, 7, 13, and 18 are patentable over *Sammour* in view of *Dalsgaard*, and Claims 4, 10, 15, and 19 are also patentable over the references as they depend from the allowable base claims in addition to reciting further distinguishing features.

2) ***The proposed modification resulting from the combination of Sammour and Dalsgaard render the references unsatisfactory for their intended purpose***

According to the MPEP, the proposed modification resulting from the combination cannot render the references unsatisfactory for their intended purpose. See MPEP 2143.01 ¶ V. Specifically, the MPEP states that if the “proposed modification would render the prior art invention being modified unsatisfactory for its intended purpose, then there is no suggestion or motivation to make the proposed modification.” Id. (citing In re Gordon, 733 F.2d 900 (Fed. Cir. 1984)) (emphasis added). Additionally, the proposed modification cannot change the principle of operation of a reference. See id. ¶ VI. “If the proposed modification or combination of the prior art would change the principle of operation of the prior art invention being modified, then the teachings of the references are not sufficient to render the claims prima facie obvious.” Id. (citing In re Ratti, 270 F.2d 810 (CCPA 1959)).

With respect to the features recited in Claims 4, 10, 15, and 19, Applicant respectfully submits that ***proposed modification by the combination of Sammour and Dalsgaard changes the principle of operation of the Sammour reference.***

The Sammour reference relies at least partly on the absence of data packets. For example, *Sammour* describes that “if the eNB has not or will not transmit data for the WTRU during this DRX cycle, it does not send the command 708 [in the minimum active time 710]. ***The WTRU may interpret the lack of command as an indication that it can go back to sleep until the next DRX cycle, as it has no data to receive.***” See *Sammour* ¶¶ [0055] and [0056] and Figures 7A–7D reproduced below.



Sammour, figs. 7A–D.

Sammour states:

FIG. 7A shows a signal diagram for DRX operation 700 in accordance with one embodiment. The DRX cycle 704 includes a minimum active time 710 and a sleep time 702. The WTRU may receive a command 708 in each minimum active time 710. If data is available for the WTRU, the WTRU receives an indication in the command 708, receives the data 710, and stays awake until the next DRX cycle 704.

In an alternative embodiment, if the eNB has not or will not transmit data for the WTRU during this DRX cycle, it does not send the command 708. *The WTRU may interpret the lack of command as an indication that it can go back to sleep until the next DRX cycle, as it has no data to receive.*

Sammour ¶¶ [0055]–[0056] (emphasis added). *Thus, Sammour's scheme relies in part on the absence of data packets during the minimum active time 710. Therefore, Sammour's scheme would not work if it is required to "transmit [], by the base station, a plurality of downlink layer 1 CCE's consecutively to the mobile device during at least one of the awake periods,"* as recited in Claim 4, even in view of *Dalsgaard*. To that end, *the proposed modification (as in Claim 4) would change the principle of operation of the Sammour reference.*

As noted above, *if the proposed modification or combination of the prior art would change the principle of operation of the prior art invention being modified, then the teachings of the references are not sufficient to render the claims prima facie obvious.* *Id.* (citing *In re*

Ratti, 270 F.2d 810 (CCPA 1959)). Therefore, Claim 4 is allowable over the combination of *Sammour* and *Dalsgaard* (or any other reference).

Similarly, Applicant respectfully submits that Claims 10, 15, and 19 are also allowable over *Sammour*, even in view of *Dalsgaard* for at least the reasons described above. As such, Applicants respectfully request reconsideration and allowance of claims 4, 10, 15, and 19, and all claims depending therefrom.

No Disclaimers

The present response may include amendments to the claims, or characterizations of claim scope or referenced art. However, Applicants are not conceding in this application that previously pending claims are not patentable over the cited references. Rather, any amendments or characterizations are being made solely to expedite the prosecution of this application. Applicants reserve the right to later pursue any previously pending or other broader claims that are supported by the present disclosure. Therefore, reviewers of this or any parent, child or related prosecution history shall not reasonably infer that Applicants have made any disclaimers of any subject matter supported by the present application.

CONCLUSION

Applicant has made an earnest attempt to place this case in condition for allowance. It is believed that all of the pending claims have been addressed. Applicant notes that the absence of a reply to a specific rejection, issue or comment does not signify agreement with or concession of that rejection, issue or comment. In addition, because the arguments made above may not be exhaustive, there may be reasons for patentability of any or all pending claims (or other claims) that have not been expressed. Finally, nothing in this paper should be construed as an intent to concede any issue with regard to any claim, except as specifically stated in this paper, and the amendment of any claim does not necessarily signify concession of unpatentability of the claim prior to its amendment. For the foregoing reasons, and for other reasons clearly apparent, Applicant respectfully requests full allowance of all claims.

If the present application is not allowed and/or if one or more of the rejections is maintained, Applicant hereby requests a telephone conference with the Examiner and further request that the Examiner contact the undersigned attorney to schedule the telephone conference.

Applicant believes no fees to be due, however, the Commissioner is hereby authorized to charge any fees or credit any overpayments to deposit account 06-1050.

Respectfully submitted,

Date: March 9, 2012

/Rishi Gupta/
Rishi Gupta
Reg. No. 64,768

Customer Number 94149
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Appendix 3-A: Patent attorneys names' cleaning process

#	Step Name	Description
1	Capitalising all letters	I capitalise all letters in the string variable containing patent attorneys' names (Bessen, 2009; Autor et al., 2020).
2	Standardizing words for "and"	I recode all common words for "and" to "&". This includes "+", "ET", "UND", "AND" (Bessen, 2009).
3	Removing punctuation characters	I remove characters such as ",", "<", "%", "#", "/", "-", "(", "!", etc. from the string variable (Bessen, 2009; Autor et al., 2020). I do not remove "&".
4	Deleting addresses	In some cases, the name variable mistakenly contains an address instead of patent attorneys' name. I drop observations that contain words such as "STREET", "ROAD", "BOULEVARD", etc.
5	Standardizing commonly used words	I standardize commonly used words. For example, I change "CORPORATION" to "CORP", "CHEMICAL" to "CHEM", "LABORATORIES" to "LABS", "TECHNOLOGY" to "TECH", "LIMITED" to "LTD", etc. (Autor et al., 2020; Bessen, 2009). This helps in cleaning the names of companies that use their own law departments to file the patent applications. An example of a business that does that is the IBM Corporation.
6	Removing redundant phrases	I remove words that do not convey useful information. These include "LAW OFFICE OF", "DEPARTMENT OF", "ATTORNEY AT LAW", "INTELLECTUAL PROPERTY LAW DEPARTMENT". For example, this step allows me to identify "DEBORAH A GADOR" and "DEBORAH A GADOR ATTORNEY AT LAW" as the same patent attorney.
7	Manual cleaning	I conduct an extensive manual cleaning of the name variable. For example, I change "ADRIENNE B NAUMANNLAW" and "ADRIENNE B NAUMANN8210" to "ADRIENNE B NAUMANN". I also correct "SKJERVENMORRILLMACPHERSON" and "SKJERVEN MORRILL MCPHERSON" to "SKJERVEN MORRILL MACPHERSON", etc.

This table describes the cleaning process of patent attorneys' names from the Patent Examination Research Dataset.

Appendix 3-B: Variable definitions

Variable	Definition	Source
Any tier attorney	This is a dummy variable which is equal to 1 if a patent attorney firm has been listed by the Legal500 in any of the five ranking tiers, and 0 otherwise.	Legal500
Applications filed (attorney process experience)	Applications filed is a natural logarithm of one plus the total number of patent applications filed by a particular patent attorney. It is updated on a yearly basis.	Patent Examination Research Dataset
Backward citations	Backward citations is a natural logarithm of the number of prior art references that a patent makes to other patents (Fung, 2003).	PatentsView
Better patent attorney	Better patent attorney is a dummy variable equal to 1 if the same company changed to a different patent attorney with a higher rolling success rate than the previous attorney, and 0 otherwise.	Patent Examination Research Dataset
Difference in capability	Difference in capability is calculated by subtracting the rolling success rate of a new patent attorney from the rolling success rate of the previous patent attorney.	Patent Examination Research Dataset
Firm age	Firm age is natural logarithm of the number of years since the firm first appearance in CRSP.	CRSP
Forward citations	Forward citations is the truncation-adjusted number of citations received by a patent, excluding examiner citations and self-citations, divided by the number of citations received by an average patent granted in the same year.	PatentsView
Independent claims	Independent claims is a natural logarithm of the number of independent claims of a patent (Marco et al., 2019).	PatentsView
Institutional ownership (%)	Institutional ownership is the proportion of a company's shares owned by institutional investors.	Ghaly et al. (2020)
Leverage	Leverage is defined as total liabilities (Compustat item: lt) divided by total assets (Fang et al., 2014).	Compustat
Market cap. (\$bn)	Market capitalisation is the natural logarithm of the number of shares outstanding multiplied by the share price.	CRSP
New offices	New offices is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise.	N/A
Patent grants volume	Patent grants volume is a logarithm of one plus the number of patents that a particular company obtained from the USPTO on the same trading day.	Patent Examination Research Dataset
R&D	R&D is defined as research and development expense (Compustat item: xrd) divided by total assets (Hirshleifer et al., 2012). Missing R&D values are replaced with zeros, as advocated by Koh and Reeb (2015).	Compustat
Return on assets	Return on assets is defined as operating income before depreciation (Compustat item: oibdp) divided by total assets (Fang et al., 2014).	Compustat
Rolling success rate (attorney substantive expertise)	Rolling success rate measures a patent attorney's effectiveness in obtaining patent protection. It takes a value between 0 and 1. It is calculated by dividing the number of successful patent applications of a particular patent attorney by the total number of successful and abandoned applications filed by that patent attorney. This measure is updated yearly.	Patent Examination Research Dataset

