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By

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*« L'université n'entend ni approuver ni désapprouver les
opinions particulières de l'auteur. »*

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Chapter 1

Introduction

This thesis, which consists of three chapters, empirically studies the relationships between firm ownership, firm value, and innovation strategy. In particular, it examines how firms operating under modern corporate finance arrangements manage the challenges of financing, organising, protecting, and directing corporate innovation. Chapter 2 studies how common ownership can influence inter-firm technological similarity, innovation quality, and potentially contribute to product market concentration.¹ Chapter 3 focuses on climate-related innovation to show how financial markets respond to firms buying and selling climate patents. Chapter 4 investigates whether dual-class structures help alleviate short-term financial pressures to support long-term investment in innovation.

Innovation is the engine of long-term economic growth. Economic theory states that only innovation can increase productivity over time (Solow, 1956; Romer, 1990; Aghion and Howitt, 1992). While accumulating capital and labour can generate short-term economic growth, their diminishing marginal returns imply that technological progress is the only sustainable source of long-term economic growth. Public companies play an important role in producing, developing, diffusing and commercialising innovation. Out of 7,456,760 granted patents between 1980 and 2020, 2,894,170 were produced by a publicly listed firm according to the Dyèvre and Seager (2023) patent to public firm database.

¹The common ownership phenomenon occurs when the same institutional investors hold stakes in multiple competing firms.

This represents around 39% of all US patents granted in this period.²

Despite their central role in producing innovation, public firms face important constraints in their ability to invest in innovation. Innovation is a noisy and costly process with an uncertain payoff. Public firms are subject to capital market expectations, investor scrutiny, and short-term performance benchmarks, which can discourage long-term investments with hard-to-measure returns. [Holmstrom \(1989\)](#) argues that such an environment can discourage exploration and risk-taking, leading to underinvestment in innovation. Moreover, [Bernstein \(2015\)](#) shows that in comparison to remaining a private entity, becoming a public firm is linked with a decline in R&D spending and innovation outcome due to investor and capital market pressures.

Moreover, traditional corporate finance is characterised by principal-agent models emphasising shareholder value maximisation through close monitoring, short-term incentives, and a preference for projects with measurable cash flows. These mechanisms stifle innovation. The innovation-related corporate finance literature explores how deviations from traditional corporate finance can spur corporate innovation. For example, [Manso \(2011\)](#) shows that conventional corporate finance incentive structures penalise failure, which discourages innovation, while [Aghion et al. \(2013\)](#) show that long-term oriented shareholders can promote corporate innovation.

In this thesis, I examine three departures from traditional corporate finance principles and analyse their effects on corporate innovation and firm value.

Chapter 2 focuses on the shift from firm value maximisation to shareholder portfolio value maximisation induced by common ownership. The common ownership hypothesis suggests that when the same shareholders hold significant stakes in multiple competing firms, those firms have less incentives to compete aggressively. This is because common owners prioritise portfolio profits over individual firm gains, making rivalry counterproductive. In the context of innovation, common ownership is suggested to solve underinvestment problems in R&D and improve knowledge output by encouraging firms to internalise innovation spillovers ([Anton et al., 2024](#); [Geng et al., 2025](#); [Kostovetsky and](#)

²Non-public firms, universities, individuals, and public research institutions are also important innovation producers.

[Manconi, 2020](#)). I extend this literature by studying whether common ownership plays a role in corporate innovation strategy and direction and its subsequent implications. More precisely, I study whether common ownership affects innovation similarity between firms and what this implies for innovation quality and inter-firm product competition.

To investigate the relationship between common ownership and patent similarity, I construct a new panel dataset that includes firm-pair measures of common ownership intensity and innovation similarity. I construct firm-pair innovation similarity measures based on patent application text abstracts over varying periods. My causal methodology relies on a dyadic regression model and exogenous variation in common ownership through a set of financial institution mergers.

The results show that common ownership increases patent similarity between firms. This relationship is driven by low-quality innovation and innovation that develops new products rather than new processes.³ The intuition behind these results is as follows. Firm-pair common ownership increases incentives to implicitly or explicitly collaborate on innovation. Such coordination through knowledge sharing, reduced R&D duplication, and more helps maximise joint profits that accrue to the common owners. In my results, the collaboration observed (i.e. increase in patent similarity) stems from low-quality patents as soon as one year after the increase in common ownership. Therefore, common ownership may encourage firms to excessively patent in each other’s technological domains, leading to knowledge fragmentation. This behaviour is enabled by the lower likelihood of patent litigation between commonly owned firms ([Geng et al., 2025](#)). From the perspective of the common owner, knowledge fragmentation may be strategically beneficial as it discourages breakthrough innovations, which tend to be motivated by private returns. Breakthrough innovations, though valuable to an individual firm, can disrupt industry dynamics and threaten the profitability of other portfolio firms. Finally, the alignment of innovation strategies across commonly owned firms can contribute to product market concentration, enabling common owners to exert anti-competitive influence

³Innovation quality is defined through two measures in this thesis. The first is a text-based measure where the patent abstract’s similarity with future patents is divided by its similarity with past patents. The second is a citation-based measure that counts the three-year post patent application number of forward citations received. The second measure is patent-weighted when used for firm-level innovation. In Chapter 2 low-quality innovation is measured at the firm-pair level and is attributed to firm-pairs where both firms are in the bottom quartile of the innovation quality measure used.

through coordinated pricing strategies ([Antón et al., 2023](#)).

This chapter complements previous findings by suggesting that common ownership may increase innovation output, but at the cost of innovation quality and technological differentiation. This chapter also contributes to the understanding of the mechanisms behind the observed rise in product market concentration associated with common ownership ([Kini et al., 2023](#); [Aslan, 2024](#)) in the form of knowledge fragmentation and product innovation alignment. Therefore, contrary to the literature, the common ownership effect on innovation is not necessarily positive. This chapter raises antitrust concerns on the long-run impact of common ownership on technological diversity and suggests it may play a role in the documented decline of breakthrough innovations ([Park et al., 2023](#); [Bloom et al., 2020](#)).

Chapter 3 focuses on the departure from traditional investment intuition in corporate finance. Agency costs should lead managers to prefer short-term and incremental innovations where the private returns exceed the social returns. Firms that engage in climate change mitigation and adaptation innovation challenge this framework. Climate technologies are characterised by positive externalities and long development horizons. In the absence of strong climate regulation, which can make these innovations valuable for owners, engaging in climate-related innovation is not necessarily profitable.

The goal of this chapter is to examine whether markets assign value to strategic decisions involving climate technologies. The existing literature finds mixed evidence on the relationship between climate patent grants and firm value ([Dechezleprêtre et al., 2021](#); [Hege et al., 2023](#); [Reza and Wu, 2024](#); [Klausmann et al., 2025](#); [Andriosopoulos et al., 2024](#); [Leippold and Yu, 2024](#)). However, the firms best positioned to develop climate mitigation and adaptation technologies may not necessarily be the ones that ultimately implement them. For example, [Kwon et al. \(2024\)](#) show that brown firms that produce climate technologies lobby against climate agendas to profit from the status quo. By using climate patent acquisition and divestment data, I study a clearer signal of firms' strategic engagement with climate technologies and its value implications.

I employ the knowledge capital valuation regression model proposed by [Griliches \(1981\)](#) to explore this chapter's research questions. I make two adaptations to this model.

First, I introduce two new variables to this model in the form of patent sales and patent acquisitions. Second, I separate climate-related patents to all other patents to isolate the climate-related valuation information. To implement this methodology, I build a panel dataset that includes rich firm-to-firm patent transaction data for a sample of climate patent-producing or acquiring firms. To reduce endogeneity concerns, I employ a sample that accounts for possible omitted variable bias and carry out a propensity score matching analysis. Additionally, for climate patent divestment, I also show the effects to be stronger when the firm is exposed to climate risk, and I employ an instrumental variable approach using state-level climate regulation stringency to tackle endogeneity concerns.

This chapter shows that climate patent sales are linked to an immediate reduction in firm value, whereas climate patent acquisitions are associated with a one-year delayed increase in firm value. These relationships are not observed for non-climate patent transactions. This suggests that financial markets value engagement with climate-related innovation. Divesting climate patents signals low environmental commitment and the abandonment of important real options in case of future climate regulations. The signalling effect of climate patent acquisition is limited. The delayed effect suggests that implementing the technology matters as much as signalling the acquisition of climate-related innovation options. This chapter demonstrates that the market regards climate-related innovation as a strategically valuable asset, the worth of which is contingent upon firms' dedication and ability to effectively implement such innovations. This chapter also calls for a reevaluation of how firm-level climate innovation is measured and assessed.

Chapter 4 focuses on the departure from one share-one vote governance to control-insulating dual-class shares. These arrangements decouple ownership from control through super-voting shares which attribute effective control of a firm to certain agents who do not own the majority of the firm's equity. Dual-class structures, where founders have an important management role in the company and hold effective control of the firm, have become popular in technology firms. This popularity is anecdotally argued to be beneficial because it helps innovation-producing companies to disregard short-term market pressures and implement long-term value-enhancing strategies. This chapter empirically investigates this argument.

This chapter employs discretionary accruals as a proxy for earnings management and

R&D stability, measured by year-to-year variation in R&D expenditures, to capture short-term market pressure and long-term value focus, respectively. It also uses an estimated dual-class structure value instrumented from a state-level anti-takeover stringency score and an industry-level dual-class popularity variable to mitigate endogeneity concerns. Surprisingly, I find that founder-led dual-class structures (i.e. where at least one founder has effective control of the company and an important management role) are more likely than one share-one vote firms to manage earnings. They are also just as likely as one share-one vote firms to amputate long-term value to comply with short-term market pressures. These results persist when I incorporate non-founder-led dual-class structures in the sample. These results can be explained by institutional investor pressure against dual-class structures and monetary incentives in dual-class structures. Dual-class structure owners can sell a significant portion of super-voting shares for personal enrichment while maintaining effective control of the firm. This likely motivates short-term pressure compliance to maximise firm value and sell shares at a high price. Overall, this chapter suggests that founder-led dual-class structures do not promote long-term value and instead predominantly serve as an entrenchment mechanism, much like their non-founder-led counterparts.

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Chapter 2

Common ownership and patent similarity

2.1 Introduction

The common ownership hypothesis suggests that firms with overlapping shareholders should maximize the aggregate value of their investors' portfolios rather than maximizing standalone firm profits (Rotemberg, 1984; Bresnahan and Salop, 1986; Hansen and Lott, 1996; Azar, 2012). The literature shows that common ownership can dampen product market competition and promote innovation output among commonly held firms.¹ I extend this literature by studying whether common ownership affects how firms innovate and not just how much they innovate. In other words, does common ownership impact technological differentiation between firms and if so, what are the implications for innovation quality and product market competition?

¹Common ownership and product market literature: Azar (2012), Azar et al. (2018), Azar et al. (2021), Torshizi and Clapp (2021), Bindal and Nordlund (2024), Antón et al. (2023)

Recent, real-world repercussions can also be observed with the Texas and ten other states' lawsuit against the potential common ownership power exerted by BlackRock to reduce coal output and further climate agendas. <https://climatecasechart.com/case/texas-v-blackrock-inc/>

It should be noted that common ownership also ties into the green finance literature because as universal owners they are exposed to systemic climate risks and should have an incentive to combat it. Biais and Landier (2022) model the role they can play in advancing green finance agendas.

Common ownership and innovation literature: Anton et al. (2024), Kostovetsky and Manconi (2020), Geng et al. (2025)

Recent studies have documented diminishing research productivity that has resulted in a decline of radical innovations (Bloom et al., 2020; Park et al., 2023). At the same time, concentration in the asset management industry and the popularity of passive investment has led to a rapid rise in common ownership.² The literature suggests that common ownership reduces concerns about rival firms benefiting from innovation spillovers (Anton et al., 2024; Geng et al., 2025; Kostovetsky and Manconi, 2020). This reduces underinvestment and patent litigation between commonly held firms leading to more R&D, patents, citations, and cross-citations. However, it remains unclear whether common ownership should lead firms to converge or diverge in their technological choices. While common shareholders may encourage coordination to internalize innovation spillovers, they may also prefer technological differentiation to avoid product market cannibalization and reduce direct competition. Similarly, even if common owners foster coordination among portfolio firms, the type of innovation this coordination should promote is ambiguous. On the one hand, they could promote breakthrough innovations through knowledge spillovers and other collaboration mechanisms. On the other hand, they could promote incremental overlapping innovations aimed at preserving the status quo without incurring competitive risks associated with pursuing radical innovations that might jeopardize portfolio profits.

There are three empirical challenges in implementing this study.

First, to measure technological similarity between firms, I build a textual patent abstract similarity measure. I use a new set of granted and rejected firm patents to accurately gauge patent similarity between firms. This measure outperforms patent classification-based similarity measures such as the Jaffe (1986) patent similarity measure. It is also statistically similar to other patent text-based measures such as Arts et al. (2023).

Second, I implement a dyadic regression model to study the relationship between my pairwise common ownership and patent similarity measures. This allows a more granular

²<https://www.forbes.com/sites/bobeccles/2019/04/17/concentration-in-the-asset-management-industry-implications-for-corporate-engagement/>
Appel et al. (2016) shows that passive investors are not necessarily passive owners by showing that they are heavily involved in the governance of portfolio companies.

analysis than a firm-year level analysis which would instead reveal whether commonly owned firms, on average, innovate in more or less differentiated technological areas relative to the rest of the market, without capturing whether their innovations converge with each other.

Third, to establish causality I implement a robust baseline analysis and a causal analysis. In the baseline analysis, I demonstrate that the common ownership effect on patent similarity is due to subsequent patent applications (i.e. year t common ownership only significantly impacts patent applications from year $t+1$ onward). I follow the [Lewellen and Lowry \(2021\)](#) procedure for the causal analysis. I do this by exploiting a set of three financial institution mergers in 2008 and 2009 that created an exogenous increase in a selection of 271 firms out of the original 1,642 innovative firms I track. These 271 firms are matched to a set of control firms and are analysed using a difference in difference model. Again, the causal common ownership effect on patent similarity is only observed in subsequent patent applications. All results are consistent between the baseline and causal analysis.

The results show that common ownership increases patent similarity. In the baseline analysis, common ownership is correlated with a 7.78% increase in patent similarity in comparison to the average patent similarity level. In the causal analysis, an exogenous increase in common ownership is shown to generate a 11.67% increase in patent similarity in comparison to the pre-event treatment average of patent similarity. Given the novelty requirement for patents and the rigid nature of innovation paths in firms, the magnitude of this increase is significant.

Common ownership leading to patent similarity between firms can be argued to be both positive and negative. On the one hand, it can be explained by collaborations or knowledge diffusion that pushes these firms to create high-quality innovation. On the other hand, it can be explained by common ownership incentives that push firms to patent in each others' fields. For example, firms can take advantage of the lower likelihood of patent litigation pursuits when firms share common owners ([Geng et al., 2025](#)) to patent excessively. Similarly, common ownership can incite knowledge fragmentation to reduce disruptive technology entry or simply reduce individual firm value increasing technological differentiation to ensure stable portfolio firm value. Knowledge fragmentation reduces the

likelihood of one firm gaining a dominant technological edge which ensures a more stable and predictable return across the owner’s portfolio.

To separate these two potential drivers, I construct two measures that separate firm pairs into low-quality patent producers and high-quality patent producers. The first is a text measure that divides the firm’s patent applications’ similarity with future patents (novelty) by its similarity with past patents (low quality) following [Kelly et al. \(2021\)](#). The second is a citation per patent received measure. Through both measures, firm pairs that are in the bottom quartile (low-quality innovation) are shown to drive the main results. The top quartile (high-quality innovation) firm pairs sub-sample has no common ownership to patent similarity link.

The effect of common ownership on patent similarity is not solely negative. The positive relationship between common ownership and patent similarity persists when studying firm pairs where one firm produces high-quality patents and the other low-quality patents. This means that low-quality innovating firms can benefit from common ownership links with high-quality innovation-producing firms. Therefore, common ownership can help reduce knowledge concentration and other innovation barriers created by technologically leading firms to protect their dominance ([Akcigit and Ates, 2023](#)).

In the last part of this paper, I study what type of innovation is favoured by common ownership. [Bena and Simintzi \(2022\)](#) and [Bena et al. \(2022\)](#) state that there are two dominant types of innovation. Process innovations, that are identified by the use of the term “A method of” in their leading patent claim. This type of innovation contributes to reducing production costs. The other type of innovation is product innovations which tend to bring forward new product developments or new products to the market. I find that common ownership is only linked to an increase in product innovation similarity. This means that commonly owned firms produce similar product innovations that could eventually lead to product market overlap. Product market concentration is welcomed in the common ownership hypothesis because it allows profit-increasing non-competitive pricing strategies ([Antón et al., 2023](#)).

This paper is divided as follows. Section [2.2](#) states the contributions I make to the related literature. Section [2.3](#) develops this paper’s hypotheses. Section [2.4](#) details the

data sources, construction, and descriptive statistics. Sections 2.5 and 2.6 develop the methodologies and report the baseline and causal results respectively. Section 2.7 concludes.

2.2 Related literature

I make several contributions to the literature. First, I contribute to the literature on how common ownership affects innovation. Theoretical work suggests that in the presence of technological spillovers, common ownership leads to higher R&D investment, which then lowers production costs and raises output (Lopez and Vives, 2019; Vives, 2020). Therefore, common ownership fosters innovation and reduces product market competition through non-competitive pricing. Empirical evidence demonstrates that common ownership promotes innovation through lower patent litigation and higher cross-citations (knowledge spillover) (Geng et al., 2025; Kostovetsky and Manconi, 2020) when technological spillover effects outweigh business stealing or product overlap concerns (Anton et al., 2024). In pharmaceutical start-ups, Li et al. (2023) demonstrate that common venture capital owners reallocate innovation resources from technologically lagging firms to high performers and encourage lagging firms to adjust their technological focus. I contribute to this strand of the literature by showing that common ownership increases inter-firm technological similarity through a novel patent text measure. I also complement this literature by showing that common ownership increases innovation through low-quality patents and product innovations. To the best of my knowledge, this is the first study to document the negative effects of common ownership on innovation quality and technological differentiation.

Second, I contribute to the literature on the anti-competitive effects of common ownership. On the one hand, this literature shows that common ownership leads to higher prices, mark-ups, and profitability (Azar, 2012; Azar et al., 2018, 2021; Torshizi and Clapp, 2021; Bindal and Nordlund, 2024). On the other hand, this literature finds no evidence of the common ownership hypothesis when using different measures, industries, and time frames (Dennis et al., 2022; Koch et al., 2021; Lewellen and Lowry, 2021). Kini et al. (2023) and Aslan (2024) complement this literature by showing that firms have

more product overlap following an exogenous increase in common ownership. [Antón et al. \(2023\)](#) identify lower CEO pay-performance sensitivity as a potential mechanism for the common ownership effect. I contribute to this literature by unveiling innovation overlap as a channel through which common ownership can lead to product market overlap and anti-competitive effects.

Third, I contribute to several strands of the innovation literature. First, I extend the literature on inter-firm innovation coordination, which has traditionally focused on formal relationships such as M&A, strategic alliances, and joint ventures ([Hsu et al., 2022](#); [Cunningham et al., 2021](#); [Arora et al., 2021a](#)). I show that common ownership can serve as an alternative coordination mechanism, implicitly aligning innovation strategies across firms without official contractual ties. Second, I contribute to the literature on technological concentration and innovation competition. Prior studies document that competitive pressure in innovation can lead to duplicated effort, wasted resources, and a widening gap between technological leaders and laggards ([Aghion et al., 2005](#); [Autor et al., 2020](#); [Aghion et al., 2021](#); [Akcigit and Liu, 2016](#); [Bena and Garlappi, 2020](#); [Akcigit and Ates, 2023](#); [Fadeev, 2024](#)). I show that common ownership incentives between technologically leading and lagging firms can mitigate this problem. Finally, I contribute methodologically to the growing literature that uses patent text data to construct new indicators of innovation ([Whalen et al., 2020](#); [Younge and Kuhn, 2016](#); [Arts et al., 2021](#); [Hain et al., 2022](#); [Arts et al., 2023](#); [Kelly et al., 2021](#); [Bowen et al., 2023](#)). I build on this work by incorporating both granted and rejected patents and by using patent text similarity to capture implicit innovation alignment between firms. In doing so, I show that patent text measures can uncover coordinated innovation strategies beyond what is observable in citation-based or patent classification-based indicators.

2.3 Hypothesis development

2.3.1 Common ownership and patent similarity

The impact of common ownership on patent similarity is unclear. The common ownership hypothesis states that when institutional investors hold multiple companies, they

have an incentive to influence firm dynamics by reducing competition and increasing coordination on matters such as innovation strategies. However, the common ownership hypothesis and its coordination effect remain questionable in the literature (Lewellen and Lowry, 2021; Koch et al., 2021). Some studies have shown the impact of common owners to be bounded by industry characteristics (Schmalz, 2018; Backus et al., 2021a). Therefore, we can expect an inability of common owners to influence industry-wide firms' technological output strategy. Moreover, proof of coordination from common owners to firms is limited to weakly incentivised CEO contracts and investor attention based on investment size (Antón et al., 2023; Gilje et al., 2020). When coupled with the uncertain nature of innovation and the complex incentive schemes required to obtain particular types of technological output (Holmstrom, 1989; Aghion and Tirole, 1994; Manso, 2011; Ederer and Manso, 2013), we can question whether such coordination mechanisms would suffice to obtain any form of innovation based strategic alignment between firms. Further concern can be added by Antón et al. (2023) showing that firms with non-concentrated decision-making units are less impacted by common ownership. Therefore, the often detached innovation units in firms should bear little influence from common ownership. Additionally, investor exit opportunities make long-term innovation coordination tough.

Hypothesis 1.0: *Common ownership has no impact on patent similarity*

Nonetheless, studies have shown common ownership to increase innovation-related input, output and collaborations in firms (Anton et al., 2024; Lopez and Vives, 2019; Freeman, 2025; He and Huang, 2017; Geng et al., 2025; Kostovetsky and Manconi, 2020; Chen, 2024). This relationship can be driven by two events. First, by internalizing competitive externalities common ownership reduces under-investments that stem from competition-benefiting knowledge spillovers (Lopez and Vives, 2019). This incentive should promote cooperative innovation strategies between commonly held firms. Second, through the direct voice channel (Edmans et al., 2018), common owners can communicate innovation-related incentives directly to firms. This channel is likely at play in prior studies documenting common ownership coordination in corporate financial decisions and strategies (Giuli et al., 2021).

In line with the common ownership hypothesis, we can expect common owners to incite independent innovation paths. Patents protect both intellectual property and the

commercialization potential of intangible goods ([Argente et al., 2020](#)). To avoid product market competition, commonly held firms may therefore avoid pursuing the same innovation path. Independent innovation paths can also reduce winner-takes-all patent races ([Bena and Garlappi, 2020](#)) that leave the common owner’s portfolio worse off.

Hypothesis 1.A: *Common ownership decreases patent similarity between firms*

Common ownership can also increase technology similarity between firms. Innovation within firms follow phases of stagnation and booms ([Bustamante et al., 2021](#); [Ma, 2025](#)). These phases are dependent on the stage of the firm’s product life cycle and economy-wide technology shocks. An example of a recent technology shock is the industry-wide application of artificial intelligence. As technology cycles become shorter and more disruptive ([Bustamante et al., 2021](#)), developing a wide array of knowledge is primordial to not be left behind ([Cohen and Levinthal, 1990](#)). To avoid obsolescence and systemic technological risk, common owners therefore have an incentive to hold firms with expanded knowledge and a willingness to learn from one another ([Bena and Garlappi, 2020](#)).

Trade secrets are used in the innovation field to limit learning and imitation by competitors ([Fadeev, 2024](#)). They take the form of non-patenting decisions on intellectual property or willful omissions from patent documents. With common ownership, competitive externalities are internalized. This makes knowledge sharing, innovation synergies and avoiding excessive or duplicative R&D attractive ([Lewellen and Lowry, 2021](#); [Gutiérrez and Philippon, 2017](#)). As a result, patenting on private information increases (trade secrets decrease) and building new knowledge on previous innovation becomes easier. This can generate a positive relationship between common ownership and patent similarity. Likewise, common owners should incite patent fragmentation, where multiple entities share ownership on an intellectual property. This dispersion weakens technology leaders’ legal threats to the development of new knowledge or products by other firms ([Geng et al., 2025](#); [Bena and Garlappi, 2020](#); [Noel and Schankerman, 2013](#); [Galasso and Schankerman, 2010](#)). This allows more firms to patent on similar technologies.

Convergence in technology can lead to convergence in product markets ([Argente et al., 2020](#); [Arts et al., 2023](#)). Since common ownership effects are primarily argued to take place through price competition behaviour ([Antón et al., 2023](#)), product market concen-

tration should be desired by common owners. Consequently, the incentive for commonly owned firms to enter each other’s product markets can be understood as a downstream effect of increased technological overlap. In this context, common ownership may foster technological convergence as a precursor to strategic product market convergence found in [Aslan \(2024\)](#) and [Kini et al. \(2023\)](#).³

Hypothesis 1.B: *Common ownership increases patent similarity between firms*

2.3.2 Source of patent similarity

The null (Hypothesis 1.0) and negative (Hypothesis 1.A.) relationships between common ownership and patent similarity depict a normal functioning innovation environment. This is the case because patents are expected to be unique. By contrast, a positive relationship (Hypothesis 1.B) can come from multiple avenues. For simplicity, I will assume that hypothesis 1.B (a positive relationship) holds going forward to dissect its mechanisms.

On the one hand, patent similarity can arise from low-quality patents. This can come from knowledge fragmentation. Dispersed knowledge is less likely to be novel. As common ownership reduces legal threats ([Geng et al., 2025](#)), patenting costs also decrease (e.g. less patent attorney work to describe originality, lower future litigation cost). Meanwhile, markets continue valuing innovation output ([Kogan et al., 2017](#)) which signals future patent-related income (e.g. licensing deals).⁴ Commonly owned firms can take advantage of this situation by increasing patent applications on the knowledge (patent base) of firms they share investors with. Prior to this relationship, doing so would have been risky. Moreover, incremental innovation is contractually simpler to motivate ([Manso, 2011](#); [Ederer and Manso, 2013](#); [Antón et al., 2023](#)). In general, discouraging

³In the Appendix, Table 2.8.3 shows that my patent similarity measure is strongly correlated with the product market overlap measure developed by [Hoberg and Phillips \(2016\)](#). Moreover, [Arts et al. \(2023\)](#) demonstrate that there is a link between firms’ patent differentiation and their product market differentiation. This suggests that an increase in patent similarity can have product market concentration effects.

⁴Low-quality innovation such as patents with limited novelty or scientific value can still generate a positive market response if it is associated with monetization opportunities (e.g. licensing, blocking competitors, signalling innovation activity). In particular, regardless of quality, patenting can signal a firm’s readiness to enter new product markets.

breakthrough innovations, where some commonly held firms are left behind, is in the interests of common owners. Knowledge fragmentation can also help here by stifling breakthrough innovations from non-commonly held entrants.

On the other hand, patent similarity can be driven by high-quality patents. There can be instances where knowledge spillovers between firms allow for breakthrough innovations on similar technologies. [He and Huang \(2017\)](#), [Kostovetsky and Manconi \(2020\)](#), [Anton et al. \(2024\)](#) and [Geng et al. \(2025\)](#) state that common ownership leads to more innovation output (R&D investments and patents) and higher quality patents. The primary channels stated for this link are learning from one another, reduced business stealing effects, and reduced legal challenges. By internalizing benefits from R&D spillovers, firms are said to be more willing to undertake risky innovations. Similarly, if the knowledge spillover channel is at play, commonly held firms are expected to take advantage of potential trade secrets that may have previously stopped breakthrough innovations ([Hutschenreiter, 2023](#); [Fadeev, 2024](#)).

We can also envisage instances where the patent similarity effect is driven across both types of innovations. This means that explanations from both low-quality and high-quality innovations are at play. For example, R&D expense reductions that are linked to common ownership ([Gutiérrez and Philippon, 2017](#); [Lewellen and Lowry, 2021](#)) can lead to lower quality innovation or higher quality innovation. The former outcome is expected if cost-cutting reduces exploratory research or shifts focus toward defensive strategies that prioritize breadth over depth. The latter outcome is expected if R&D duplication is eliminated and there are resource allocation towards frontier projects.