Tobin's Q	Tobin's Q is the ratio of market value to book value of assets (Hirshleifer et al., 2012).	Compustat and CRSP
Top tier attorney	This is a dummy variable which is equal to 1 if a patent attorney firm has been listed by the Legal500 in any of the five ranking tiers, and 0 otherwise.	Legal500
Worse patent attorney	Worse patent attorney is a dummy variable equal to 1 if the same company changed to a different patent attorney with a lower rolling success rate than the previous attorney, and 0 otherwise.	Patent Examination Research Dataset

**Appendix 3-C: Patents granted by year, and yearly grants to unique firms
(2003-2019)**

Year	Patents granted	Number of announcements	Unique firms	Announcements per unique firm this year	Patents per unique firm this year(s)
2003	33,983	8,897	1,267	7	27
2004	46,443	10,895	1,364	8	34
2005	47,616	11,313	1,346	8	35
2006	61,045	12,521	1,467	9	42
2007	55,448	11,538	1,411	8	39
2008	57,435	11,536	1,330	9	43
2009	60,705	11,703	1,281	9	47
2010	77,365	13,327	1,301	10	59
2011	78,846	13,477	1,291	10	61
2012	84,559	13,431	1,308	10	65
2013	91,974	14,701	1,320	11	70
2014	100,990	15,635	1,360	11	74
2015	97,544	15,099	1,387	11	70
2016	98,387	14,878	1,392	11	71
2017	99,433	14,707	1,347	11	74
2018	93,286	14,142	1,334	11	70
2019	106,271	15,405	1,385	11	77
2003-2019	1,291,330	223,205	3,461	64	373

This table breaks the sample down by year. Announcements (patents) per unique firm this year are calculated by dividing patent announcements (patents) by the number of unique firms that obtained patents that year.

Appendix 3-D: Top 25 patent owners by the number of patents obtained (2003-2019)

#	Patent owner name	Grants per firm	% of sample	Cumulative %
1	IBM Corp	80,278	6.2%	6.2%
2	Canon Inc	43,314	3.4%	9.6%
3	Sony Group Corp	33,738	2.6%	12.2%
4	Intel Corp	29,367	2.3%	14.5%
5	Microsoft Corp	29,231	2.3%	16.7%
6	General Electric Co	26,514	2.1%	18.8%
7	Panasonic Corp	21,259	1.6%	20.4%
8	Hitachi Ltd	19,931	1.5%	22.0%
9	Alphabet Inc	19,795	1.5%	23.5%
10	Qualcomm Inc	19,735	1.5%	25.0%
11	Toyota Motor Corp	18,566	1.4%	26.5%
12	Micron Technology Inc	17,633	1.4%	27.8%
13	Xerox Holdings Corp	16,923	1.3%	29.1%
14	Apple Inc	16,408	1.3%	30.4%
15	HP Inc	16,251	1.3%	31.7%
16	Taiwan Semiconductor Manufacturing Co	16,057	1.2%	32.9%
17	AT&T Inc	14,583	1.1%	34.0%
18	Honeywell International Inc	14,392	1.1%	35.2%
19	Honda Motor Co Ltd	14,244	1.1%	36.3%
20	Telefonaktiebolaget Lm Ericsson	13,845	1.1%	37.3%
21	Koninklijke Philips Nv	13,059	1.0%	38.3%
22	Ford Motor Co	12,616	1.0%	39.3%
23	Siemens Ag	12,276	1.0%	40.3%
24	Texas Instruments Inc	11,534	0.9%	41.2%
25	Nokia Corp	11,437	0.9%	42.1%

This table shows the top 25 patent owners in the sample by patents obtained during 2003-2019.

**Appendix 3-E: Top 25 of Fama and French industries (49) by patent grants
during 2003-2019**

	Industry	Patent grants	% of sample	Cumulative %
1	Electronic Equipment	299,834	23.2	23.2
2	Computer Software	205,277	15.9	39.1
3	Computer Hardware	138,442	10.7	49.8
4	Automobiles and Trucks	77,936	6.0	55.9
5	Electrical Equipment	65,492	5.1	60.9
6	Medical Equipment	60,422	4.7	65.6
7	Pharmaceutical Products	58,015	4.5	70.1
8	Machinery	44,835	3.5	73.6
9	Communication	39,958	3.1	76.7
10	Petroleum and Natural Gas	33,174	2.6	79.3
11	Chemicals	27,312	2.1	81.4
12	Aircraft	26,785	2.1	83.4
13	Measuring and Control Equipment	21,537	1.7	85.1
14	Consumer Goods	20,267	1.6	86.7
15	Business Supplies	12,989	1.0	87.7
16	Retail	12,811	1.0	88.7
17	Defense	5,586	0.4	89.1
18	Business Services	4,930	0.4	89.5
19	Recreation	4,195	0.3	89.8
20	Agriculture	4,114	0.3	90.1
21	Construction Materials	3,825	0.3	90.4
22	Apparel	3,276	0.3	90.7
23	Entertainment	2,868	0.2	90.9
24	Wholesale	2,695	0.2	91.1
25	Healthcare	1,741	0.1	91.3

This table breaks the sample down by 49 Fama and French industries. Only the top 25 industries are shown.

**Appendix 3-F: Forward citations and patent attorney process experience
(applications filed)**

	(1)	(2)	(3)
Applications filed	-0.0094** (0.0044)	-0.0099** (0.0044)	-0.0092** (0.0044)
Market capitalisation		-0.0677* (0.0350)	-0.0714** (0.0348)
Independent claims			-0.0069 (0.0239)
Backward citations			0.1425*** (0.0112)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,287,963	1,256,800	1,171,856
R-squared	0.1270	0.1242	0.1310

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 3-G: Control and Treatment groups summary statistics

Panel A1: Treatment firms' characteristics

	Mean	Median	SD	25 th	75 th	Firms	Total events
Market cap. (\$bn)	36.5	9.9	93.5	2.2	31.3	533	9,448
Firm age	26.4	21.7	21.9	8.8	34.6	583	9,767
Return on assets (%)	8.5%	12.0%	24.1%	6.7%	17.2%	533	9,448
Leverage (%)	56.6%	55.3%	28.9%	41.0%	71.2%	533	9,448
R&D (%)	10.2%	6.3%	14.9%	3.0%	12.4%	533	9,448
Tobin's Q	2.4	1.8	2.3	1.2	3.0	533	9,448
Institutional ownership (%)	68.5%	72.0%	20.3%	59.0%	82.8%	451	5,012

Panel A2: Treatment firms' patent characteristics

Forward citations (truncation adjusted)	0.6	0.0	1.8	0.0	0.1	583	9,767
Backward citations	34.4	12.5	53.0	6.0	33.0	568	9,471
Independent claims	1.0	1.0	0.1	1.0	1.0	583	9,767

Panel A3: Treatment firms' patent attorney characteristics

Rolling success rate (%)	83.0%	83.9%	11.5%	73.9%	92.5%	583	9,767
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Panel B1: Control firms' characteristics

	Mean	Median	SD	25 th	75 th	Firms	Total events
Market cap. (\$bn)	27.3	5.2	64.1	1.2	21.7	3,151	204,859
Firm age	28.9	20.5	24.6	10.5	41.5	3,410	213,438
Return on assets (%)	8.2%	12.1%	22.3%	7.0%	16.9%	3,151	204,859
Leverage (%)	51.5%	50.9%	27.4%	33.4%	66.1%	3,151	204,859
R&D (%)	9.2%	5.5%	13.9%	2.1%	11.2%	3,151	204,859
Tobin's Q	2.1	1.7	1.8	1.2	2.6	3,151	204,859
Institutional ownership (%)	66.0%	73.0%	24.0%	57.0%	83.0%	3,214	186,201

Panel B2: Control firms' patent characteristics

Forward citations (truncation adjusted)	1.1	0.3	2.0	0.0	1.1	3,410	213,438
Backward citations	29.4	14.0	42.6	7.0	30.0	3,387	209,364
Independent claims	1.0	1.0	0.1	1.0	1.0	3,410	213,438

Panel B3: Control firms' patent attorney characteristics

Rolling success rate (%)	83.8%	85.2%	11.6%	75.8%	93.1%	3,408	213,197
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This table reports the summary statistics for the treatment and control groups used in the analysis presented in Table 3-9 and Table 3-10. Panels A1, A2, and A3 show the characteristics of firms, patents, and patent attorneys associated with patent applications that were filed by patent attorneys located in states in which the USPTO opened a new office. Panels B1, B2, and B3 show the same set of characteristics for the control group. Total assets and market capitalisation are displayed in \$billion, and the rest of the firm variables are expressed in %. Rolling success rate is in %, and applications filed is a simple count. See Appendix 3-B for variable definitions.