Hypothesis 2.A: *Common ownership increases patent similarity through low-quality innovation*

Hypothesis 2.B: *Common ownership increases patent similarity through high-quality innovation*

Hypothesis 2.C: *Common ownership increases patent similarity through both types of innovation*

The growing gap between technology leading and lagging firms has been blamed for

the downturn in US firm dynamism over the last decade ([Akcigit and Ates, 2023](#); [Bloom et al., 2020](#)). Technology-lagging firms are finding it harder to remain competitive due to disruptive innovations and strategic patents (to stop disruptive entrants or competitors) from technology leaders. Under normal circumstances, this trend leads to lower imitation which can help laggards remain competitive. Common ownership incentives, which encourage implicit (more fluid patent licensing, lower legal risk, ...) and explicit (alliances, knowledge spillovers, ...) collaborations ([Geng et al., 2025](#); [Chemmanur et al., 2025](#); [He and Huang, 2017](#)), should allow lagging portfolio firms to catch up to leading portfolio firms. In using technology leaders to help lagging firms, common owners' general portfolio profits are improved. A positive relationship between common ownership and patent similarity can indicate an ability to imitate or catch up to technology leaders thanks to common ownership.

Hypothesis 3: *Common ownership increases patent similarity between technologically leading and lagging firms*

[Bena and Simintzi \(2022\)](#) and [Bena et al. \(2022\)](#) distinguish two types of innovation. One that is linked to cost reductions in the production process of the firm called process innovations. Another that is linked to new product developments called product innovations.

Common ownership increasing patent similarity in process innovation demonstrates the sharing of efficient production processes between firms. However, process innovations are harder to imitate because firms tend to have specialized production processes. This means that patenting on similar process technologies to partnering firms is difficult. Similarly, unlike the product innovation case, process innovations can be applied across commonly held firms rather easily through licensing agreements. They can also be subject to less dispute than more lucrative product innovations.

Hypothesis 4.0.: *Common ownership has no impact on patent similarity between firms in process innovations*

Hypothesis 4.A: *Common ownership increases patent similarity between firms in process innovations*

The common ownership to patent similarity relationship for product innovations is more nuanced. It is essentially dependent on the outcome of hypothesis 1. Product innovations are, upon the firm’s choice, converted into product market goods and services. Given the industry-wide scope of this study, where product-market overlap between commonly owned firms may be limited, the coordination effect of common ownership may have no observable impact on product patent similarity (Schmalz, 2018; Lewellen and Lowry, 2021; Koch et al., 2021; Antón et al., 2023). Increases in product innovation similarity can also be discouraged. With an increase in product innovation similarity between commonly held firms, we can expect an influx of product market entries, which can potentially increase unwanted competition between commonly held firms (Kini et al., 2023; Aslan, 2024). However, product market concentration can be desired by common owners since they exert influence through indirect pricing coordination (Antón et al., 2023; Aslan, 2024). Moreover, as previously mentioned, to avoid harmful disruption from systemic technology shocks a wide array of product innovation patents can be useful for future learning, innovation, and adaptation.

Hypothesis 5.0: *Common ownership has no impact on patent similarity in product innovations*

Hypothesis 5.A: *Common ownership decreases patent similarity between firms in product innovations*

Hypothesis 5.B: *Common ownership increases patent similarity between firms in product innovations*

2.4 Data

2.4.1 Sample and sources

This paper combines multiple sources of data to build a panel dataset that ranges from 2003 to 2020. I build a sample of 1,642 unique public firms from the Compustat database that have at least one reported patent application every three years between

2003 and 2020 to track the common ownership to patent similarity relationship reliably within a set of innovative firms. This choice ensures that low patenting firms do not drive my results through zero patent similarity levels. The panel dataset starts in 2003 because accurate patent application text (granted and rejected) is published from 2003 onward on PatentsView.⁵ I stop the sample in 2020 to avoid truncation bias for forward citation measures which I stop counting three years after the application date. This means that the latest patent data are forward citations from 2023 for patents applied in 2020.

Patent data are gathered from PatentsView and matched to Compustat firms by application year using the matching dataset provided by [Dyèvre and Seager \(2023\)](#).⁶ I also include rejected patent applications in my dataset to provide a more comprehensive view of firms' innovation activity and underlying knowledge base. Since existing firm-patent matching datasets only cover eventually granted patents, I link rejected patents to my sample firms using a matching procedure detailed in Appendix 2.8.2.1. In total, I identify 1,477,620 patents attributed to my 1,642 unique innovative firms. Precisely 1,290,100 of these patents are granted and 187,520 are rejected. For comparison, [Kogan et al. \(2017\)](#) report 1,009,082 eventually granted patent applications for my sample firms between 2003 and 2020. Over the same period, [Dyèvre and Seager \(2023\)](#) identify 1,734,260 granted patent applications by 5,015 public firms. This implies that my sample, which is restricted to firms that file a patent at least once every three years, covers approximately 75% of all granted patenting activity by U.S. public firms between 2003 and 2020.

All firm characteristics data are obtained from Compustat's annual company fundamentals data. Professor Jay Ritter's website is used for firm founding date data.⁷ Institutional ownership and common ownership data are constructed in this paper or obtained based on publicly available [Backus et al. \(2021b\)](#) data.⁸

⁵The data is available from 2001 on the PatentsView website. However, the data is inaccurate with a few missing granted patent cases until 2003.

⁶[Dyèvre and Seager \(2023\)](#) extend the [Arora et al. \(2021b\)](#) firm-patent matching dataset in coverage and in time by updating it through 2020. [Dyèvre and Seager \(2023\)](#) also extend the [Kogan et al. \(2017\)](#) firm-patent matching dataset by accounting for firm name changes and including patents assigned to private subsidiaries of publicly listed firms.

⁷Data can be found here: <https://site.warrington.ufl.edu/ritter/ipo-data/>

⁸[Backus et al. \(2021b\)](#) make their institutional investor filings (13F) data and kappa common ownership measure data publicly available here: <https://sites.google.com/view/msinkinson/research/common-ownership-data>

2.4.2 Dependent variable: Patent similarity

This paper captures the technological similarity between firms through a [Hoberg and Phillips \(2016\)](#) inspired patent abstract text measure. I calculate patent similarities between firms for different scopes ranging from a one-year scope (year t patent applications) to a five-year forward scope ($t+1$ to $t+5$ patent applications).⁹

To construct this data, I concatenate firm-year level patent text abstracts for the time scope being studied.¹⁰ For example, for the year 2015 and five-year forward time scope, I concatenate patent applications from 2016 to 2020 by firm. The concatenated patent abstracts then follow a set of standardization procedures that are detailed in [Appendix 2.8.2.2](#). The concatenated abstracts are then tokenised into individual words where each unique word in the firm-year corpus of abstracts is given a numerical score based on TF-IDF (term frequency-inverse document frequency). Equations [2.1](#) and [2.2](#) show the decomposition of the TF-IDF while Equation [2.3](#) shows the interaction that gives each word a score.

$$\text{Term frequency} = \frac{\text{Frequency of the word in the document}}{\text{Total number of words in the document}} \quad (2.1)$$

$$\text{Inverse document frequency} = \log \left(\frac{\text{Total number of firm-years}}{1 + \text{Number of firm-years containing the word}} \right) \quad (2.2)$$

$$\text{TF-IDF} = \text{Term Frequency score} \times \text{Inverse Document Frequency score} \quad (2.3)$$

⁹The three-year forward scope ($t+1$ to $t+3$ patent applications) provides a balanced panel dataset since my sample of firms has at least one patent application every three years. This is why I will focus on the three-year forward scope for my baseline analysis. In the causal analysis, I will refer to the one-year forward patent application scope ($t+1$) due to overlap bias.

¹⁰Patent abstracts can be found in the pre-grant section of PatentsView data: <https://patentsview.org/download/pg-download-tables>

More precisely, in Equation 2.1 “the word” represents the particular tokenized word in the corpus of abstracts for a firm-year and “the document” refers to the corpus of abstracts of a particular firm-year in the defined time scope. In Equation 2.2, “total number of firm-years” refers to the number of firms that have at least one patent abstract for a specified time scope. Therefore, on the one hand, we are able to obtain a score that reflects the importance of certain technical terms in the firm’s patents (the higher the frequency of the word in the firm’s abstracts, the higher Equation 2.1 is). On the other hand, the IDF (Equation 2.2) ensures that frequently mentioned terms across all firms are given a lower score which ensures a focus on technical terms.¹¹ Moreover, using the logarithmic form of the IDF ensures that terms appearing in many documents do not receive a score of zero, thereby avoiding a downward bias in the similarity measures. Ultimately, the TF-IDF measure (Equation 2.3) assigns a weight to each term based on its frequency in a firm’s documents and its rarity across the entire set of firms. This is optimal for patent abstract similarities where rare words should be given more importance. Moreover, the denominator in Equation 2.1 makes sure that firms with longer abstracts are not automatically attributed higher similarity scores with other firms.

The similarity between the vectors of two firm-years’ patent abstracts is then calculated through the cosine similarity formula in Equation 2.4, where A and B represent the numerical score vectors for each firm. This formula gives us a technological similarity score of 0 if the vectors are orthogonal meaning that there is no similarity. On the contrary, if the vectors are identical, we have a score of 1 meaning complete similarity. Since the word vectors only have positive scores, there are no negative cosine similarity scores.

$$\text{Cosine Similarity} = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \times \|\mathbf{B}\|} \quad (2.4)$$

In Appendix 2.8.2.3 I verify the validity of my patent similarity measure by comparing it to previous measures used in the literature.

¹¹This reduces noise by giving remaining common and stop words in the cleaned patent abstracts a smaller influence.

2.4.3 Independent variable: Common ownership

This paper uses two well-established common ownership measures from the literature.¹² From here on, I will be referring to them as the beta and kappa measures. Both of these measures are based on the reported shares held by institutional investors in their end-of-year 13-F filings.

The beta measure, referred to as the pair-level c-index in [Lewellen and Lowry \(2021\)](#), is defined in Equation 2.5 as the dot product of the ownership vectors of firms i and j , where γ_{ik} and γ_{jk} denote the fraction of shares in firms i and j , respectively, held by investor k . The aggregate is taken over all investors who simultaneously hold shares in both firms.

$$\text{Beta}_{i,j} = \sum_{k=1}^N (\gamma_{ik} \cdot \gamma_{jk}) \quad (2.5)$$

The kappa measure used in this paper is the annual average of the quarterly common ownership measure introduced by [Backus et al. \(2021b\)](#). As shown in Equation 2.6, this measure combines two key components. The first measures the overlap in investor bases between firms i and j through the cosine formula. The overlapping ownership component is a normalized version of the beta measure described above. The second component (relative Investor Herfindahl-Hirschman Index) measures investor concentration by aggregating the squared percentage shareholding of common investors in each firm. Together, this measure incorporates both the ownership structure and incentives to internalize another firm's profits based on relative investor concentration. As demonstrated in Equation 2.6, the more concentrated firm j 's overlapping investors, the higher the kappa and thus firm i cares more about firm j 's outcome. In my dyadic analysis, kappa_{ij} becomes the common ownership measure of firm i towards firm j and kappa_{ji} becomes the common ownership measure of firm j towards firm i .

¹²[Backus et al. \(2021b\)](#) provide an in-depth analysis on how best to measure common ownership.

$$\text{Kappa}_{ij} = \frac{\sum_{k=1}^N (\gamma_{ik} \cdot \gamma_{jk})}{\underbrace{\sqrt{\sum_{k=1}^N (\gamma_{ik}^2)} \cdot \sqrt{\sum_{k=1}^N (\gamma_{jk}^2)}}_{\text{overlapping ownership}}} \cdot \underbrace{\sqrt{\frac{IHHI_j}{IHHI_i}}}_{\text{relative IHHI}}. \quad (2.6)$$

2.4.4 Summary statistics

Table 2.1 presents the summary statistics of the main variables used in this paper. The Table is decomposed into three sections corresponding to the main dependent variable, the main independent variables and the control variables. Each section describes the first quartile, median, mean, third quartile, standard deviation and number of observations respectively. In the Appendix, Table 2.8.1 provides an overview of how each variable is calculated.

Panel A of Table 2.1 contains the descriptive statistics of my patent similarity measure between firms over different scopes. The scopes presented go from the one-year forward scope (which includes patents applications in year $t+1$) to the five-year forward scope (which includes patent applications between year $t+1$ and year $t+5$). We can see that the patent similarity measure has a median that varies between 0.04 and 0.07 and a mean that varies between 0.07 and 0.1 depending on the scope. Figure 2.8.1 in the Appendix shows an upward trend in the average patent similarity for all scopes over time. The relatively low measures of similarity are not surprising, given that patents are inherently intended to reflect original contributions. Missing observations before the three-year forward scope are due to firms with no patent applications for the shorter time frames.

Panel B of Table 2.1 reports the summary statistics of the common ownership measures I use. The beta measure has 4,838,517 unique firm-pair values. In contrast, the kappa measure has 9,677,034 firm-level common ownership values within firm pairs. The beta measure from Lewellen and Lowry (2021) has a similar mean and median value in comparison to the literature that multiplies this value by 10,000 (Lewellen and Lowry, 2021; Bindal and Nordlund, 2024). The kappa measure, which is winsorized at the 1% level to control for extreme values, has an average of 0.3.

Panel C of Table 2.1 reports the firm-year level firm characteristics that will be used

as control variables in my analysis. They show the distribution of patent applications, R&D expenditure, firm size, firm age, leverage, CAPEX (capital expenditure), PPE (property, plant, and equipment), cash holdings, ROA (return on assets), Tobin's Q, and institutional ownership. Panel D of Table 2.8.1 details how these variables were calculated. With the exception of institutional ownership, all firm characteristics variables are winsorized at the 1% level due to outliers. For the sake of conciseness, I only include the summary statistics of yearly patent applications. The patent application variable is highly right-skewed with a per firm-year average of 53 applications and a median of 8 patent applications. Going forward, this variable will be left as such for most of my analysis. Nonetheless, the use of its log transformation to account for the skewness does not modify my main results. Elsewhere, the average R&D expense to assets ratio is 9%. The average firm has been in operation for 30 years. The average leverage ratio is 18%. The average capital expenditure to total asset ratio, net property, plant, and equipment to asset ratio and cash holdings to asset ratio are 4%, 19% and 27% respectively. Tobin's Q and the logarithmic transformation of total assets are respectively at average values of 2.32 and 7.01. The firms in my sample have an average and median institutional ownership of 54% and 61%, respectively.

Table 2.1: Summary statistics

This Table respectively reports the first quartile, median, mean, third quartile, standard deviation, and number of observations for each of the main variables used. Panel A reports the different time scopes of my firm-pair patent similarity measure. Panel B reports the unique firm-pair beta and the two-way firm-pair kappa common ownership measures. Panel C reports the firm-year-level firm characteristics. Apart from the percentage of institutional ownership, firm characteristics variables and the kappa common ownership measure are winsorized at the 1% level.

Panel A: Pairwise technological similarity						
	Q1	Median	Mean	Q3	SD	Obs
Technological similarity _{$t+1$}	0.02	0.04	0.07	0.09	0.08	8,358,272
Technological similarity _{$t+1-t+2$}	0.02	0.05	0.08	0.11	0.09	9,323,100
Technological similarity _{$t+1-t+3$}	0.03	0.06	0.09	0.12	0.09	9,677,034
Technological similarity _{$t+1-t+4$}	0.03	0.07	0.10	0.13	0.10	9,677,034
Technological similarity _{$t+1-t+5$}	0.04	0.07	0.10	0.14	0.10	9,677,034
Panel B: Common ownership measures						
	Q1	Median	Mean	Q3	SD	Obs
Beta similarity	0	0.002	0.003	0.01	0.04	4,838,517
Kappa similarity	0.09	0.22	0.30	0.40	0.21	9,677,034
Panel C: Firm characteristics						
	Q1	Median	Mean	Q3	SD	Obs
Patent applications _{t}	2	8	53	28	145.6	11,131
R&D	0.01	0.05	0.09	0.11	0.12	11,131
Firm size	5.35	6.84	7.01	8.50	2.24	11,131
Firm age	15	25	29.64	43	18.47	11,131
Leverage	0.002	0.15	0.18	0.28	0.21	11,131
CAPEX	0.015	0.03	0.04	0.05	0.04	11,131
PPE	0.06	0.14	0.19	0.26	0.17	11,131
Cash	0.07	0.19	0.27	0.40	0.24	11,131
ROA	0.05	0.11	0.06	0.16	0.23	11,131
Tobin's Q	1.30	1.74	2.32	2.66	1.10	11,131
Institutional ownership	0.29	0.61	0.54	0.80	0.31	11,131

2.5 Baseline analysis

2.5.1 Methodology

$$\begin{aligned} \text{Patent Similarity} \times 100_{i,j,t+1:t+3} = & \alpha + \beta_1 \text{Common Ownership}_{i,j,t} + \beta' \text{Control Variables}_{i,t} \\ & + \gamma_t + \delta_{i,j} + \eta_{\text{ind}(i,j)} + \theta_{\text{ind}(i,j),t} + \epsilon_{i,j,t} \end{aligned} \quad (2.7)$$

Equation 2.7 presents the regression model I will be using for the baseline analysis. The dependent variable measures technological proximity between firm pairs (i,j) calculated over a certain time scope (three-year forward scope in this specification) and scaled by 100 for coefficient readability. The main independent variable is the common ownership variable between firms i and j at time t. The time lag to the dependent variable limits reverse causality and resolves measurement discrepancy since patent similarity is calculated over the whole year while common ownership is calculated at the end of the year. I also only include firm i's control variables in the regression model because of the two-way nature of the kappa firm-pair common ownership measure. Therefore, the 1,642 unique sample firms are turned into 4,838,517 unique firm-pairs and 9,677,034 two-way firm-pairs for this paper's analysis.¹³

I also include year fixed effects (γ_t), firm-pair fixed effects ($\delta_{i,j}$), industry-pair fixed effects ($\eta_{\text{ind}(i,j)}$) and industry-pair by year fixed effects ($\theta_{\text{ind}(i,j),t}$) in the regression model. Firm pair fixed effects ensure that firm pair specific factors driving patent similarity are accounted for. Year fixed effects account for time-specific trends that could impact the similarity between firms. Since I study cross-industry common ownership and innovation, industry-pair fixed effects control for industry-existing factors that could drive patent similarity. The industry-pair-by-year fixed effect accounts for industry-specific trends and shocks across time, such as renewable energy technology breakthroughs impacting the transportation and energy industries. The regression model also includes two-way

¹³The use of the unique firm-pair dyad regression model for the beta and kappa similarity measures do not change the results and interpretation of my main variables.

firm i and firm j clustering for robust standard errors and to account for within-pair serial correlation of residuals.

I implement a firm-pair regression model because common ownership and patent similarity are pairwise variables.¹⁴ Averaging these pairwise measures for a firm-year level analysis does not answer the questions posed in this paper. In a firm-year analysis, the regression model would indicate if commonly owned firms innovate differently to the market without capturing whether their innovations converge with each other. Moreover, except [Anton et al. \(2024\)](#), the common ownership literature focuses on within-industry investor overlap. However, the same set of innovations can impact firms across industries. The current application of artificial intelligence technologies in manufacturing industries as much as the medical industries stands as proof. Similarly, cross-industry alliances such as the global data alliance span multiple industries and make innovative spillovers related to data maintenance more likely between firms of different industries.¹⁵ Due to the cross-industry nature of innovation, I use cross-industry firm pairs, meaning that the two firms in a pair can come from different industries in my dyadic regression model.

2.5.2 Results

2.5.2.1 Common ownership and patent similarity

Table 2.2 shows the results of the regression model in Equation 2.7. Columns 1 and 2 use the real value of patent applications as a control variable while Columns 3 and 4 use the one plus logarithmic transformation of patent applications. The common ownership variables (independent variables) are stated in the title row as beta or kappa.

In Columns 1 and 2, both measures of common ownership show a statistically significant positive correlation with pair-wise patent similarity. The beta similarity measure

¹⁴These models are used in the M&A branch of the finance literature ([Bena and Li, 2014](#)). However, they tend to use unique firm-pair observations because of clear distinctions between acquirer and target firms. This distinction does not exist in my sample.

¹⁵For example, the Global Data alliance is open to firms that have to deal with data and transfer data across borders. This alliance regroups a large amount of firms from different industries ranging from Visa to United Airlines.

shows that a one standard deviation increase in common ownership between two firms increases patent similarity by 0.007 (0.1734×0.04). When compared to the average similarity across my sample, this relationship corresponds to a 7.78% ($0.007/0.09$) increase in the fairly low average patent similarity between firms. The moderate economic significance of this result should be interpreted in light of innovation path dependencies in public firms, which limit their ability to make substantial shifts in their innovation strategies to align with another firm (Aghion et al., 2016; Cohen and Levinthal, 1990). Therefore, moderate correlations between common ownership and patent similarity suffice to show an important economic impact.

The control variables are consistent in Columns 1 and 2. For the most part, they are statistically insignificant. This is surprisingly the case for the patent applications and R&D variables. One of two things can be at play in this regression model. On the one hand, since we are looking at pair-wise data the firms in a dyad can have different behaviors. One can be leading more R&D intensive and patent application intensive behaviour to catch up to the other firm who may be the one sharing their expertise. On the other hand, controlling the patent application skewness with a 1% winsorization may not be sufficient. Firm size is shown to play a positive role in similarity as bigger firms can be associated with a more diverse use of technologies. Firm age and property, plant, and equipment to asset ratio are negatively related to firm-to-firm patent similarity, demonstrating more technological differentiation with maturity and tangible assets.

In Columns 3 and 4, where the log transformation of the patent application measure is used, the coefficient and statistical significance of the main independent variable remain unchanged. However, the more patenting there is, the higher the patent similarity. Patent similarity also seems to be associated with lower R&D intensity here, which hints towards excessive patenting on lower quality innovations. The change in the direction of the firm size variable can hint at multicollinearity due to the patent application variable's transformation.

The results so far point towards the validation of hypothesis 1.B which suggests that a rise in common ownership increases technological proximity between firms. I further test this possibility by looking at the impact of common ownership on patent proximity in different scopes. Table 2.8.4 shows the effects of common ownership on patent similarity

on the patent applications of year t (one-year scope), year $t+1$ (one-year forward scope), years $t+1$ to $t+2$ (two-year forward scope) and so on until years $t+1$ to $t+5$ (five-year forward scope). The Table is split between two panels with each panel using a different common ownership measure as the independent variable. The beta measure shows a positive, statistically significant and growing correlation between common ownership and patent similarity from the two-year forward ($t+1$ to $t+2$) scope. The kappa measure in panel B indicates a similar trend for the two-year forward ($t+1$ to $t+2$) and three-year forward ($t+1$ to $t+3$) scopes. However, the lower significance level for the four-year forward and five-year forward scopes with the kappa measure suggests no patent similarity over the long term. This can give us an early indication of the type of patenting that is driving the correlation between common ownership and patent similarity.

Table 2.8.5 further corroborates the results from Table 2.8.4.¹⁶ The regression model used in Table 2.8.5 shows how the correlation between common ownership and patent similarity varies between the different scopes. The beta measure in Panel A shows that the positive correlation between common ownership and patent similarity comes from a quasi-immediate convergence in patent similarity in the earlier years. The kappa measure in Panel B shows a high similarity in patent applications between the one-year forward scope and the two-year forward scope. The other scopes' results for the kappa measure fizzle out after. This trend is also observed in the beta measure. Together this shows that common ownership is associated with a convergence in patent content, which becomes more similar between commonly owned firms through patent applications one to three years after an increase in common ownership.

¹⁶The variation in the number of observations across the results in Tables 2.8.4 and 2.8.5 are due to missing patent similarity data between some firms before the three-year forward scope and observations made redundant by the regression model after the three-year forward scope.

Table 2.2: Common ownership and patent similarity

This Table reports the correlation between common ownership and patent similarities. The dependent variable is the three-year ($t+1$ to $t+3$) forward pairwise patent application abstract similarity between two firms. The main independent variable is pairwise common ownership in year t , measured using the beta and kappa measures as indicated at the top of each column. The dyadic regression includes duplicate firm pairs (i.e., both Firm A–Firm B and Firm B–Firm A) and controls for the leading firm's characteristics in year t , except for the patent application variable, which aggregates applications from $t+1$ to $t+3$. Columns 1 and 2 use raw patent applications as a control variable while Columns 3 and 4 use its one plus log transformation as indicated at the top of each column. Coefficients are adjusted for patent applications and firm age for readability, as noted in the Table. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Patent Applications		Log(1 + Applications)	
	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	17.34*** (4.88)	0.26** (0.12)	17.44*** (4.84)	0.30** (0.12)
Patent applications _A $\times 10,000$	0.11 (0.07)	0.11 (0.07)		
Log(1+Patent applications) _A			0.18*** (0.01)	0.18*** (0.01)
R&D _A	0.02 (0.10)	0.07 (0.16)	-0.60*** (0.18)	-0.60*** (0.18)
Firm size _A	0.02*** (0.004)	0.02*** (0.004)	-0.08*** (0.01)	-0.09*** (0.01)
Firm age _A $\times 100$	-0.10*** (0.03)	-0.10*** (0.03)	-0.1*** (0.04)	-0.1** (0.04)
Leverage _A	0.05 (0.07)	0.04 (0.07)	0.09 (0.07)	0.09 (0.07)
CAPEX _A	0.64 (0.52)	0.62 (0.51)	-0.29 (0.53)	-0.30 (0.53)
PPE _A	-0.23**	-0.22***	0.19*	0.19*

Continued on next page

Table 2.2 – *Continued from previous page*

	Raw Applications		Log(1 + Applications)	
	Beta	Kappa	Beta	Kappa
	(0.09)	(0.10)	(0.11)	(0.11)
Cash _A	-0.05	-0.05	-0.11	-0.11
	(0.08)	(0.08)	(0.08)	(0.08)
ROA _A	-0.01	-0.02	-0.16	-0.17
	(0.07)	(0.08)	(0.08)	(0.08)
Tobin's Q _A	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Institutional ownership _A	0.05	0.08*	0.06	0.09*
	(0.04)	(0.05)	(0.04)	(0.05)
Firm-Pair FE	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Observations	9,677,034	9,677,034	9,677,034	9,571,733
Adjusted R-squared	0.914	0.914	0.914	0.914

2.5.2.2 Type of innovative firms

Initial correlations point towards common ownership increasing patent similarity between firms while the early convergence in patent text hints towards firms patenting on previously accumulated knowledge using each others' technical words. Together, the results suggest that commonly held firms increase patenting similarity through low-quality innovation. To test this intuition and hypothesis 2, I study whether the positive correlation between common ownership and patent similarity is due to high-quality or low-quality innovation. I do this through a split sample analysis based on two variables. Both variables use the patent applications involved in the patent similarity scope in question. The first variable divides the concerned firm's patent applications' similarity with all fu-

ture patent applications by its similarity with all past patent applications (Kelly et al., 2021). The higher the score, the higher the quality of the firm’s innovations and vice versa. The more traditional second variable looks at the three-year forward citations received per patent by the firm. These variables are divided into a top and bottom quartile for the split sample analysis.

Panel A of Table 2.3 reports the results for firm pairs where both firms are part of the top patent quality quartile. Columns 1 and 2 use the text-based measure while Columns 3 and 4 use the citation-based measure for the split sample analysis. The dependent variable used is the three-year forward patent similarity scope. The only statistically significant result is the citation-based kappa common ownership measure in Column 4. It shows that an increase in common ownership is associated with a decrease in patent similarity between highly innovative firms. This set of results shows that the common ownership association with patent similarity is unlikely to come from firms that are producing high-quality innovations.

Panel B of Table 2.3 reports the results for firm pairs where both firms are part of the bottom patent quality quartile. The dependent variable, independent variable and sample splitting variables in panels A and B are the same. Panel B of Table 2.3 indicates that the relationship between common ownership and patent similarity is likely driven by low-quality innovation firms. For example, in the beta measure and text splitting of innovation quality (Column 1), a one-standard-deviation increase in common ownership increases patent similarity by 0.008 which corresponds to an increase in the average patent similarity of around 8.89%. This corresponds to a 0.009 and 10% increase in the citation-based split sample of low-quality innovation (Column 3).