Appendix 3-H: Market reaction (CAR 0,+2) and attorney substantive expertise (rolling success rate). Exploiting the openings of new USPTO offices. Robustness test using firms located in the states where new offices were opened.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.0030*** (0.0010)		0.0030*** (0.0010)	0.0030*** (0.0010)	0.0034*** (0.0010)
New offices (firm location)		0.0002 (0.0005)	-0.0065 (0.0069)	-0.0065 (0.0069)	-0.0069 (0.0070)
New offices (firm location) x Rolling success rate			0.0082 (0.0083)	0.0081 (0.0083)	0.0089 (0.0085)
Patent grant volume				-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation					-0.0015*** (0.0004)
Firm age					-0.0023*** (0.0007)
Return on assets					-0.0017 (0.0020)
Leverage					-0.0010 (0.0010)
R&D					0.0031 (0.0038)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	222,431	222,472	222,431	222,431	213,608
R-squared	0.0292	0.0291	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 3-I: Robustness test I: Rolling success rate calculated from 2001 and the effect of patent attorney substantive expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0025*** (0.0008)	0.0025*** (0.0008)	0.0029*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	-0.0000 (0.0001)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023*** (0.0007)
Return on assets			-0.0017 (0.0020)
Leverage			-0.0010 (0.0010)
R&D			0.0031 (0.0037)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 3-J: Robustness test II: Rolling success rate calculated based on customer id and the effect of patent attorney substantive expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0029*** (0.0009)	0.0030*** (0.0009)	0.0034*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0002)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023** (0.0007)
Return on assets			-0.0022 (0.0021)
Leverage			-0.0005 (0.0010)
R&D			0.0033 (0.0038)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	213,688	213,688	205,245
R-squared	0.0295	0.0295	0.0289

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 3-K: Robustness test III: Rolling success rate calculated based on different patent technology groups and the effect of patent attorney substantive expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0019** (0.0009)	0.0019** (0.0009)	0.0019*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation			-0.0014*** (0.0004)
Firm age			-0.0022*** (0.0007)
Return on assets			-0.0016 (0.0020)
Leverage			-0.0038*** (0.0009)
R&D			0.0015 (0.0035)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	220,412	220,412	213,589
R-squared	0.0291	0.0291	0.0285

The dependent variable is CAR (0,+2) calculated using market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

**Appendix 3-L: Robustness test IV: Patent attorney substantive expertise
(success rate) and the market reaction (CAR 0,+2) calculated using the Fama-
French 5-Factor model**

	(1)	(2)	(3)
Rolling success rate	0.0027*** (0.0010)	0.0026*** (0.0010)	0.0032*** (0.0010)
Patent grants volume		0.0002 (0.0001)	0.0003*** (0.0001)
Market capitalisation			-0.0018*** (0.0003)
Firm age			-0.0007 (0.0005)
Return on assets			0.0007 (0.0019)
Leverage			-0.0038*** (0.0009)
R&D			0.0015 (0.0035)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	220,755	220,755	213,024
R-squared	0.0269	0.0269	0.0266

The dependent variable is CAR (0,+2) calculated using the Fama-French 5-factor model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. Constant has been omitted for brevity. See Appendix 3-B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-A. Variable definitions

Variable	Definition	Source
Cash	Cash is defined as cash (Compustat item: ch) divided by total assets.	Compustat
CCMT applications ratio	This variable is defined as the yearly number of patent applications covering climate change mitigation technologies divided by the yearly number of all patent applications filed during the same year.	N/A
CCMT applications stock ratio	This variable is defined as the cumulative number of patent applications covering climate change mitigation technologies divided by the cumulative number of all patent applications filed by a company. The variable has been adjusted for depreciation of applications stock at a yearly rate of 15%.	N/A
CCMT citations ratio	This variable is the yearly number of citations received by patents covering climate change mitigation technologies divided by the yearly number of citations received by all patents during the same year.	N/A
CCMT citations stock ratio	This variable is the cumulative number of citations received by patents covering climate change mitigation technologies divided by the cumulative number of citations received by all patents. The variable has been adjusted for depreciation of citations stock at a yearly rate of 15%.	N/A
CCMT patents ratio	CCMT patents ratio is the yearly number of patents covering climate change mitigation technologies divided by the yearly number of all patents obtained during the same year.	N/A
CCMT patent stock ratio	This variable is defined as the cumulative number of patents covering climate change mitigation technologies divided by the cumulative number of all patents obtained by a company. The variable has been adjusted for depreciation of patent stock at a yearly rate of 15%.	N/A
CCMT patent volume	This variable the number of patents covering climate change mitigation technologies granted to the same company on the same day. I classify CCMT patents based on the classification developed by the European Patent Office (Angelucci et al., 2018).	N/A
Climate concerns	Climate concerns is the average level of the Unexpected Media Climate Change Concerns (UMC) index (Ardia et al., 2022) over a three-day window (0,+2).	Ardia et al. (2022)
CO ₂ Intensive Industry	CO ₂ Intensive Industry is a dummy variable equal to 1 if a firm is operating in a carbon intensive industry, and 0 otherwise.	Krey et al. (2014)
Firm age	Firm age is the number of years since the firm first appearance in CRSP.	CRSP
Green applications ratio	Green applications ratio is defined as the yearly number of green patent applications divided by the yearly	N/A

	number of all patent applications filed during the same year.	
Green applications stock ratio	This variable is defined as the cumulative number of green patent applications divided by the cumulative number of all patent applications filed by a company. The variable has been adjusted for depreciation of applications stock at a yearly rate of 15%.	N/A
Green citations ratio	Green citations ratio is the yearly number of citations received by green patents divided by the yearly number of citations received by all patents during the same year.	N/A
Green citations stock ratio	Green citations stock ratio is the cumulative number of citations received by green patents divided by the cumulative number of citations received by all patents. The variable has been adjusted for depreciation of citations stock at a yearly rate of 15%.	N/A
Green patent stock ratio	Green patent stock ratio is defined as the cumulative number of green patents divided by the cumulative number of all patents obtained by a company. The variable has been adjusted for depreciation of patent stock at a yearly rate of 15%.	N/A
Green patent volume	Green patent volume is the number of green patents granted to the same company on the same day. I classify green patents using the classification developed by Haščič and Migotto (2015).	N/A
Green patents ratio	Green patents ratio is defined as the yearly number of green patents divided by the yearly number of all patents obtained by a company that year.	N/A
High climate exposure	High climate exposure is a dummy variable that is equal to 1 when the level of a firm's exposure to climate change (cc_expo variable in Sautner et al., 2022) is in the top 33% of the variable's distribution, and 0 otherwise.	Sautner et al. (2022)
Institutional attention	Institutional attention is the average level of the Bloomberg Heat Score over a three-day window (0,+2) around a patent announcement (Ben-Rephael et al., 2017; Chiu et al., 2021).	Bloomberg
IO	IO is the proportion of a company's shares owned by institutional investors.	Ghaly et al. (2020)
IO dedicated	IO dedicated is the proportion of a company's shares owned by dedicated institutional investors.	Ghaly et al. (2020)
IO quasi-indexer	IO quasi-indexer is the proportion of a company's shares owned by quasi-indexer investors.	Ghaly et al. (2020)
IO transient	IO transient is the proportion of a company's shares owned by transient institutional investors.	Ghaly et al. (2020)
Leverage	Leverage is defined as total liabilities (Compustat item: lt) divided by total assets (Fang et al., 2014).	Compustat
Low environmental score	Low environmental score is a dummy variable that is equal to 1 when the firm's Asset4 environmental score is in the bottom 33% of the variable's distribution, and 0 otherwise.	Asset4
Market capitalization	Market capitalization is the number of shares outstanding multiplied by the share price.	CRSP

Paris Agreement	Paris Agreement is a dummy variable equal to 1 if a patent announcement takes place after 12 December 2015, and 0 otherwise.	N/A
Patent citations	Patent citations is the number of citations received by a patent, excluding examiner citations and self-citations, divided by the number of citations received by an average patent granted in the same year.	PatentsView
Patent claims	Patent claims is a simple count of the number of independent claims of a patent (Marco et al., 2019).	PatentsView
Patent volume	Patent volume is the number of patents that a particular company obtained from the USPTO on the same trading day.	PatentsView
R&D	R&D is defined as research and development expense (Compustat item: xrd) divided by total assets (Hirshleifer et al., 2012). Missing R&D values are replaced with zeros, as advocated by Koh and Reeb (2015).	Compustat
Tobin's Q	Tobin's Q is the ratio of market value to book value of assets (Hirshleifer et al., 2012).	Compustat and CRSP

Appendix 4-B. Descriptive statistics of CAR (0,+2)

Panel A: All patent announcements								
	Mean (%)	Median (%)	SE (%)	25th	75th	Min (%)	Max (%)	N
All events	0.028	-0.060	0.005	-1.751	1.694	-22.175	25.517	467,502
Grey events	0.033	-0.059	0.006	-1.781	1.729	-22.175	25.517	428,026
Green events	-0.021	-0.069	0.016	-1.462	1.355	-22.175	24.987	39,476
Panel B: Announcements of single patents only								
All events	0.021	-0.084	0.008	-2.005	1.909	-22.175	25.517	248,411
Grey events	0.023	-0.082	0.009	-2.008	1.918	-22.175	25.517	238,412
Green events	-0.031	-0.123	0.039	-1.921	1.693	-22.175	24.415	9,999
Panel C: All announcements in polluting industries								
All events	0.032	-0.069	0.007	-1.800	1.736	-22.175	25.517	323,983
Grey events	0.038	-0.068	0.007	-1.828	1.778	-22.175	25.517	293,390
Green events	-0.026	-0.071	0.018	-1.533	1.402	-22.175	23.669	30,593
Panel D: All announcements with high technological value								
All events	0.060	-0.044	0.010	-1.776	1.775	-22.175	25.517	149,299
Grey events	0.069	-0.042	0.011	-1.807	1.815	-22.175	25.517	136,046
Green events	-0.005	-0.040	0.028	-1.437	1.413	-22.175	24.415	12,846
Panel E: All announcements with high climate change concerns								
All events	0.004	-0.041	0.014	-1.457	1.450	-22.175	25.517	56,186
Grey events	0.009	-0.041	0.015	-1.486	1.482	-22.175	25.517	50,805
Green events	-0.041	-0.042	0.039	-1.228	1.208	-19.760	23.167	5,381
Panel F: All announcements with high institutional investor ownership								
All events	0.087	0.005	0.009	-1.643	1.719	-22.175	25.517	134,901
Grey events	0.093	0.007	0.010	-1.646	1.729	-22.175	25.517	125,844
Green events	0.012	-0.016	0.033	-1.606	1.571	-19.760	23.167	9,057

Panel G: All announcements with high institutional investor attention								
All events	0.113	0.048	0.016	-1.348	1.517	-19.892	25.517	38,219
Grey events	0.126	0.067	0.018	-1.404	1.582	-19.892	25.517	31,929
Green events	0.047	-0.015	0.032	-1.145	1.217	-16.256	16.204	6,290

This table reports descriptive statistics for all CARs (0,+2) presented in Table 4-2. “All events” refers to all announcements. “Green events” (“Grey events”) refers to events that do (do not) include a green patent. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value; when the truncation-adjusted number of citations is in the top 33% of its distribution. Panel E shows events with a high level of climate change concerns; when the value of the UMC index measured over a three-day window (0,+2) is in the top 33% of its distribution. Panel F shows events that include firms with a high level of institutional investor ownership; when the institutional ownership variable is in the top 33% of its distribution. Panel G shows events that are accompanied by high levels of institutional investor attention; when the value of the attention variable over a three-day window (0,+2) is in the top 33% of its distribution. Standard errors are adjusted for the number of patent announcement observations to calculate the cross-sectional t-statistics as in Barber and Lyon (1997).

Appendix 4-C: Event study results (1976-1990)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
All events	-0.013**	0.008	0.011*	0.020***	-0.005	0.006	0.026**	111,746
Grey events	-0.013**	0.007	0.012**	0.022***	-0.006	0.006	0.028***	102,810
Green events	-0.017	0.016	-0.001	0.002	-0.001	-0.002	0.000	8,936
<i>Panel B: Announcements of single patents only</i>								
All events	-0.033***	0.012	0.036***	0.050***	-0.021*	0.015	0.065***	63,659
Grey events	-0.030***	0.009	0.033***	0.049***	-0.021*	0.012	0.061***	61,025
Green events	-0.095**	0.088**	0.101**	0.073*	-0.007	0.094	0.166**	2,634
<i>Panel C: All announcements in polluting industries</i>								
All events	-0.004	0.012*	0.009	0.015***	0.008	0.017	0.032***	85,179
Grey events	-0.003	0.012*	0.010	0.015**	0.009	0.019*	0.034***	78,391
Green events	-0.020	0.014	0.000	0.014	-0.006	-0.006	0.008	6,788
<i>Panel D: All announcements with high technological value</i>								
All events	-0.005	0.008	0.021*	0.001	0.003	0.024	0.025	33,416
Grey events	-0.006	0.011	0.028**	0.004	0.004	0.033*	0.037	30,617
Green events	0.019	-0.005	-0.048	-0.042	0.014	-0.035	-0.077	2,723

Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
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Panel E: All announcements with high institutional investor ownership (N/A)

This table presents the event study results during 1976-1990, in %. “All events” refers to all announcements. “Green events” (“Grey events”) refers to events that do (do not) include a green patent. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value; when the truncation-adjusted number of citations is in the top 33% of its distribution. Panel E shows events that include firms with a high level of institutional investor ownership; when the institutional ownership variable is in the top 33% of its distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-D: Event study results (1991-2005)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
All events	-0.016***	0.020***	0.046***	0.029***	0.004	0.050***	0.079***	162,353
Grey events	-0.016**	0.022***	0.050***	0.031***	0.006	0.056***	0.087***	150,987
Green events	-0.021	-0.001	0.000	-0.004	-0.022	-0.022	-0.026	11,366
<i>Panel B: Announcements of single patents only</i>								
All events	-0.029***	0.010	0.063***	0.055***	-0.018	0.044***	0.099***	92,516
Grey events	-0.027***	0.011	0.062***	0.056***	-0.016	0.047***	0.102***	89,341
Green events	-0.078*	-0.022	0.081*	0.026	-0.100	-0.020	0.007	3,175
<i>Panel C: All announcements in polluting industries</i>								
All events	-0.013*	0.025***	0.044***	0.027***	0.012	0.056***	0.083***	116,481
Grey events	-0.013*	0.028***	0.047***	0.029***	0.014	0.062***	0.091***	107,790
Green events	-0.013	-0.005	0.002	0.001	-0.018	-0.016	-0.015	8,691
<i>Panel D: All announcements with high technological value</i>								
All events	-0.020*	0.048***	0.070***	0.020*	0.028*	0.097***	0.118***	55,075
Grey events	-0.020	0.049***	0.075***	0.023*	0.029*	0.104***	0.127***	51,223
Green events	0.009	-0.004	0.038	0.004	0.005	0.042	0.046	3,855

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel E: All announcements with high institutional investor ownership</i>								
All events	0.025***	0.043***	0.055***	0.026***	0.068***	0.123***	0.148***	54,363
Grey events	0.027***	0.048***	0.058***	0.026***	0.075***	0.133***	0.158***	50,426
Green events	-0.001	-0.021	0.018	0.023	-0.022	-0.004	0.018	3,937

This table presents the event study results during 1991-2005, in %. “All events” refers to all announcements. “Green events” (“Grey events”) refers to events that do (do not) include a green patent. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value; when the truncation-adjusted number of citations is in the top 33% of its distribution. Panel E shows events that include firms with a high level of institutional investor ownership; when the institutional ownership variable is in the top 33% of its distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-E: Event study results (2006-2019)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
All events	-0.015***	0.034***	0.004	-0.003	0.019***	0.023***	0.020	193,403
Grey events	-0.016***	0.038***	0.007	-0.001	0.022***	0.029***	0.028	174,229
Green events	-0.008	-0.002	-0.021*	-0.017	-0.009	-0.030	-0.047**	19,174
<i>Panel B: Announcements of single patents only</i>								
All events	-0.031***	0.032***	0.000	-0.001	0.001	0.001	0.000	92,236
Grey events	-0.030***	0.034***	0.003	-0.002	0.004	0.006	0.005	88,046
Green events	-0.044	-0.008	-0.066**	0.026	-0.052	-0.118	-0.093	4,190
<i>Panel C: All announcements in polluting industries</i>								
All events	-0.019***	0.045***	-0.006	-0.015***	0.026***	0.019*	0.005	122,323
Grey events	-0.021***	0.051***	-0.002	-0.015***	0.030***	0.028***	0.013	107,209
Green events	-0.004	-0.002	-0.035***	-0.013	-0.006	-0.042	-0.055**	15,114
<i>Panel D: All announcements with high technological value</i>								
All events	0.002	0.037***	0.007	-0.001	0.039***	0.046***	0.045***	60,808
Grey events	0.001	0.042***	0.014	0.003	0.043***	0.057***	0.060***	54,206
Green events	0.008	0.006	-0.035**	-0.041**	0.014	-0.021	-0.062	6,268

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel E: All announcements with high institutional investor ownership</i>								
All events	0.002	0.063***	0.009	-0.005	0.065***	0.074***	0.069***	56,029
Grey events	0.001	0.065***	0.011	-0.003	0.066***	0.077***	0.073***	52,614
Green events	0.017	0.038	-0.022	-0.028	0.056	0.034	0.006	3,415

This table presents the event study results during 2006-2019, in %. “All events” refers to all announcements. “Green events” (“Grey events”) refers to events that do (do not) include a green patent. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value; when the truncation-adjusted number of citations is in the top 33% of its distribution. Panel E shows events that include firms with a high level of institutional investor ownership; when the institutional ownership variable is in the top 33% of its distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-F: Event study results (environmental management technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	-0.033***	0.002	-0.014	-0.006	-0.031*	-0.045**	-0.051**	20,106
<i>Panel B: Announcements of single patents only</i>								
Green events	-0.112***	0.016	0.049*	0.056*	-0.095**	-0.046	0.010	5,396
<i>Panel C: All announcements in polluting industries</i>								
Green events	-0.028**	-0.002	-0.022	0.001	-0.030	-0.052**	-0.051*	16,453
<i>Panel D: All announcements with high technological value</i>								
Green events	0.014	0.002	-0.033	-0.026	0.016	-0.017	-0.042	5,875
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	0.001	0.039	-0.071**	-0.012	0.041	-0.031	-0.042	2,254
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	-0.030	-0.017	-0.013	-0.007	-0.047	-0.060	-0.067	4,821
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	-0.028	0.024	-0.018	-0.008	-0.004	-0.022	-0.030	2,762

This table presents the event study results for patents covering environmental management green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-G: Event study results (water-related technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	0.005	0.013	0.015	-0.020	0.018	0.033	0.013	2,392
<i>Panel B: Announcements of single patents only</i>								
Green events	0.099	-0.052	0.027	0.102	0.047	0.075	0.177	307
<i>Panel C: All announcements in polluting industries</i>								
Green events	0.015	0.026	0.050	0.006	0.041	0.090	0.097	1,354
<i>Panel D: All announcements with high technological value</i>								
Green events	-0.040	-0.057	-0.027	0.029	-0.097	-0.124	-0.095	761
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	-0.120**	-0.063	0.018	0.020	-0.183**	-0.165	-0.145	377
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	0.002	0.023	0.089	0.083	0.025	0.114	0.197	363
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	-0.072	0.064	-0.010	0.000	-0.008	-0.018	-0.019	426