Together Table 2.3 points towards common ownership increasing patenting overlap between firms because of strategic or knowledge fragmentation patenting instead of collaborations and spillovers in producing high breakthrough patents. This suggests that common ownership can be linked to the negative slowdown observed in breakthrough innovations. Nonetheless, these results should be taken with a pinch of salt because the kappa measure of common ownership in the low-quality patenting scenario lacks statistical significance. I address this point in section 2.5.2.3, where the results become significant across the different measures of common ownership for low-quality innovations.

I also study whether common ownership can help with knowledge concentration problems of innovation. Previous research has documented a decline in business adaptability driven by the concentration of technology and knowledge among leading firms, which hinders smaller firms’ ability to adopt and implement new innovations ([Akcigit and Ates, 2023](#); [Bloom et al., 2020](#)). Table 2.4 looks at firm pairs where one is classified as a technological leader (top quartile of innovation quality measure) and the other is in the bottom quartile of the measure (technological lagger). Across both of the split sample methods (text-based in Columns 1 and 2 and citation-based in Columns 3 and 4), there is a positive and statistically significant relationship between common ownership and patent similarity. This suggests that common ownership can be beneficial to innovation and firm dynamism by allowing knowledge spillovers between technologically leading and technologically lagging firms.

In all, this set of results points towards patent similarity increasing with common ownership because of more low-quality patenting. However, there can be a beneficial impact in the form of reducing the gap between technologically leading and lagging firms.

2.5.2.3 Type of innovation

Next, I look at the type of innovation that is driving patent similarity following [Bena and Simintzi \(2022\)](#) and [Bena et al. \(2022\)](#). Table 2.5 is divided into two parts. Columns 1 and 2 look at the impact of common ownership on patent similarity from process innovations. This means that only process innovation patents, as defined by patents that have the terms “A process” or “A method” in their controlling claim, are used for the pairwise patent similarity measure ([Bena and Simintzi, 2022](#); [Bena et al., 2022](#)).¹⁷ Process innovations are associated with production and production cost-improving innovation ([Bena and Simintzi, 2022](#); [Bena et al., 2022](#)). In Columns 1 and 2, we can observe that common ownership has no association with process innovation similarity between firms. This lack of association is likely driven by the firm-specific nature of production methods that process innovation patents apply to. Likewise, if good production processes are encouraged

¹⁷Patent claims define the scope of the legal protections of a patent. The controlling claim is the leading claim of the patent and it showcases the newest element of the patent ([Bena and Simintzi, 2022](#))

across commonly held firms, patent licensing rather than patenting may be preferred for this type of knowledge sharing. The lower number of firms (1,441 unique firms) and observations in this set of regressions can also explain the results. The drop in observations suggests that firms are less likely to patent consistently on process innovations.

Columns 3 and 4 of Table 2.5 focus on the association between common ownership and patent similarity due to product innovations. Product innovations are all patents that are not classified as process innovations as stated above. They are associated with the introduction of novel products. Here, there is a strong and positive correlation between common ownership and firms patenting on product innovation that are more similar to one another. Importantly, the coefficients are higher than the baseline coefficients presented in Table 2.2 across both common ownership measures.

This set of results therefore supports hypotheses 4.0 and 5.B. Common ownership is linked to patent similarity through a concentration in product market innovation while not playing a role in the concentration of process innovation. Overall, this suggests that firms become concentrated in the product market while not necessarily looking to reduce production cost as suggested in [Antón et al. \(2023\)](#), [Aslan \(2024\)](#) and [Kini et al. \(2023\)](#).

In the Appendix, Table 2.8.6 completes the high-quality (Columns 1 to 4) versus low-quality (Columns 5 to 8) sources of patent similarity studied in section 2.5.2.2. Here, I only use product innovations to construct the dependent variable (i.e. the patent similarity measure). Columns 1 to 4 continue to show that patent similarity is not driven by common ownership between firms producing high-quality innovation. However, in the low-quality innovation sub-samples (Columns 5 to 8) the relationship is positive and statistically significant across both common ownership measures in the weighted citations received sub-sample (Columns 6 and 7). As for the text-based split sample, the result is positive across both common ownership measures but only statistically significant for the beta measure in Column 5. These findings further support hypothesis 2.A, which states that common ownership increases patenting overlap between firms through mechanisms such as knowledge fragmentation and a lack of breakthrough innovation.

Table 2.3: Common ownership and patent similarity by innovation quality
This Table reports the correlation between common ownership and patent similarity based on innovation quality. Panel A includes a sub-sample where both firms in a firm pair are in the top quartile of innovation quality. Panel B does the same for bottom quartile firm pairs. A text-based approach (Columns 1 and 2) and a citation-based approach (Columns 3 and 4) are used to calculate innovation quality. The dependent variable is the three-year forward patent abstract similarity. The main independent variable is pairwise common ownership in year t , measured using the beta and kappa measures. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A: High-quality innovation				
	Text-based		Citation-based	
	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	10.38 (6.89)	0.01 (0.13)	7.87 (8.85)	-0.37** (0.17)
Firm controls	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
Industry-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	390,547	390,547	744,470	744,470
Adjusted R-squared	0.920	0.920	0.942	0.942
Panel B: Low-quality innovation				
	Text-based		Citation-based	
	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	20.21** (10.21)	0.18 (0.13)	22.59*** (7.50)	0.20* (0.11)
Firm controls	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
Industry-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	308,349	308,349	1,242,466	1,242,466
Adjusted R-squared	0.836	0.836	0.810	0.810

Table 2.4: Common ownership and patent similarity: Lead–Lag relationship
This Table reports the correlation between common ownership and patent similarity in firm pairs where one firm is a technological leader and the other a laggard. A text-based approach (Columns 1 and 2) and a citation-based approach (Columns 3 and 4) are used to create the sub-samples. The dependent variable is the three-year forward patent abstract similarity. The main independent variable is pairwise common ownership in year t , measured using the beta and kappa measures. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Text-based measure		Citation-based measure	
	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	16.28*** (5.98)	0.12* (0.07)	16.46*** (8.03)	0.24* (0.13)
Firm controls	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
Industry-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	849,407	849,407	1,183,513	1,183,513
Adjusted R-squared	0.900	0.900	0.930	0.930

2.6 Causal analysis

2.6.1 Methodology

2.6.1.1 Construction

The baseline results of this paper are subject to multiple endogeneity problems. For example, one of the more important problems is reverse causality. Investors may prefer to invest in firms with a similar technology base, leading to future similarity in innovation. The use of lagged independent and control variables coupled with non-significant contemporaneous effects between common ownership and patent similarity mitigates this

issue. Nonetheless, we can imagine instances where similar prior innovations influence my baseline results.

Table 2.5: Common ownership and patent similarity by innovation type
This Table reports the correlation between common ownership and patent similarity for process and product innovations. The dependent variable is the three-year forward patent abstract similarity. The main independent variable is pairwise common ownership in year t , measured using the beta and kappa measures. Columns 1 and 2 report the results for process innovations and Columns 3 and 4 report the results for product innovations. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Process innovation		Product innovation	
	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	2.20 (4.70)	0.07 (0.06)	17.99*** (4.44)	0.36*** (0.12)
Firm controls	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
Industry-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	6,605,822	6,605,822	9,112,522	9,112,522
Adjusted R-squared	0.885	0.885	0.910	0.910

I solve the endogeneity problems related to my baseline results by exploiting a set of financial institution mergers. Mergers between financial institutions are unrelated to firm strategies, technological trajectories and many other firm characteristics ([Anton et al., 2024](#); [Lewellen and Lowry, 2021](#); [Kini et al., 2023](#); [He and Huang, 2017](#)). When two financial institutions merge, the firms that they separately hold experience an exogenous increase in common ownership post-merger. For example, if institution A holds firm A and institution B holds firm B, a merger (or acquisition of one institution by the other)

between the two institutions creates an increase in the common ownership between firms A and B as now more of their respective shares are owned by the same investor.

A firm pair is considered treated if in the quarter before the merger announcement date between two financial institutions, firm A is blockheld by one of the institutions and firm B is blockheld by the other.¹⁸¹⁹ I focus on blockholdings to ensure an increased common ownership power by the merging institution. Each treatment firm is propensity score matched to a control firm. Control firms must be blockheld by an institution other than the merged institutions studied. Control firms must also be exactly matched to treatment firms on the year variable and the two-digit SIC industry codes. Eligible control firms are then propensity score matched at the 1 to 1 level to treatment firms on pre-event firm size, R&D expenses, and patent applications. These matching variables are chosen as they are theoretically the more likely to influence patent similarity between firms. The two-way dyad nature of my methodology induces the following two firm setting treatment pairs: Firm A-Firm B and Firm B-Firm A. The corresponding control pairs are the following: Firm A'-Firm B and Firm B'-Firm A, where the "'' represents the matched control firm. I choose an event window of four years before and after the merger due to the long-term nature of change in innovation and patenting. Firm pairs are only kept in the treatment group if they continue to be blockheld by the newly merged institution for at least three years after the merger.²⁰

Datastream is used for a sample of financial institution merger and acquisition data between 2006 and 2013. Table 2.8.7 displays the set of merger and acquisition instances that qualify (i.e. where in a merger, one institution blockholds at least one of my sample

¹⁸A blockhold refers to ownership of at least 5% of a firm's outstanding shares. This is consistent with regulatory discourse of an important ownership stake. The U.S. Securities and Exchange Commission (SEC) mandates that any individual or entity acquiring beneficial ownership of 5% or more of a public company's voting shares must publicly disclose this stake within 10 days. The 5% benchmark is widely used in financial economics as the minimum level at which ownership is considered economically significant and potentially influential in corporate governance.

¹⁹A firm pair (e.g. firms A and B from the example above) is still considered treated if one institution blockholds firm A and the other institution holds a non-zero but negligible stake (less than 1%) in firm A also. Due to index funds and passive ownership in general, not allowing for this type of arrangement would significantly reduce my treated firm pair sample.

²⁰Whether the merged institution decides to continue holding the treatment firms impacts the results of this paper. There are drop-offs in these instances two years following the merger. This is a problem that is often not highlighted in previous papers. I account for it by assuring a reasonable holding of treated firms three years post-merger.

firms and the other institution blockholds another). Table 2.8.8 in the Appendix explains why only a select amount of financial merger instances are used in my analysis by showing the drop-off in the blockownership of eligible treatment firms three years after the merger. Ultimately, I end up using three mergers including the Wells Fargo & Co-Wachovia Corp 2008 acquisition, the Bank of America Corp-Merrill Lynch & Co Inc 2008 acquisition and the widely used Blackrock Inc-Barclays Global Fund Advisors acquisition in 2009.

Equation 2.8 sets out the difference in difference specification used for the causal analysis. The index i represents the leading firm, j represents the second firm, and t represents the year. Treatment is equal to one if the firm pair i, j are a treatment pair and zero otherwise. The post variable is equal to one if we are in the years following the merger and zero otherwise. The coefficient associated with β_3 captures the causal effect between the treatment and control group after the merger. As observed in Equation 2.8, I continue to use year, firm-pair, industry-pair and industry-pair-year fixed effects as previously explained in Equation 2.7. A slight modification from the baseline methodology is that in the causal analysis, I focus on the one-year forward patent similarity scope. Using the three-year forward measure of patent similarity yields biased results because of the pre-merger to post-merger overlap over my event window and because of the drop-off in treatment-pairs post-2013. Ultimately, the substantial increase in common ownership power in this setting due to the exogenous addition of newly blockheld firms to the merged institution's portfolio is likely to create a sizable and near-term impact if one exists.

$$\begin{aligned}
\text{Patent Similarity}_{i,j,t+1} = & \alpha + \beta_1 \text{Treatment}_{i,j} + \beta_2 \text{Post merger}_t \\
& + \beta_3 (\text{Treatment}_{i,j} \times \text{Post merger}_t) + \beta' \text{Control Variables}_{i,t} \\
& + \gamma_t + \delta_{i,j} + \eta_{\text{ind}(i,j)} + \theta_{\text{ind}(i,j),t} + \epsilon_{i,j,t}
\end{aligned} \tag{2.8}$$

This causal methodology partially follows Lewellen and Lowry (2021). The main differences come from the fact that Lewellen and Lowry (2021) focus on intra-industry common ownership and its impact on firm performance and R&D. These two elements lead to a slightly different definition of treatment firms and matching variables in my setting. My smaller firm sample size also means that I match on two-digit SIC industry

codes instead of three to ensure there is a unique match between treated and potential control firms. Moreover, my restrained sample size due to data availability (i.e. missing patent text data at the application stage before 2001) means that I only use the financial-crisis period institutional mergers. Patenting rests on previous work and knowledge, therefore focusing on the crisis period should not be a major problem. Also, industry-pair-year fixed effects ensure that changes in industry trends do not impact the results. The financial constraints imposed on firms could limit innovative activities but this should only foster common ownership linked coordination for innovation efficiency in treatment firms.

2.6.1.2 Validating the methodology

Table 2.6 reports the firm-year mean and median for treatment and control firms separately across my sample. There are no notable differences on average between the set of treatment and control firms. The two exceptions to this trend are institutional ownership with a 71% average in treated firms compared to 54% in control firms and return on assets (ROA) with 8.9% on average for treated firms in comparison to 4.2% for control firms. Due to the limited role played by institutional investors and ROA in the baseline analysis, I believe that this difference should not impact the results of this paper. The two-year forward to five-year forward technological similarity measures are on average slightly higher for the treatment firms. This is also the case across the different common ownership variables.

To ensure that pre-event trends are not driving the results, I carry out three further analyses. The first two consist of showing that there are parallel trends in the dependent variable and matching variables before the merger. The third shows that the treatment firms are indeed exposed to an exogenous increase in common ownership after the merger.

Table 2.7 carries out a similar methodology to Equation 2.8 for the pre-event window sample. However, instead of treatment $\times$ post, I use treatment $\times$ time. The time variable takes a different value for each pre-event year following Bindal and Nordlund (2024). This set of regressions looks to see whether treated and control firm pairs follow parallel trends for the different scopes of the patent similar measure (Columns T to T+5).

The first two columns which respectively represent the current year patent similarity and the one year forward patent similarity show highly insignificant coefficients. This is notably the case for the one-year forward patent similarity scenario (Column T+1) with a coefficient of 0.04 and a standard deviation of 0.2. This result indicates that there is no difference between treated and control firm pairs in patent similarity before the event. Starting from the two-year forward patent similarity scope, the main independent variable (treatment $\times$ time) begins to gain significance. The four and five-year forward scopes are positive and statistically significant at the 10% level. As previously explained, the quasi-natural experimental methodology used here means that the two-year and longer forward patent similarity scopes cover the pre and post-merger periods. This, coupled with the violation of the parallel trends assumption observed in the four and five-year forward patent similarity scopes, leads me to focus on the one-year forward patent similarity scope.

I conduct a similar parallel trend analysis for the firm matching control variables used. Table 2.8 uses the patent applications, R&D to asset ratio, and the firm size variable as dependent variables to show that there are no differences between control pairs and treatment pairs in these variables before the mergers. This is demonstrated through the statistically insignificant coefficients across the different columns of the Table. Ensuring that the key theoretical determinants of patent similarity do not differ between the treatment and control groups is essential to rule out the influence of pre-event corporate strategies and characteristics on post-event changes.

To ensure the quasi-natural experimental design does induce a positive shock to the treatment firms, I test whether common ownership increases for treatment firms in comparison to control firms after their respective financial mergers. Table 2.9 shows that after the event, treated firms know an exogenous increase in common ownership in comparison to control firms. This is proven to be the case across both common ownership measuring dependent variables as specified in the first row of Table 2.9. Both the beta and kappa measures are positive and statistically significant at the 1% level. The beta measure is shown to increase by 0.07% for treatment firms in comparison to control firms for the period following the merger. This value is 3.38% for the kappa measure of common ownership.

Table 2.6: Summary statistics for treatment and control firms

This Table reports the summary statistics for the treatment and control firms at the firm-year level. The variables include the patent similarity measure over different scopes, the different common ownership measures, and a set of firm characteristics used as control variables. The control variables (except institutional ownership) and the kappa common ownership measure are winsorized at the 1% level.

	Treatment Firms		Control Firms	
	Mean	Median	Mean	Median
Dependent variables				
Technological similarity _{$t+1$}	0.056	0.04	0.063	0.04
Technological similarity _{$t+1-t+2$}	0.079	0.059	0.077	0.055
Technological similarity _{$t+1-t+3$}	0.096	0.072	0.088	0.06
Technological similarity _{$t+1-t+4$}	0.11	0.08	0.096	0.07
Technological similarity _{$t+1-t+5$}	0.12	0.09	0.1	0.08
Independent variables				
Beta measure	0.008	0.007	0.006	0.005
Kappa measure	0.35	0.35	0.31	0.28
Control variables				
Patent applications	22.83	8	23.13	6
R&D	0.083	0.048	0.09	0.049
Firm size	6.64	6.5	6.63	6.7
Firm age	31.19	28	28.41	23
Leverage	0.17	0.12	0.18	0.14
CAPEX	0.037	0.027	0.038	0.027
PPE	0.18	0.14	0.18	0.13
Cash	0.27	0.2	0.28	0.19
ROA	0.089	0.11	0.042	0.11
Tobin's Q	2.1	1.66	2.3	1.74
Institutional ownership	0.71	0.78	0.54	0.58
Number of firms	271	271	271	271
Firm-year observations	2,412	2,412	2,412	2,412

Table 2.7: Pre-event parallel trends - Patent similarity

This Table uses the pre-merger firm-pair sample to show parallel trends in different patent similarity scopes between control and treatment firm pairs. The dependent variables are different patent similarity scopes ranging from the one-year (T), one-year forward (T+1) to five-year forward (T+5) scopes. The main independent variable (Treatment $\times$ Time) reports the difference between the treatment and control firm pairs during the different years preceding the merger. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	T	T+1	T+2	T+3	T+4	T+5
Treatment $\times$ Time	0.2 (0.2)	0.04 (0.2)	0.26 (0.18)	0.22 (0.16)	0.2* (0.13)	0.2* (0.12)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,268	20,972	20,972	20,972	20,972	20,972
Adjusted R-squared	0.773	0.754	0.872	0.924	0.952	0.966

Table 2.8: Pre-event parallel trends - Matching variables

This Table uses the pre-merger firm-pair sample to show parallel trends in the matching variables between control and treatment firm pairs. The dependent variables are patent applications, R&D to asset ratio and firm size in year t . The main independent variable ($\text{Treatment} \times \text{Time}$) reports the difference between the treatment and control firm pairs during the different years preceding the merger. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Patents	R&D	Firm size
Treatment $\times$ Time	-0.55 (0.88)	0.001 (0.004)	-0.01 (0.02)
Firm controls	No	No	No
Firm-Pair FE	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes
Observations	20,972	20,972	20,972
Adjusted R-squared	0.483	0.577	0.683

2.6.2 Results

2.6.2.1 Common ownership and patent similarity

I begin by exploring whether common ownership increases patent similarity between firms in the causal setting. Similarly to the baseline analysis, Table 2.10 tests hypothesis 1 in two different settings. Panel A looks at how an increase in common ownership impacts patent similarity across different time scopes. Panel B looks at the changes between the scopes as the dependent variable to identify a genuine change in patent content.

Table 2.9: Exogenous increase in common ownership

This Table uses the entire causal analysis firm-pair sample to show that treatment firms experience an increase in common ownership following financial institutional mergers. The dependent variables are the different common ownership measures indicated in the first row (beta and kappa). The coefficient of the main independent variable (Treatment $\times$ Post) is multiplied by 100 for readability. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Beta	Kappa
Treatment $\times$ Post $\times$ 100	0.07*** (0.02)	3.38*** (1.32)
Firm controls	No	No
Firm-Pair FE	Yes	Yes
Industry-Pair FE	Yes	Yes
Year FE	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes
Observations	43,298	43,298
Adjusted R-squared	0.648	0.67

In Panel A, we can see that there is a positive relationship between common ownership and patent similarity across all patent similarity scopes. This relationship is only statistically significant at the 1% level for the one-year forward scope, at the 10% level for the two-year forward scope, and at the 5% level for the four-year forward scope. As previously mentioned, the event study means that scopes longer than one year forward create confounding overlap issues. Therefore, I rely on the one-year forward scope (Column 2, T+1) to validate hypothesis 1.B which predicts that common ownership increases patent similarity between firms because of protection (avoid obsolescence or technology shock), knowledge fragmentation, knowledge sharing, and product market concentration reasons. The 0.0056 increase in patent similarity in treatment firms post-event (Column 2, T+1) corresponds to a 11.67% increase in comparison to the pre-merger average treatment group's patent similarity (0.0056/0.048). The slightly weaker association in the two-year forward scope is likely due to the effects of the one-year forward scope. The four-year forward positive and statistically significant effect can be interpreted as a delayed realignment effect. Due to the overlapping problems, I am unable to affirm if this

is a common ownership driven effect.

Panel B reiterates the findings from Panel A by looking at the year-to-year change in patent similarity as the dependent variable. We can see a positive and statistically significant change in patenting similarity compared to the previous year in the one-year forward scope (Column 1). The positive and statistically significant result at the 5% level for the four-year forward scope with a lower magnitude hints again towards a lagged convergence as previously argued.

Figure 2.1 plots the Panel A, Column 2 regression model. More precisely, it shows how common ownership impacts one-year forward patent similarity on a year-by-year basis. We can see that before the mergers, treatment and control firm pairs had similar levels of patent similarity. However, after the exogenous increase in common ownership to treatment firms, their patenting similarity increases in comparison to the control firms. This relationship is significant at least at the 5% level for the first, third and fourth years following the exogenous shock to common ownership. The p-value for the second year after the shock is 6.7% making it statistically significant at the 10% level. While the immediate impact suggests excessive patenting on previous knowledge due to lower hold-up and knowledge fragmentation, significant impacts three and four years after the shock can suggest knowledge sharing and innovative collaborations.

2.6.2.2 Type of firm

The use of a shorter time frame of the one-year forward patent similarity scope can hint that common ownership increases patent similarity by encouraging patenting on prior overlapping knowledge that would have caused infringement problems (knowledge fragmentation). This would indicate that the observed increase is driven by patents of lower quality. However, this reasoning is not clear because the high and statistically significant positive relationship between treatment firms and patent similarity four years after the event in Figure 2.1 can also indicate knowledge spillovers allowing for the production of high-quality innovations.

Table 2.10: Common ownership and patent similarity across time - Causal

This Table is decomposed into two panels that study the causal impact of common ownership on patent different patent similarity scopes as the dependent variable to show the impact. Panel B uses the different scopes to show a change in patent content following an exogenous increase in common ownership (i.e. represents patent similarity in year $t+1$ - year t patent similarity, Column 2 (T+2) in panel B represents $t+1$ to $t+2$ - year $t+1$ patent similarity, and so until the five-year forward scope minus the four-year forward scope. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is 1%, 5%, and 10% levels, respectively.

Panel A: Patent similarity scopes					
	T	T+1	T+2	T+3	T+4
Treatment $\times$ Post	0.31 (0.39)	0.56*** (0.23)	0.42* (0.25)	0.40 (0.28)	0.6 (0.3)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Observations	36,943	42,187	42,187	42,187	42,187
Adjusted R-squared	0.413	0.745	0.838	0.885	0.91

Table 2.10 – Continued from previous page

Panel B: Change in patent similarity				
	T+1	T+2	T+3	T+4
Treatment $\times$ Post	0.57** (0.3)	-0.13 (0.2)	-0.05 (0.14)	0.2 (0.1)
Firm controls	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	37,331	42,187	42,187	42,187
Adjusted R-squared	0.16	0.41	0.35	0.2

Figure 2.1: Common ownership and one-year forward patent similarity

This figure breaks down and plots the difference in difference $\text{Treatment} \times \text{Post}$ effect of common ownership on one-year forward patent similarity. This is the regression model from Column 2 (T+1) in Table 2.10.

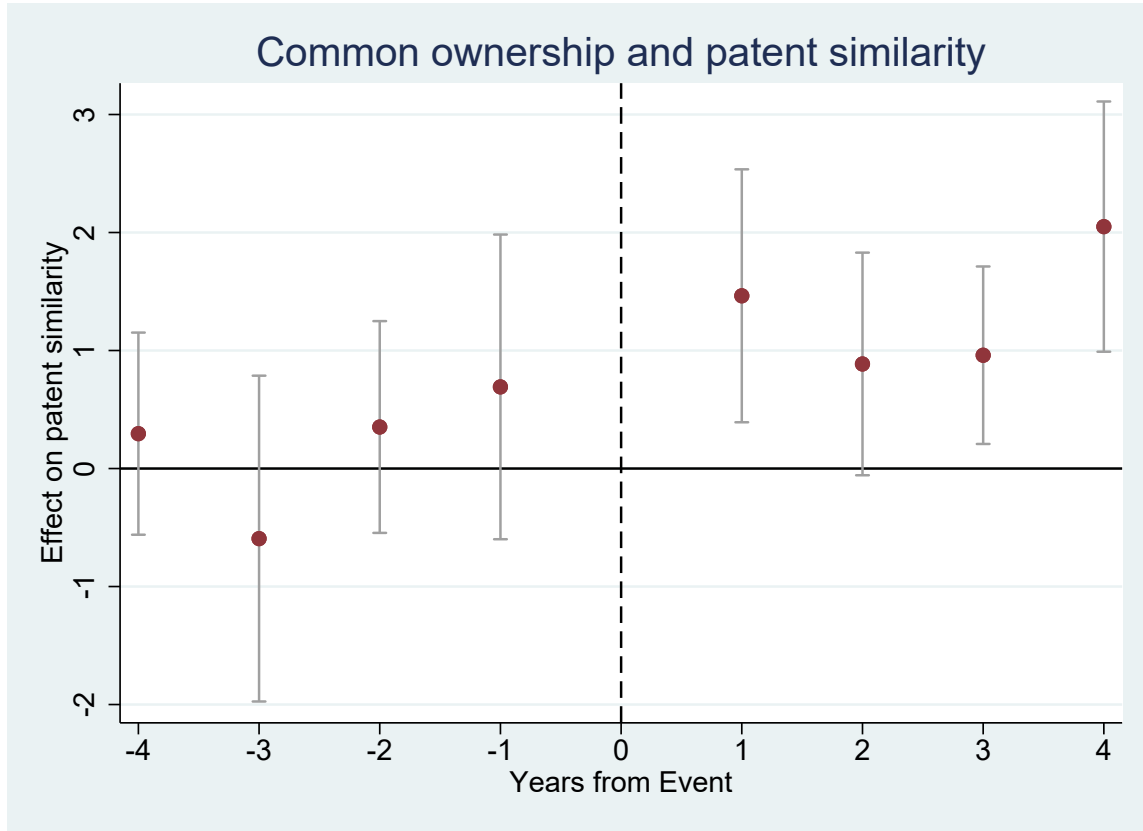


Table 2.11 looks at how common ownership impacts the one-year forward patent similarity scope in a sub-sample of high-quality patent-producing firm pairs (Column 1) and a sub-sample of low-quality patent-producing firm pairs (Column 2). Panel A creates the sub-sample based on the firms' one-year forward patent applications' similarity with all future patents divided by its similarity with all past patents (Kelly et al., 2021). Panel B creates the sub-sample based on the one-year forward patent applications' patent-weighted three-year forward citations received. Firm pairs qualify as low-quality patent producers or high-quality patent producers if both firms in the pair are in the bottom quartile or the top quartile of these measures respectively.

In both Panels of Table 2.11, we can see that high-quality patent producers that know an exogenous increase in common ownership do not exhibit an increase in patent similarity. On the contrary, through both measures (Panel A and Panel B), we can see

that the similarity is being driven by firms producing lower-quality patents (Column 2). The treatment $\times$ post coefficient is 1.45 at a 1% statistical significance level. This means that treatment pairs after the increase in common ownership find their patenting similarity to increase by 0.0145 units in comparison to control pairs that do not experience this increase. In comparison to the average pre-event treatment patent similarity, this represents a significant 48.33% increase.