This table presents the event study results for patents covering water-related green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-H: Event study results (energy-related technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	-0.015	0.009	-0.010	-0.012	-0.006	-0.016	-0.028	9,955
<i>Panel B: Announcements of single patents only</i>								
Green events	-0.108*	0.049	0.020	0.037	-0.059	-0.039	-0.002	2,024
<i>Panel C: All announcements in polluting industries</i>								
Green events	-0.020	0.010	-0.028	-0.003	-0.009	-0.037	-0.040	6,558
<i>Panel D: All announcements with high technological value</i>								
Green events	-0.025	-0.033	-0.013	-0.034	-0.058	-0.070	-0.104*	3,475
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	-0.032	0.014	-0.061	-0.046	-0.018	-0.079	-0.126	1,637
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	0.013	-0.013	0.099*	0.024	0.000	0.099	0.123	1,183
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	0.053	0.028	0.026	-0.053**	0.081*	0.106**	0.054	2,493

This table presents the event study results for patents on energy-related green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-I: Event study results (gas capture and storage technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	0.018	-0.003	0.120**	-0.005	0.015	0.135	0.130	683
<i>Panel B: Announcements of single patents only</i>								
Green events	0.156	-0.263	-0.124	0.070	-0.108	-0.231	-0.162	91
<i>Panel C: All announcements in polluting industries</i>								
Green events	0.048	0.028	0.095	0.023	0.076	0.171	0.195	521
<i>Panel D: All announcements with high technological value</i>								
Green events	0.038	0.047	0.051	0.030	0.085	0.136	0.166	277
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	-0.086	0.002	0.079	0.065	-0.084	-0.005	0.060	120
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	-0.026	0.084	0.021	0.017	0.058	0.079	0.097	200
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	0.036	-0.063	0.236**	0.051	-0.026	0.210	0.261	172

This table presents the event study results for patents covering gas capture and storage green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-J: Event study results (transportation-related technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	0.002	-0.014	-0.008	-0.009	-0.012	-0.020	-0.028	8,488
<i>Panel B: Announcements of single patents only</i>								
Green events	0.054	-0.036	-0.028	0.083	0.018	-0.010	0.073	974
<i>Panel C: All announcements in polluting industries</i>								
Green events	-0.009	-0.015	-0.015	-0.013	-0.023	-0.038	-0.051	6,047
<i>Panel D: All announcements with high technological value</i>								
Green events	0.018	0.010	-0.014	0.002	0.028	0.014	0.016	2,788
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	-0.072**	0.029	0.012	-0.005	-0.043	-0.031	-0.036	1,377
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	0.035	0.003	0.039	0.061	0.038	0.077	0.139	1,624
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	-0.021	-0.010	0.023	-0.040	-0.031	-0.008	-0.048	1,896

This table presents the event study results for patents covering transportation-related green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-K: Event study results (buildings-related technologies)

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
<i>Panel A: All patent announcements</i>								
Green events	0.003	-0.002	-0.017	-0.059***	0.002	-0.015	-0.075*	6,178
<i>Panel B: Announcements of single patents only</i>								
Green events	0.031	0.015	-0.026	-0.092	0.047	0.020	-0.072	1,207
<i>Panel C: All announcements in polluting industries</i>								
Green events	0.032	0.003	-0.011	-0.048*	0.035	0.024	-0.025	4,212
<i>Panel D: All announcements with high technological value</i>								
Green events	0.009	-0.002	-0.006	-0.082**	0.006	0.001	-0.081	2,601
<i>Panel E: All announcements with high climate change concerns</i>								
Green events	-0.015	0.051	-0.006	-0.126***	0.036	0.030	-0.096	1,180
<i>Panel F: All announcements with high institutional investor ownership</i>								
Green events	0.013	0.059	-0.042	-0.081*	0.072	0.030	-0.051	1,563
<i>Panel G: All announcements with high institutional investor attention</i>								
Green events	0.083*	-0.007	0.013	-0.075*	0.076	0.089	0.014	1,378

This table presents the event study results for patents covering buildings-related green technologies, in %. Panel A presents full sample results. Panel B shows events that include a single patent only. Panel C shows events in polluting industries only, as classified by Berrone (2013). Panel D presents events with high technological value. Panel E shows events with a high level of climate change concerns. Panel F shows events that include firms with a high level of institutional investor ownership. Panel G shows events that are accompanied by high levels of institutional investor attention. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-L: Market reaction (CAR 0,+2), climate concerns (0,+2), and carbon intensive industries

	(1)	(2)	(3)	(4)	(5)	(6)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	-0.0014 (0.0012)	-0.0014 (0.0012)	-0.0013 (0.0012)
Ln (1+green patent volume)			-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0000 (0.0003)	-0.0002 (0.0003)
Climate concerns x Ln (1+green patent volume)			0.0012 (0.0010)	0.0011 (0.0010)	-0.0006 (0.0012)	-0.0001 (0.0012)
CO ₂ Intensive Industry		0.0006 (0.0007)		0.0019* (0.0011)	0.0019 (0.0011)	0.0011 (0.0017)
CO ₂ Intensive Industry x Climate concerns x Ln (1+green patent volume)					0.0031** (0.0015)	0.0025 (0.0016)
Market capitalisation _{t-1}						-0.0022*** (0.0005)
Firm age _{t-1}						-0.0011 (0.0006)
Cash _{t-1}						0.0022 (0.0015)
Leverage _{t-1}						-0.0000 (0.0011)
R&D _{t-1}						-0.0036 (0.0039)
Tobin's Q _{t-1}						0.0001 (0.0001)
Ln (1+patent volume)						0.0002 (0.0003)
Patent citations						0.0001 (0.0002)
Patent claims						-0.0023** (0.0011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,583	466,227	170,583	170,583	170,583	163,540
R-squared	0.0297	0.0269	0.0298	0.0298	0.0298	0.02992

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-M: Market reaction (CAR 0,+2), climate concerns (0,+2), and firms with a high exposure to climate change

	(1)	(2)	(3)	(4)	(5)	(6)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	-0.0009 (0.0012)	-0.0009 (0.0012)	-0.0009 (0.0012)
Ln (1+green patent volume)			-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0002 (0.0003)
Climate concerns x Ln (1+green patent volume)			0.0012 (0.0010)	0.0014 (0.0010)	0.0014 (0.0014)	0.0013 (0.0014)
High climate exposure _{t-1}		-0.0000 (0.0002)		0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)
High climate exposure _{t-1} x Climate concerns x Ln (1+green patent volume)					0.0000 (0.0013)	-0.0000 (0.0013)
Market capitalisation _{t-1}						-0.0022*** (0.0005)
Firm age _{t-1}						-0.0004 (0.0007)
Cash _{t-1}						0.0023 (0.0016)
Leverage _{t-1}						-0.0000 (0.0011)
R&D _{t-1}						-0.0011 (0.0044)
Tobin's Q _{t-1}						0.0000 (0.0001)
Ln (1+patent volume)						0.0002 (0.0003)
Patent citations						0.0001 (0.0002)
Patent claims						-0.0022* (0.0012)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,583	199,139	170,583	146,073	146,073	145,372
R-squared	0.0297	0.0208	0.0298	0.0230	0.0230	0.0239

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-N: Market reaction (CAR 0,+2), climate concerns (0,+2), and companies with a low environmental score

	(1)	(2)	(3)	(4)	(5)	(6)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	0.0001 (0.0010)	0.0000 (0.0010)	-0.0000 (0.0010)
Ln (1+green patent volume)			-0.0001 (0.0003)	0.0003 (0.0003)	0.0002 (0.0003)	0.0003 (0.0003)
Climate concerns x Ln (1+green patent volume)			0.0012 (0.0010)	0.0004 (0.0010)	0.0001 (0.0010)	0.0000 (0.0011)
Low env. score _{t-1}		0.0006* (0.0004)		0.0006* (0.0003)	0.0006* (0.0003)	0.0006* (0.0003)
Low env. score _{t-1} x Climate concerns x Ln (1+green patent volume)					0.0068 (0.0043)	0.0074* (0.0043)
Market capitalisation _{t-1}						-0.0029*** (0.0007)
Firm age _{t-1}						0.0003 (0.0008)
Cash _{t-1}						0.0013 (0.0019)
Leverage _{t-1}						0.0004 (0.0014)
R&D _{t-1}						-0.0039 (0.0071)
Tobin's Q _{t-1}						0.0001 (0.0002)
Ln (1+patent volume)						-0.0001 (0.0003)
Patent citations						0.0001 (0.0002)
Patent claims						0.0010 (0.0012)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,583	125,928	170,583	104,086	104,086	103,746
R-squared	0.0297	0.0127	0.0298	0.0156	0.0156	0.0165

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-O: Market reaction (CAR 0,+2), and transient institutional investor ownership