Finally, Column 3 of Panels A and B in Table 2.11 look at firm pairs where one produces high-quality patents and the other lower-quality patents. Using the text-based measure (Panel A), this sub-sample demonstrates a statistically significant (5% level) increase of 0.02 units in patenting similarity due to common ownership. The citation-based measure (Panel B) shows the same positive relationship with a statistical significance at the 10% level. Even during this tumultuous crisis period, the data shows a rather positive knowledge catch-up effect between technologically leading and lagging firms due to common ownership. This result, should be taken with a pinch of salt due to the lower statistical significance level in the citation-based sub-sample.

This set of results validates hypothesis 2.A which suggests that common ownership increases patent similarity due to more negative innovation incentives. This includes producing incremental patents to take advantage of lower patent dispute risk and encouraging patent fragmentation between commonly held firms. These results can also indicate positive mechanisms at play such as patenting following learning to widen the knowledge base of the firm. Nonetheless, patent similarity increases due to the production of impactful innovations by taking advantage of lowered incentives for trade secrets or innovation collaborations from common ownership are not at play. The sole bright side of common ownership to innovation seems to be the validity of hypothesis 3 which states that commonly held firms can benefit from knowledge spillovers to catch up to one another. This can help avoid instances of knowledge concentration in leading technology firms.

2.6.2.3 Type of innovation

Next, Table 2.12 studies the type of innovation that drives patenting similarity between commonly held firms. Column 1 (process) uses the one-year forward process patent similarity between firms as the dependent variable and Column 2 (product) uses the one-year forward product patent similarity as the dependent variable.²¹

Due to the overlap with the 2008 crisis period, we can expect more similar patenting and collaborations in product cost-reducing innovations (process innovations). Although the statistical significance increases in the process innovation specification in comparison to the baseline analysis (Table 2.5), the treatment $\times$ post effect remains positive but statistically insignificant in Column 1. This means that common ownership continues to produce a negligible impact on process innovation similarity between firms which reinforces the patent licensing channel and firm-specific production technology explanations for this result.

The product patent similarity on the other hand (Column 2), continues to be positive and statistically significant at the 1% level. The coefficient of 0.38 suggests a 0.0038 unit increase in patent similarity compared to control firms post-merger. This corresponds to a 8.26% increase compared to the pre-event treatment average product patent similarity (0.0038×0.046). The lower increase in comparison to the baseline analysis (Table 2.5) and the main regression model in the causal analysis (Table 2.10) is potentially due to the additional but minimal role played by process innovations as firms look to decrease production cost during the financial crisis that occurs at the same time as my causal analysis.

Therefore, the convergence in innovation output is yet again driven by product concentration incentives produced by the common ownership hypothesis. This means that hypotheses 4.0 and 5.B are validated.

²¹Section 2.5.2.3 describes the methodology used to classify patents as process (production cost reducing) and product (new product or product improving) innovation.

Table 2.11: Common ownership and patent similarity: Firm innovation quality
This Table is decomposed into two panels that study the causal impact of common ownership on patent similarity depending on the quality of innovation produced. Panel A uses a text-based measure (similarity with future patent abstracts divided by similarity with past patent abstracts) and Panel B uses three-year forward citations received from the one-year forward patent applications to generate sub-samples of firm pairs with varying patent quality. Column 1 (high) looks at a sub-sample where both firms are in the top quartile of the measure, Column 2 (low) looks at a sub-sample where both firms are in the bottom quartile of the measure, and Column 3 (lead-lag) looks at instances where one firm is in the bottom quartile and the other in the top quartile. The dependent variable is the one-year forward patent similarity scope. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A: Text based measure			
	High	Low	Lead-lag
Treatment $\times$ Post	0.22 (0.46)	1.45*** (0.53)	2.07** (0.98)
Firm controls	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes
Observations	9,381	9,684	6,289
Adjusted R-squared	0.743	0.757	0.793
Panel B: Citation based measure			
	High	Low	Lead-lag
Treatment $\times$ Post	0.22 (0.46)	1.45*** (0.53)	1.1* (0.63)
Firm controls	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes
Observations	9,381	9,684	6,204
Adjusted R-squared	0.743	0.757	0.758

Table 2.12: Common ownership and patent similarity: Innovation type
This Table studies the causal impact of common ownership on the one-year forward patent similarity measure. Only process innovations are used in Column 1 and only product innovations are used in Column 2. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Process	Product
Treatment $\times$ Post	0.16 (0.11)	0.38*** (0.14)
Firm controls	Yes	Yes
Firm-Pair FE	Yes	Yes
Industry-Pair FE	Yes	Yes
Year FE	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes
Observations	42,187	42,187
Adjusted R-squared	0.596	0.7

2.7 Conclusion

This paper examines the impact of common ownership on patent similarity between firms. I find that when firms share common owners, they tend to patent using more similar technical terms. The similarity in patenting between firms comes from incremental innovations rather than breakthrough innovations and product instead of process innovations. Common ownership between technological leaders and laggards also fosters innovation convergence by perhaps enabling laggards to catch up technologically.

By focusing on patent-based technology overlap, this study provides a fresh perspective that complements prior work on common ownership and innovation which mainly looks at R&D spending, patent count and patent citation outcomes (Anton et al., 2024; Geng et al., 2025; Kostovetsky and Manconi, 2020). As such, I show that shareholder overlap can shape not just the quantity of innovation, but also its direction. In doing so, this paper is the first to suggest that common ownership can be negative for innovation because it reduces technological uniqueness and creates incentives for low-quality patents

that lead to knowledge fragmentation. These findings have policy implications as they highlight the need for antitrust authorities to account for strategic alignment in innovation paths when evaluating the competitive implications of common ownership. This paper raises concerns about the long-run impact of common ownership on technological diversity and breakthrough innovations.

This paper has a couple of limitations. First, the patent similarity measure can be improved using more advanced textual analysis techniques. The use of context-aware Doc2Vec or BERT models would allow for a more nuanced measure of innovation overlap. The use of such models should improve the statistical and economic magnitude of the results observed. Second, my causal analysis coincides with the 2008 financial crisis period. During this period, innovation and patenting could have become secondary both to firms and common owners. In this context, I believe that any bias that exists in my causal analysis is a downward bias that goes against my results due to a slowdown in innovation activity. Nonetheless, future improvements can look at whether the results hold in the causal setting where new firm entries in an index create an exogenous increase in common ownership ([Boller and Morton, 2020](#); [Antón et al., 2023](#); [Lewellen and Lowry, 2021](#)).

This paper opens numerous avenues for future research on common ownership and innovation. Going forward, it would be interesting to develop a measure that captures how one firm changes its patent content around the core knowledge of another firm following an increase in common ownership. This would add nuance around which firms adapt their patents in firm pairs following an increase in common ownership. On a related theme, a firm-level analysis using the patent measures created by [Bowen et al. \(2023\)](#) can provide insights on whether common ownership leads to patenting on more dispersed fields (patent breadth measure) and low-impact innovations (innovation breakthrough measure). Elsewhere, in the context of common owners being more exposed to systemic climate risk because they tend to be universal owners, it would be interesting to study if common ownership helps propagate green technologies across portfolio firms.

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2.8 Appendix

2.8.1 Descriptive statistics

Table 2.8.1: Definition of variables used

This Table presents the dependent, independent, control, and causality variables with their respective definitions.

Panel A: Dependent variable - Patent similarity	
Variable	Definition
Patent similarity measure	Cleaned granted and rejected patent abstracts are concatenated by firm years over a pre-defined period (scope). For example, the t+1 to t+3 measure concatenates firm-year t patent abstracts over this period (three-year forward scope). Using TF-IDF word scoring, firms-pairs per year t receive a patent similarity score based on cosine similarity.
Panel B: Independent variable - Common ownership	
Variable	Definition
Beta measure	This is the Lewellen and Lowry (2021) pair-level c-index. This measure is the product of investor k's percentage stake in two firms i and j aggregated among all shared investors between the firm pair as demonstrated in Equation 2.5. It is measured at time t for firm pairs using the end-of-year 13-F filings of institutional investors.
Kappa measure	This is the Backus et al. (2021b) common ownership measure. This is the cosine similarity of the vector of ownership stakes by institutional investors at the firm-pair level multiplied by the square root of the investor concentration in firm j divided by the investor concentration in firm i as demonstrated in Equation 2.6. It is measured at time t for firm-pairs using the average of the quarterly measure calculated by Backus et al. (2021b) .

Panel C: Other key independent variables

Variable	Definition
High-quality innovation	Firm pairs where both are in the top quartile in my measures of innovation quality. The first measure looks at the concerned patent applications' similarity in words with all future patents divided by its similarity with all past patents. The second measure uses the patent-weighted three-year forward citations received from the patent applications driving the technological similarity measure.
Low-quality innovation	Firm pairs in the bottom quartile in my measures of innovation quality.
Technological leading and lagging relationship	Firm pairs where one is in the top quartile and the other in the bottom quartile in my measures of innovation quality.
Official relationship	Factset sample data and WRDS segments data. A dummy variable that is equal to 1 if the firm has a strategic alliance (e.g. firms collaborating for R&D or a new product development), joint venture (i.e. firms jointly own a separate company) or customer-supplier relationship
Citation relationship	PatentsView data. Firm pairs where at least one firm cites the other obtain a dummy variable of 1.

Panel D: Control variables

Variable	Definition
Patent applications	Measured as the number of patent applications of firm i over the time period the technological similarity is being calculated. Winsorized at the 1% level.
R&D	R&D expense scaled by the firm's total assets. Winsorized at the 1% level.
Firm size	Log(total assets). Winsorized at the 1% level.

Firm age	Current year minus the founding date. The first appearance in Compustat is taken as the founding date when the data is unavailable on Professor Jay Ritter's data. Winsorized at the 1% level.
Leverage	Book value of debt (long-term and short-term) divided by total assets. Winsorized at the 1% level.
CAPEX	Capital expenditure scaled by total assets. Winsorized at the 1% level.
PPE	A proxy for tangible assets. Net property, plant, and equipment scaled by total assets. Winsorized at the 1% level.
Cash	Cash holdings and short-term investments of the firm scaled by its total assets. Winsorized at the 1% level.
ROA	Return on assets. Profitability measure. Net income divided by total assets. Winsorized at the 1% level.
Q	Proxy for investment opportunities and firm value. (Market value of equity plus total assets minus book value of equity minus deferred taxes) divided by total assets. Winsorized at the 1% level.
Institutional holding	Firm level end of year (13-F last quarter filing) institutional shareholding of the firm.

Panel E: Causality variables

Variable	Definition
Treatment	Treated firm pairs are blockheld either by the target or the acquirer (and not by both) of the financial institution merger
Control	Control firm pairs have a leading control firm and a secondary treated firm. The control firm is perfectly matched on the year and 2-digit SIC code while being propensity score matched on pre-merger patent application, R&D and firm size characteristics.

Table 2.8.2: Firm sample industry distribution

This Table presents the number of firms in each two-digit industry in my sample.

SIC Code	Industry Name	Number of firms
10	Metal Mining	9
12	Coal Mining	1
13	Oil and Gas Extraction	18
14	Nonmetallic Minerals, Except Fuels	2
16	Heavy Construction, Except Building	2
20	Food and Kindred Products	19
21	Tobacco Products	3
22	Textile Mill Products	3
23	Apparel and Other Textile Products	4
24	Lumber and Wood Products	4
25	Furniture and Fixtures	13
26	Paper and Allied Products	22
27	Printing and Publishing	10
28	Chemicals and Allied Products	316
29	Petroleum Refining and Related Industries	12
30	Rubber and Miscellaneous Plastics Products	18
31	Leather and Leather Products	3
32	Stone, Clay, Glass, and Concrete Products	10
33	Primary Metal Industries	21
34	Fabricated Metal Products	27
35	Industrial Machinery and Equipment	154
36	Electronic and Other Electrical Equipment	262
37	Transportation Equipment	63
38	Instruments and Related Products	226
39	Miscellaneous Manufacturing Industries	20
40	Railroad Transportation	1
42	Trucking and Warehousing	2
44	Water Transportation	1