	(1)	(2)	(3)	(4)
IO transient $t-1$	-0.0009 (0.0018)		-0.0010 (0.0018)	-0.0002 (0.0017)
Ln (1+green patent volume)		0.0002 (0.0002)	0.0000 (0.0004)	-0.0001 (0.0005)
IO transient $t-1$ x Ln (1+green patent volume)			0.0013 (0.0037)	0.0017 (0.0037)
Market capitalisation $t-1$				-0.0014*** (0.0003)
Firm age $t-1$				-0.0003 (0.0004)
Cash $t-1$				0.0019* (0.0011)
Leverage $t-1$				-0.0020*** (0.0007)
R&D $t-1$				-0.0005 (0.0026)
Tobin's Q $t-1$				-0.0001 (0.0001)
Ln (1+patent volume)				0.0002 (0.0002)
Patent citations				0.0003** (0.0001)
Patent claims				0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	383,005	466,227	383,005	367,997
R-squared	0.0268	0.0269	0.0268	0.0268

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-P: Market reaction (CAR 0,+2), and quasi-indexer institutional investor ownership

	(1)	(2)	(3)	(4)
IO quasi-indexer $t-1$	-0.0023*** (0.0008)		-0.0024*** (0.0008)	-0.0008 (0.0009)
Ln (1+green patent volume)		0.0002 (0.0002)	-0.0004 (0.0008)	-0.0003 (0.0008)
IO quasi-indexer $t-1$ x Ln (1+green patent volume)			0.0011 (0.0015)	0.0007 (0.0016)
Market capitalisation $t-1$				-0.0014*** (0.0003)
Firm age $t-1$				-0.0002 (0.0003)
Cash $t-1$				0.0021* (0.0011)
Leverage $t-1$				-0.0018*** (0.0007)
R&D $t-1$				-0.0007 (0.0025)
Tobin's Q $t-1$				-0.0001 (0.0001)
Ln (1+patent volume)				0.0002 (0.0002)
Patent citations				0.0003** (0.0001)
Patent claims				0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	390,161	466,227	390,161	374,645
R-squared	0.0274	0.0269	0.0275	0.0273

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-Q: Market reaction (CAR 0,+2), and dedicated institutional investor ownership

	(1)	(2)	(3)	(4)
IO dedicated $t-1$	0.0032 (0.0024)		0.0034 (0.0025)	0.0003 (0.0025)
Ln (1+green patent volume)		0.0002 (0.0002)	0.0003 (0.0003)	0.0003 (0.0003)
IO dedicated $t-1$ x Ln (1+green patent volume)			-0.0039 (0.0064)	-0.0036 (0.0068)
Market capitalisation $t-1$				-0.0015*** (0.0003)
Firm age $t-1$				-0.0003 (0.0004)
Cash $t-1$				0.0022* (0.0013)
Leverage $t-1$				-0.0017** (0.0008)
R&D $t-1$				-0.0003 (0.0030)
Tobin's Q $t-1$				-0.0001 (0.0001)
Ln (1+patent volume)				-0.0001 (0.0002)
Patent citations				0.0003* (0.0001)
Patent claims				0.0006 (0.0009)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	324,330	466,227	324,330	312,976
R-squared	0.0246	0.0269	0.0246	0.0241

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-R: Market reaction (CAR 0,+2), institutional investor attention (0,+2), and high institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0010*** (0.0002)	0.0010*** (0.0002)	0.0010*** (0.0002)
Ln (1+green patent volume)			0.0003 (0.0003)	0.0002 (0.0004)	0.0003 (0.0004)	0.0003 (0.0004)
Institutional attention x Ln (1+green patent volume)			-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)
High IO _{t-1}		-0.0004* (0.0002)		0.0002 (0.0003)	0.0003 (0.0004)	0.0004 (0.0004)
High IO _{t-1} x Institutional attention x Ln (1+green patent volume)					-0.0008 (0.0007)	-0.0009 (0.0007)
Market capitalisation _{t-1}						- 0.0024*** (0.0005)
Firm age _{t-1}						-0.0006 (0.0010)
Cash _{t-1}						-0.0041** (0.0020)
Leverage _{t-1}						0.0035** (0.0014)
R&D _{t-1}						-0.0014 (0.0039)
Tobin's Q _{t-1}						0.0003** (0.0001)
Ln (1+patent volume)						-0.0002 (0.0002)
Patent citations						0.0002 (0.0002)
Patent claims						-0.0009 (0.0013)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,305	390,611	128,305	105,681	105,681	102,758
R-squared	0.0239	0.0275	0.0239	0.0259	0.0259	0.0263

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-S: Market reaction (CAR 0,+2), institutional investor attention (0,+2), and high climate change concerns (0,+2)

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Ln (1+green patent volume)			0.0003 (0.0003)	0.0004 (0.0004)	0.0004 (0.0004)	0.0005 (0.0004)
Institutional attention x Ln (1+green patent volume)			-0.0003 (0.0002)	-0.0004* (0.0002)	-0.0004* (0.0002)	-0.0004* (0.0002)
High climate concerns		-0.0005 (0.0006)		-0.0001 (0.0006)	-0.0001 (0.0006)	-0.0001 (0.0006)
High climate concerns x Institutional attention x Ln (1+green patent volume)					0.0000 (0.0003)	0.0000 (0.0003)
Market capitalisation $t-1$						- 0.0026*** (0.0005)
Firm age $t-1$						-0.0005 (0.0009)
Cash $t-1$						-0.0036* (0.0019)
Leverage $t-1$						0.0027* (0.0014)
R&D $t-1$						0.0025 (0.0043)
Tobin's Q $t-1$						0.0003** (0.0001)
Ln (1+patent volume)						-0.0001 (0.0002)
Patent citations						-0.0001 (0.0002)
Patent claims						-0.0003 (0.0013)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,305	170,583	128,305	107,784	107,784	104,529
R-squared	0.0239	0.0297	0.0239	0.0249	0.0249	0.0255

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-T: Market reaction (CAR 0,+2), institutional investor attention (0,+2), and high climate exposure (t-1)

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0009*** (0.0002)	0.0009*** (0.0002)	0.0010*** (0.0003)
Ln (1+green patent volume)			0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)	0.0003 (0.0003)
Institutional attention x Ln (1+green patent volume)			-0.0003 (0.0002)	-0.0002 (0.0002)	-0.0003 (0.0003)	-0.0003 (0.0003)
High climate exposure _{t-1}		-0.0000 (0.0002)		-0.0004* (0.0002)	-0.0004* (0.0002)	-0.0004 (0.0002)
High climate exposure _{t-1} x Institutional attention x Ln (1+green patent volume)					0.0000 (0.0003)	0.0000 (0.0003)
Market capitalisation _{t-1}						-0.0015*** (0.0005)
Firm age _{t-1}						0.0001 (0.0008)
Cash _{t-1}						0.0018 (0.0017)
Leverage _{t-1}						0.0031** (0.0014)
R&D _{t-1}						0.0038 (0.0039)
Tobin's Q _{t-1}						0.0003** (0.0001)
Ln (1+patent volume)						-0.0001 (0.0002)
Patent citations						0.0001 (0.0002)
Patent claims						-0.0005 (0.0012)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,305	199,139	128,305	115,860	115,860	115,149
R-squared	0.0239	0.0208	0.0239	0.0225	0.0225	0.0229

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-U: Market reaction (CAR 0,+2), climate concerns (0,+2), and the Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	-0.0014 (0.0012)	-0.0014 (0.0012)	-0.0013 (0.0012)
Ln (1+green patent volume)			-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0002 (0.0003)
Climate concerns x Ln (1+green patent volume)			0.0012 (0.0010)	0.0012 (0.0010)	0.0004 (0.0012)	0.0006 (0.0012)
Paris Agreement		0.0010 (0.0014)		0.0007 (0.0014)	0.0007 (0.0014)	0.0011 (0.0015)
Paris Agreement x climate concerns x Ln (1+green patent volume)					0.0024 (0.0020)	0.0022 (0.0020)
Market capitalisation $t-1$						-0.0022*** (0.0005)
Firm age $t-1$						-0.0011 (0.0006)
Cash $t-1$						0.0022 (0.0015)
Leverage $t-1$						-0.0000 (0.0011)
R&D $t-1$						-0.0036 (0.0039)
Tobin's Q $t-1$						0.0001 (0.0001)
Ln (1+patent volume)						0.0002 (0.0003)
Patent citations						0.0001 (0.0002)
Patent claims						-0.0023** (0.0011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,583	466,227	170,583	170,583	170,583	163,540
R-squared	0.0297	0.0269	0.0298	0.0298	0.0298	0.0292

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year.

Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-V: Market reaction (CAR 0,+2), institutional investor ownership, and the Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
IO _{t-1}	-0.0014** (0.0007)		-0.0015** (0.0007)	-0.0015** (0.0007)	-0.0015** (0.0007)	-0.0004 (0.0007)
Ln (1+green patent volume)			-0.0003 (0.0008)	-0.0003 (0.0008)	-0.0004 (0.0008)	-0.0003 (0.0008)
IO _{t-1} x Ln (1+green patent volume)			0.0007 (0.0012)	0.0007 (0.0012)	0.0008 (0.0013)	0.0006 (0.0014)
Paris Agreement		0.0010 (0.0014)		0.0007 (0.0012)	0.0007 (0.0012)	0.0013 (0.0014)
Paris Agreement x IO _{t-1} x Ln (1+green patent volume)					-0.0003 (0.0007)	-0.0005 (0.0008)
Market capitalisation _{t-1}						-0.0014*** (0.0003)
Firm age _{t-1}						-0.0003 (0.0003)
Cash _{t-1}						0.0020* (0.0011)
Leverage _{t-1}						-0.0018** (0.0007)
R&D _{t-1}						-0.0007 (0.0025)
Tobin's Q _{t-1}						-0.0001 (0.0001)
Ln (1+patent volume)						0.0002 (0.0002)
Patent citations						0.0003** (0.0001)
Patent claims						0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	390,611	466,227	390,611	390,611	390,611	375,051
R-squared	0.0275	0.0269	0.0275	0.0275	0.0275	0.0274

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one

year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-W: Market reaction (CAR 0,+2), institutional investor attention (0,+2), and the Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0010*** (0.0002)	0.0010*** (0.0002)	0.0010*** (0.0002)
Ln (1+green patent volume)			0.0003 (0.0003)	0.0003 (0.0003)	0.0004 (0.0003)	0.0003 (0.0003)
Institutional attention x Ln (1+green patent volume)			-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0002 (0.0002)	-0.0001 (0.0002)
Paris Agreement		0.0010 (0.0014)		0.0011 (0.0011)	0.0011 (0.0011)	0.00016 (0.0012)
Paris Agreement x institutional attention x Ln (1+green patent volume)					-0.0003 (0.0003)	-0.0004 (0.0003)
Market capitalisation _{t-1}						-0.0016*** (0.0005)
Firm age _{t-1}						-0.0006 (0.0008)
Cash _{t-1}						0.0030* (0.0017)
Leverage _{t-1}						0.0028** (0.0013)
R&D _{t-1}						0.0046 (0.0035)
Tobin's Q _{t-1}						0.0004*** (0.0001)
Ln (1+patent volume)						-0.0001 (0.0002)
Patent citations						0.0002 (0.0002)
Patent claims						-0.0005 (0.0012)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,305	466,227	128,305	128,305	128,305	124,326
R-squared	0.0239	0.0269	0.0239	0.0239	0.0240	0.0238

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one

year. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-X: Green patenting activity and transient institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	-0.00 (0.00)	-0.00 (0.01)										
Green applications ratio $t-1$			-0.00 (0.00)	-0.00 (0.01)								
Green citations ratio $t-1$					0.00 (0.00)	-0.00 (0.01)						
Green patent stock ratio $t-1$							0.01 (0.01)	-0.00 (0.01)				
Green applications stock ratio $t-1$									0.01 (0.01)	-0.01 (0.01)		
Green citations stock ratio $t-1$											0.01 (0.01)	-0.01 (0.01)
Market capitalisation $t-1$		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)
Firm age $t-1$		0.01** (0.00)		0.01** (0.00)		0.00 (0.00)		0.00 (0.00)		0.00* (0.00)		0.00 (0.00)
Cash $t-1$		0.01* (0.01)		0.01*** (0.00)		0.02*** (0.01)		0.02*** (0.00)		0.01*** (0.00)		0.02*** (0.00)
Leverage $t-1$		-0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)
R&D $t-1$		-0.06*** (0.01)		-0.05*** (0.01)		-0.06*** (0.01)		-0.05*** (0.01)		-0.04*** (0.01)		-0.05*** (0.01)
Tobin's Q $t-1$		0.01*** (0.00)		0.01*** (0.00)		0.00*** (0.00)		0.00*** (0.00)		0.00*** (0.00)		0.00*** (0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,658	39,435	44,534	40,648	48,335	44,524	66,455	60,727	75,643	66,713	54,380	49,951
R-squared	0.62	0.64	0.60	0.63	0.62	0.64	0.62	0.64	0.60	0.64	0.62	0.64

The dependent variable is the proportion of a company's shares owned by transient institutional investors. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-Y: Green patenting activity and quasi-indexer institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	-0.00 (0.01)	-0.00 (0.01)										
Green applications ratio $t-1$			-0.00 (0.01)	0.01 (0.01)								
Green citations ratio $t-1$					0.01 (0.01)	0.01 (0.01)						
Green patent stock ratio $t-1$							0.01 (0.02)	0.01 (0.02)				
Green applications stock ratio $t-1$									0.01 (0.02)	0.02 (0.02)		
Green citations stock ratio $t-1$											0.02 (0.03)	0.03 (0.02)
Market capitalisation $t-1$		0.05*** (0.00)		0.05*** (0.00)		0.05*** (0.00)		0.05*** (0.00)		0.05*** (0.00)		0.05*** (0.00)
Firm age $t-1$		0.04*** (0.00)		0.04*** (0.00)		0.03*** (0.01)		0.03*** (0.00)		0.04*** (0.00)		0.03*** (0.01)
Cash $t-1$		-0.01 (0.01)		-0.01* (0.01)		-0.01 (0.01)		-0.02** (0.01)		-0.02*** (0.01)		-0.01 (0.01)
Leverage $t-1$		-0.04*** (0.01)		-0.04*** (0.01)		-0.04*** (0.01)		-0.03*** (0.01)		-0.03*** (0.01)		-0.04*** (0.01)
R&D $t-1$		0.01 (0.01)		0.01 (0.01)		0.01 (0.01)		0.01 (0.01)		0.01 (0.01)		0.00 (0.01)
Tobin's Q $t-1$		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,769	41,113	46,550	42,402	51,153	46,822	71,201	64,638	80,980	71,011	57,922	52,838
R-squared	0.77	0.82	0.76	0.83	0.78	0.82	0.78	0.82	0.76	0.82	0.78	0.83

The dependent variable is the proportion of a company's shares owned by quasi-indexer institutional investors. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-Z: Green patenting activity and dedicated institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green patents ratio $t-1$	-0.00 (0.00)	-0.00 (0.01)										
Green applications ratio $t-1$			0.00 (0.00)	0.00 (0.01)								
Green citations ratio $t-1$					0.01 (0.01)	0.01 (0.01)						
Green patent stock ratio $t-1$							-0.01 (0.01)	0.00 (0.01)				
Green applications stock ratio $t-1$									0.00 (0.01)	-0.01 (0.01)		
Green citations stock ratio $t-1$											0.01 (0.01)	0.01 (0.01)
Market capitalisation $t-1$		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)
Firm age $t-1$		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)		0.01*** (0.00)
Cash $t-1$		0.01* (0.00)		0.01* (0.00)		0.01 (0.00)		0.01** (0.00)		0.01* (0.00)		0.01* (0.00)
Leverage $t-1$		-0.01* (0.00)		-0.01 (0.00)		-0.01** (0.00)		-0.01 (0.00)		-0.00 (0.00)		-0.01* (0.00)
R&D $t-1$		-0.02** (0.01)		-0.01* (0.01)		-0.01 (0.01)		-0.01* (0.01)		-0.01* (0.01)		-0.01 (0.01)
Tobin's Q $t-1$		0.00 (0.01)		0.00 (0.00)		0.00 (0.01)		0.00 (0.01)		0.00 (0.00)		0.00 (0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,587	30,411	34,276	31,652	36,078	33,599	48,020	44,466	53,983	48,379	40,084	37,246
R-squared	0.55	0.56	0.56	0.56	0.53	0.54	0.54	0.55	0.54	0.55	0.53	0.54

The dependent variable is the proportion of a company's shares owned by dedicated institutional investors. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AA: Market reaction (CAR 0,+2), climate change mitigation technologies (CCMT) patents, and high-risk firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln (1+CCMT patent volume)	0.0003* (0.0002)		0.0003 (0.0002)	0.0004 (0.0003)		-0.0000 (0.0003)	-0.0000 (0.0003)		0.0002 (0.0003)	0.0002 (0.0003)
CO ₂ Intensive Industry		0.0006 (0.0007)	0.0006 (0.0007)	-0.0002 (0.0011)						
CO ₂ Intensive Industry x Ln (1+CCMT patent volume)			0.0000 (0.0004)	-0.0001 (0.0004)						
Low env. score _{t-1}					0.0006* (0.0004)	0.0006* (0.0003)	0.0006* (0.0003)			
Low env. score _{t-1} x Ln (1+CCMT patent volume)						0.0002 (0.0012)	0.0004 (0.0012)			
High climate risk exposure _{t-1}								-0.0000 (0.0002)	-0.0001 (0.0002)	0.0001 (0.0002)
High climate risk exposure _{t-1} x Ln (1+CCMT patent volume)									-0.0005 (0.0004)	-0.0006 (0.0004)
Market capitalisation _{t-1}				-0.0013*** (0.0002)			-0.0028*** (0.0006)			-0.0016*** (0.0004)
Firm age _{t-1}				-0.0005 (0.0003)			0.0006 (0.0006)			-0.0005 (0.0005)
Cash _{t-1}				0.0019* (0.0010)			0.0025 (0.0016)			0.0022* (0.0013)
Leverage _{t-1}				-0.0015** (0.0006)			-0.0015 (0.0013)			-0.0007 (0.0009)
R&D _{t-1}				0.0001 (0.0023)			-0.0021 (0.0063)			-0.0002 (0.0033)
Tobin's Q _{t-1}				-0.0000 (0.0001)			0.0001 (0.0001)			0.0001 (0.0001)
Ln (1+patent volume)				0.0001 (0.0001)			-0.0000 (0.0002)			0.0000 (0.0002)
Patent citations				0.0002* (0.0001)			0.0001 (0.0002)			0.0001 (0.0002)
Patent claims				0.0002 (0.0008)			0.0010 (0.0011)			-0.0014 (0.0010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466,227	466,227	466,227	433,690	125,928	125,928	125,536	199,139	199,139	198,027
R-squared	0.0269	0.0269	0.0269	0.0265	0.0127	0.0127	0.0137	0.0208	0.0208	0.0211

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AB: Market reaction (CAR 0,+2), climate change mitigation technologies (CCMT) patents, and climate concerns (0,+2)

	(1)	(2)	(3)	(4)
Climate concerns	-0.0013 (0.0011)		-0.0014 (0.0012)	-0.0013 (0.0012)
Ln (1+CCMT patent volume)		0.0003* (0.0002)	0.0000 (0.0003)	-0.0000 (0.0003)
Climate concerns x Ln (1+CCMT patent volume)			0.0011 (0.0009)	0.0010 (0.0009)
Market capitalisation $t-1$				-0.0022*** (0.0005)
Firm age $t-1$				-0.0010 (0.0006)
Cash $t-1$				0.0022 (0.0015)
Leverage $t-1$				-0.0000 (0.0011)
R&D $t-1$				-0.0037 (0.0039)
Tobin's Q $t-1$				0.0001 (0.0001)
Ln (1+patent volume)				0.0001 (0.0003)
Patent citations				0.0001 (0.0002)
Patent claims				-0.0023** (0.0011)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	170,583	466,227	170,583	163,540
R-squared	0.0297	0.0269	0.0298	0.0292

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AC: Market reaction (CAR 0,+2), climate change mitigation technologies (CCMT) patents, and institutional investor ownership

	(1)	(2)	(3)	(4)
IO _{t-1}	-0.0014** (0.0007)		-0.0014** (0.0007)	-0.0003 (0.0007)
Ln (1+CCMT patent volume)		0.0003* (0.0002)	0.0006 (0.0007)	0.0007 (0.0007)
IO _{t-1} x Ln (1+CCMT patent volume)			-0.0006 (0.0011)	-0.0007 (0.0011)
Market capitalisation _{t-1}				-0.0014*** (0.0003)
Firm age _{t-1}				-0.0003 (0.0003)
Cash _{t-1}				0.0020* (0.0011)
Leverage _{t-1}				-0.0018** (0.0007)
R&D _{t-1}				-0.0007 (0.0025)
Tobin's Q _{t-1}				-0.0001 (0.0001)
Ln (1+patent volume)				0.0001 (0.0002)
Patent citations				0.0003** (0.0001)
Patent claims				0.0002 (0.0008)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	390,611	466,227	390,611	375,051
R-squared	0.0275	0.0269	0.0275	0.0274

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AD: Market reaction (CAR 0,+2), climate change mitigation technologies (CCMT) patents, and institutional investor attention (0,+2)

	(1)	(2)	(3)	(4)
Institutional attention	0.0009*** (0.0002)		0.0010*** (0.0002)	0.0010*** (0.0002)
Ln (1+CCMT patent volume)		0.0003* (0.0002)	0.0005* (0.0003)	0.0005 (0.0003)
Institutional attention x Ln (1+CCMT patent volume)			-0.0003 (0.0002)	-0.0003* (0.0002)
Market capitalisation t_{-1}				-0.0016*** (0.0005)
Firm age t_{-1}				-0.0005 (0.0008)
Cash t_{-1}				0.0030* (0.0017)
Leverage t_{-1}				0.0028* (0.0013)
R&D t_{-1}				0.0046 (0.0035)
Tobin's Q t_{-1}				0.0004*** (0.0001)
Ln (1+patent volume)				-0.0001 (0.0002)
Patent citations				0.0002 (0.0002)
Patent claims				-0.0005 (0.0012)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	128,305	466,227	128,305	124,326
R-squared	0.0239	0.0269	0.0240	0.0237

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of patent announcements. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AE: Climate change mitigation technologies (CCMT) patenting activity and environmental score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CCMT patents ratio $t-1$	1.43 (2.06)	1.32 (2.02)										
CCMT applications ratio $t-1$			3.84 (2.37)	3.65 (2.23)								
CCMT citations ratio $t-1$					-0.29 (3.42)	-0.45 (3.26)						
CCMT patent stock ratio $t-1$							-9.10 (7.97)	-9.86 (7.44)				
CCMT applications stock ratio $t-1$									-0.87 (8.76)	-2.15 (8.34)		
CCMT citations stock ratio $t-1$											-1.54 (7.88)	-0.86 (7.32)
Market capitalisation $t-1$		2.59*** (0.82)		2.64*** (0.89)		2.81*** (0.83)		2.35 (0.72)		2.27*** (0.68)		2.73*** (0.81)
Firm age $t-1$		2.07 (1.73)		2.03 (1.54)		2.52 (2.72)		2.45 (1.61)		1.90 (1.38)		2.53 (2.67)
Cash $t-1$		-1.28 (3.28)		0.15 (3.24)		0.88 (4.00)		-1.13 (3.18)		-1.10 (2.92)		0.73 (3.86)
Leverage $t-1$		0.56 (2.87)		0.05 (2.80)		0.95 (2.61)		-0.49 (2.38)		-0.98 (2.25)		0.53 (2.55)
R&D $t-1$		2.63 (5.34)		3.54 (5.39)		4.70 (6.60)		2.62 (4.49)		2.69 (4.31)		3.94 (5.50)
Tobin's Q $t-1$		-0.13 (0.24)		-0.21 (0.23)		0.03 (0.27)		-0.00 (0.23)		-0.14 (0.23)		0.02 (0.26)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,714	7,704	7,911	7,798	8,426	8,417	10,273	10,258	10,873	10,739	9,110	9,101
R-squared	0.84	0.84	0.83	0.84	0.83	0.83	0.84	0.84	0.84	0.84	0.83	0.84

The dependent variable is environmental score (out of 100). Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AF: Climate change mitigation technologies (CCMT) patenting activity and institutional investor ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CCMT patents ratio $t-1$	-0.00 (0.01)	-0.00 (0.01)										
CCMT applications ratio $t-1$			-0.01 (0.01)	-0.01 (0.01)								
CCMT citations ratio $t-1$					0.01 (0.01)	0.01 (0.01)						
CCMT patent stock ratio $t-1$							0.02 (0.02)	0.02 (0.02)				
CCMT applications stock ratio $t-1$									0.03 (0.02)	0.03 (0.02)		
CCMT citations stock ratio $t-1$											0.02 (0.03)	0.01 (0.03)
Market capitalisation $t-1$		0.06*** (0.00)		0.06*** (0.00)		0.06*** (0.00)		0.07*** (0.00)		0.07*** (0.00)		0.06*** (0.00)
Firm age $t-1$		0.05*** (0.00)		0.05*** (0.00)		0.04*** (0.01)		0.04*** (0.01)		0.04*** (0.00)		0.04*** (0.01)
Cash $t-1$		0.01 (0.01)		0.00 (0.01)		0.01 (0.01)		0.00 (0.01)		-0.01 (0.01)		0.01 (0.01)
Leverage $t-1$		-0.04*** (0.01)		-0.04*** (0.01)		-0.04*** (0.01)		-0.03*** (0.01)		-0.03*** (0.01)		-0.04*** (0.01)
R&D $t-1$		-0.08*** (0.02)		-0.07*** (0.02)		-0.06*** (0.02)		-0.04** (0.02)		-0.04*** (0.01)		-0.05*** (0.02)
Tobin's Q $t-1$		-0.01** (0.00)		-0.00 (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)		-0.01*** (0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,960	41,253	46,746	42,548	51,377	46,978	71,674	64,983	81,597	71,428	58,214	53,048
R-squared	0.79	0.83	0.78	0.83	0.79	0.84	0.79	0.84	0.78	0.84	0.80	0.84

The dependent variable is the proportion of a company's shares owned by institutional investors. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix 4-AG: Climate change mitigation technologies (CCMT) patenting activity and Tobin's Q

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CCMT patents ratio $t-1$	-0.05 (0.08)	-0.04 (0.07)										
CCMT applications ratio $t-1$			0.06 (0.07)	0.07 (0.07)								
CCMT citations ratio $t-1$					-0.13 (0.10)	-0.16 (0.10)						
CCMT patent stock ratio $t-1$							-0.18 (0.14)	-0.17 (0.12)				
CCMT applications stock ratio $t-1$									-0.10 (0.16)	-0.12 (0.14)		
CCMT citations stock ratio $t-1$											-0.12 (0.17)	-0.17 (0.16)
Market capitalisation $t-1$		0.28*** (0.02)		0.27*** (0.02)		0.27*** (0.02)		0.26*** (0.02)		0.25*** (0.02)		0.27*** (0.02)
Firm age $t-1$		-0.46*** (0.05)		-0.48*** (0.04)		-0.52*** (0.09)		-0.44*** (0.05)		-0.47*** (0.04)		-0.52*** (0.09)
Cash $t-1$		1.17*** (0.14)		1.22*** (0.13)		1.23*** (0.13)		1.20*** (0.12)		1.21*** (0.11)		1.21*** (0.13)
Leverage $t-1$		0.55*** (0.10)		0.50*** (0.10)		0.54*** (0.10)		0.52*** (0.09)		0.49*** (0.08)		0.55*** (0.09)
R&D $t-1$		3.27*** (0.34)		3.56*** (0.37)		3.61*** (0.38)		3.15*** (0.30)		3.31*** (0.29)		3.51*** (0.37)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,645	50,405	54,589	51,695	54,641	54,271	77,968	77,378	88,926	84,746	61,530	61,113
R-squared	0.55	0.58	0.53	0.58	0.54	0.57	0.54	0.57	0.53	0.57	0.54	0.57

The dependent variable is Tobin's Q. Standard errors are clustered at firm and year-level and are reported in parentheses. All control variables are winsorized at the 1% and 99% tails. All regressions include firm fixed effects and year fixed effects. All firm control variables are lagged by one year. Observations is the number of firm-year observations. Constant has been omitted for brevity. See Appendix 4-A for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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