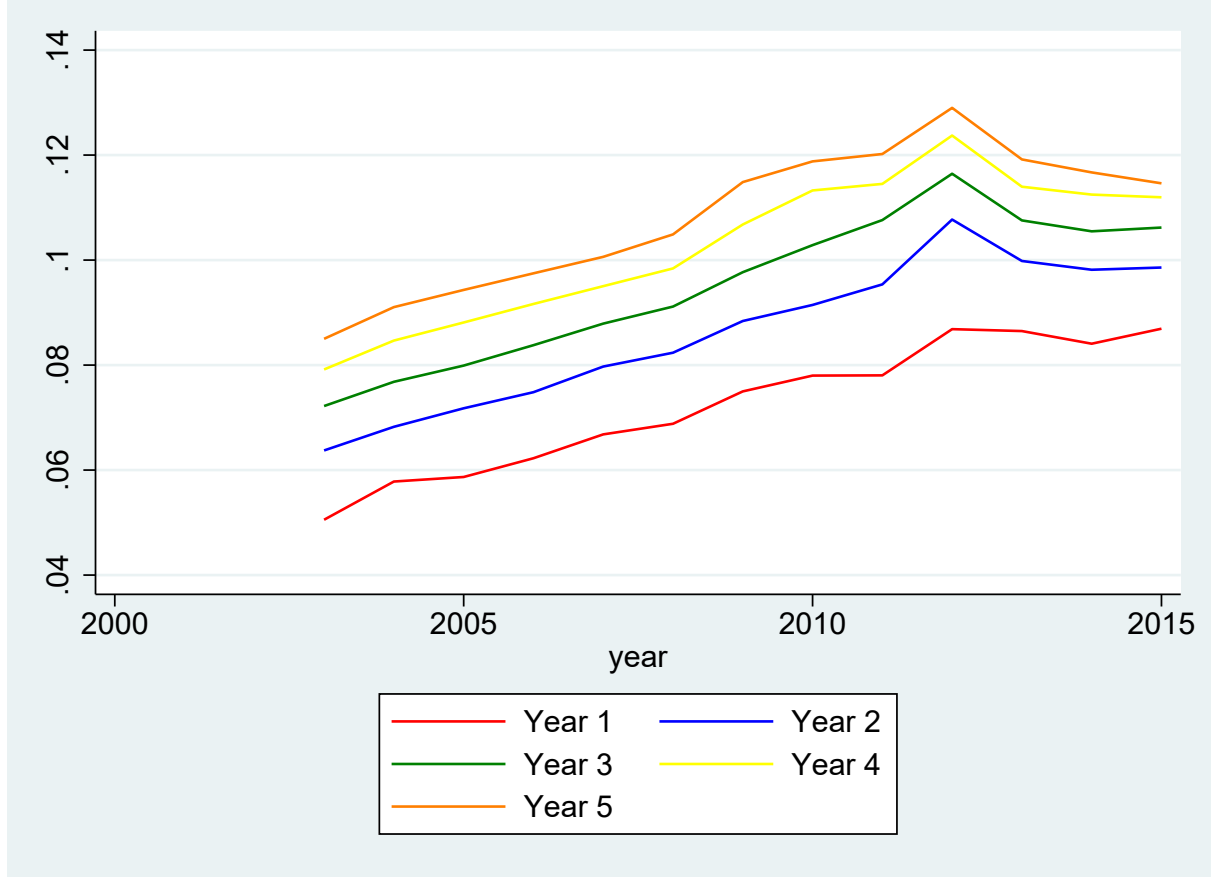
Continued on next page

Table 2.8.2 – *Continued from previous page*

SIC Code	Industry Name	Number of firms
45	Transportation by Air	4
47	Transportation Services	3
48	Communications	45
49	Electric, Gas, and Sanitary Services	19
50	Wholesale Trade-Durable Goods	9
51	Wholesale Trade-Nondurable Goods	4
52	Building Materials and Garden Supplies	1
53	General Merchandise Stores	5
54	Food Stores	2
56	Apparel and Accessory Stores	2
57	Furniture and Homefurnishings Stores	1
58	Eating and Drinking Places	4
59	Miscellaneous Retail	12
60	Depository Institutions	6
61	Nondepository Institutions	4
62	Security and Commodity Brokers	9
63	Insurance Carriers	8
64	Insurance Agents, Brokers, and Service	2
65	Real Estate	1
67	Holding and Other Investment Offices	10
73	Business Services	187
75	Automotive Repair, Services, and Parking	1
78	Motion Pictures	2
79	Amusement and Recreation Services	5
80	Health Services	11
81	Legal Services	1
82	Educational Services	3
87	Engineering and Management Services	23
99	Nonclassifiable Establishments	12

Figure 2.8.1: Patent similarity

This Figure plots the yearly average of my patent similarity measure for my sample. Year 1 corresponds to technological similarity for patent applications in year $t+1$, Year 2 corresponds to technological similarity for patent applications in years $t+1$ and $t+2$ and so until Year 5.



2.8.2 Data construction appendix

2.8.2.1 Rejected patent-firm matching

Existent firm to patent matching databases ([Dyèvre and Seager, 2023](#); [Arora et al., 2021b](#); [Kogan et al., 2017](#)) do not include non-granted patent applications. However, these patents contain rich information on my sample firms' innovation activity and underlying knowledge base. To generate the match I use a similar methodology to [Dyèvre and Seager \(2023\)](#).

This process starts by linking CRSP firm names (which account for historical firm name changes) to unique GVKEYs. Subsidiary firm names from WRDS subsidiary data and acquired or merged firm names from Refinitiv M&A data are linked to their unique

parent firm GVKEYs from the Compustat database for the concerned years. I then use a [Dyèvre and Seager \(2023\)](#) inspired name-cleaning algorithm to match rejected PatentsView patent application data to their respective firms.

Following an initial exact match, I carry out a one-to-one fuzzy match using the FuzzyWuzzy python package and Levenstein distance scores. The Levenstein distance looks for string matches based on the least amount of character manipulations needed to obtain a perfect match. The proposed match is given an accuracy score ranging from 0% to 100%, where 100% identifies a perfect original match on the remaining patent applications. This matches each non-matched rejected patent application to a re-matchable firm with a GVKEY based on the patent application year and firm name possibilities.

I then manually validate or reject the fuzzy name matches. I arbitrarily reject name matches with an accuracy score lower than 40% because of the size of the database. Most valid matches have an accuracy score of 95% or above. Many subsidiaries such as the different Boeing entities are matched at low levels of accuracy. For example, BOEINGCO after name cleaning is correctly fuzzy matched with BOEINGAIRBONESURVEILLANCEENT at 40%. I manually fix these issues by attributing the BOEING name to all cleaned patent application firm names that start as such.

2.8.2.2 Patent similarity

I use standardized NLP techniques to prepare the patent abstracts for my similarity measure. This is done using the NLTK and spaCy packages on Python.

More precisely, the steps carried out in the text cleaning process include setting all characters to lowercase case and removing stop words and numbers. Hyphenated words have the hyphen removed and are considered as one word. I use the spaCy python package for the lemmatization process which reduces words to their base form. This has numerous advantages over the stemming procedures previously used which mainly removes the “s” at the end of plural terms or “ing” at the end of action words.²² Word order and the

²²To be more precise, the word running becomes run in both stemming and lemmatization whereas the word better becomes “bett” through stemming while becoming “good” in the lemmatization process.

context of sentences (semantics) are not taken into account here because using patent abstracts enables focus on the technical terms of the patents.

2.8.2.3 Validating patent similarity measure

To ensure the validity of my technological similarity measure, I compare it to a set of pre-defined and validated measures in the literature. The measures I use are from [Arts et al. \(2023\)](#) and [Jaffe \(1986\)](#).

The [Arts et al. \(2023\)](#) measures go up to 2010 and include firm-pair patent keyword similarity over 5 years of eventually granted patents based on the TF-IDF measure and a more advanced doc2vec model that captures textual context and semantics. They use patent abstracts, claims and titles in their measure. I refrain from using the latter two to avoid noise and the attorney manipulated claims section which is used to prove the patent's contributions.

[Jaffe \(1986\)](#) used 49 patent classification categories and built firm vectors indicating the strength (number of patents) in each classification before proceeding to a cosine similarity calculation between firms to measure their technological positioning and distance from one another. I use the more elaborate IPC classification to carry out the same task.²³ The IPC is divided into six hierarchical groups: the section, subsection, class, subclass, main group and subgroup. The section classification is the broadest classification group and the subgroup is the narrowest. Following the literature ([Anton et al., 2024](#); [Arts et al., 2023](#)), I combine the section, subsection, class, and subclass classifications into one variable. [Bloom et al. \(2013\)](#) propose an enhanced version of the [Jaffe \(1986\)](#) measure named the Mahalanobis similarity measure.²⁴ I focus on the [Jaffe \(1986\)](#) version to ensure my measure fares well in comparison to the minimal standards. Moreover, [Bloom et al. \(2013\)](#) find similar results through both the [Jaffe \(1986\)](#) similarity and Mahalanobis similarity measures. Alongside many missing patent classifications, the [Jaffe \(1986\)](#) measure

²³Despite being more comprehensive (notably for non-granted patents) than the USPC classification or the CPC classification, the IPC classification does not report patent classifications on 81,000 non-granted patents in my sample.

²⁴The main difference between the [Bloom et al. \(2013\)](#) measure and the Mahalanobis measure is that the latter accounts for the correlation between patent classes.

also lacks precision in identifying technological market rivals and partners ([Arts et al., 2023](#); [Whalen et al., 2020](#)). As stated in [Jaffe \(1986\)](#), in the classifications system we can find technologies that are put together but have nothing to do with one another as demonstrated through the toothpaste and manure spreader in the “dispensing of solids” classification of the US patents office.

Figure 2.8.2: Comparison with other patent similarity measures

This Figure represents a correlation matrix between my measure of patent similarity (TF_IDF) and a set of similarity variables constructed in previous papers. These measures include my version of the [Jaffe \(1986\)](#) similarity measure (Jaffe) and the two measures constructed by [Arts et al. \(2023\)](#) that are publicly available (Arts.doc2vec and Arts_TF_IDF). The corresponding data used goes from 2003 to 2010 for a sample of firms I use and that matches with [Arts et al. \(2023\)](#).

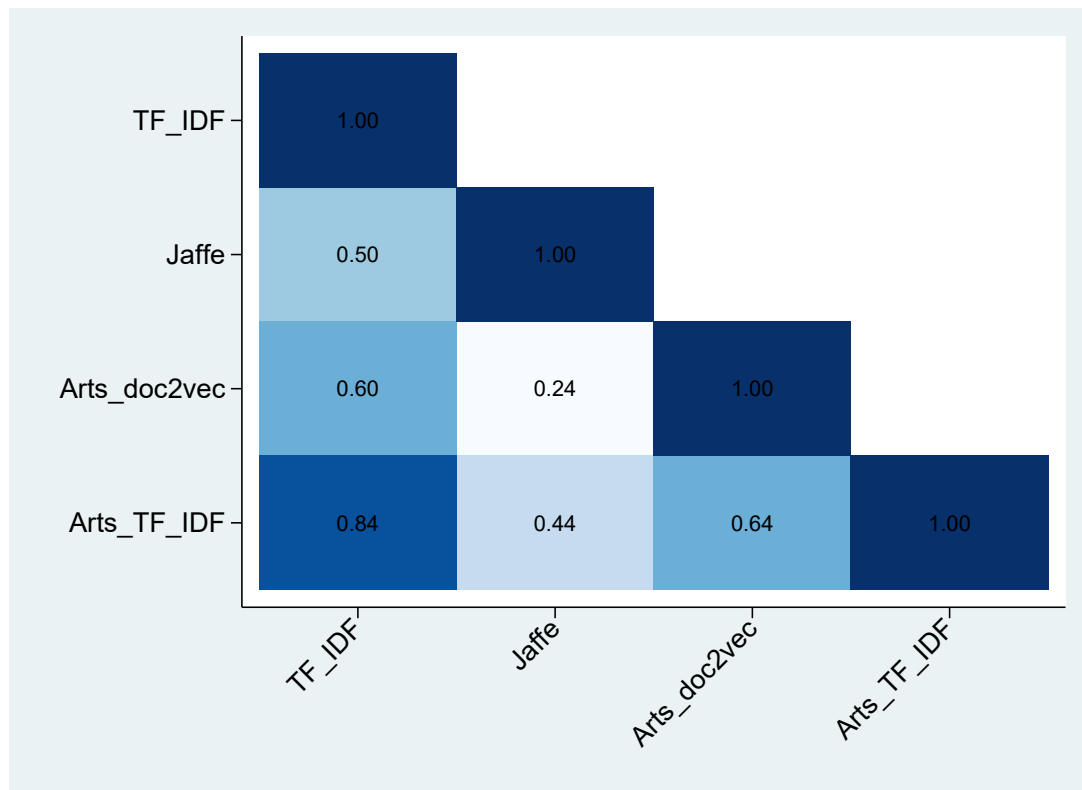


Figure 2.8.2 shows the correlation matrix between my patent similarity measure named TF-IDF and a set of comparable patent similarity measures previously discussed. The data used here goes from 2003 to 2010 for a sample of firms I use and that matches with Arts et al. (2023). In the first column of this matrix, we can observe that there's an extremely high positive correlation between the Arts et al. (2023) patent similarity score and the one I created despite some methodological differences.²⁵ The small difference between the two measures can be attributed to the use of patent claims and titles in Arts et al. (2023). The correlation decreases but remains strong and positive between my measure and the more computationally advanced context understanding doc2vec measure employed by Arts et al. (2023). Despite taking a more granular version of the Jaffe (1986) measure, we can see that the correlation between my main variable and the Jaffe (1986) measure is moderately positive. This is nonetheless higher than the correlation found in Arts et al. (2023) of 0.14 between their Jaffe (1986) differentiation measure and their patent text differentiation measure. The weaknesses of the Jaffe (1986) measure are further demonstrated by its low but positive correlation of 0.24 with the advanced Arts et al. (2023) doc2vec model. Figure 2.8.2 therefore provides insightful evidence on the validity of my patent similarity variable.

²⁵The main methodological difference comes from the fact that Arts et al. (2023) compile a list of key patent related technical words that they base their similarity calculations on. On the contrary, I use the full patent abstract assuming the TF-IDF measure will lower the importance of non-key words and that patent abstracts will mainly include key terms.

2.8.3 Baseline analysis appendix

Table 2.8.3: Patent similarity and product market overlap

This Table demonstrates that product market overlap/competition is correlated with patent similarity. This shows that an increase in patent similarity can have product market concentration effects. The dependent variable is the current year's patent similarity measure. The independent variable is the product market similarity measure from [Hoberg and Phillips \(2016\)](#). Standard errors are reported in parentheses. The standard error is clustered at the firm-pair level for Column 2. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Patent similarity	Patent similarity
Product Similarity	0.43*** (0.001)	0.06*** (0.01)
Firm controls	No	Yes
Firm-Pair FE	No	Yes
Industry-Pair FE	No	Yes
Year FE	No	Yes
Industry-Pair $\times$ Year	No	Yes
Observations	8,358,272	8,358,272
Adjusted R-squared	0.04	0.85

Table 2.8.4: Common ownership and patent similarity across time

This Table reports the correlation between common ownership and patent similarity through different time scopes. The dependent variable is the pairwise textual similarity of patent application abstracts between two firms, measured at time t , $t+1$, $t+1$ to $t+2$ ($T+2$) and so on until $T+5$. The main independent variable is pairwise common ownership in year t , measured using two different approaches. The beta measure in Panel A and the kappa measure in Panel B. The dyadic regression includes duplicate firm pairs (i.e., both Firm A–Firm B and Firm B–Firm A) and controls for the leading firm’s characteristics in year t , except for the patent application variable, which aggregates applications for the time scope in question. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A: Beta measure						
	T	T+1	T+2	T+3	T+4	T+5
Common ownership _{A,B}	-7.61*	3.32	13.18***	17.34***	18.45***	19.89***
	(4.36)	(4.34)	(4.63)	(4.88)	(4.94)	(4.85)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,076,216	8,358,272	9,323,100	9,677,034	9,677,034	9,677,034
Adjusted R-squared	0.853	0.852	0.914	0.914	0.929	0.939
Panel B: Kappa measure						
	T	T+1	T+2	T+3	T+4	T+5
Common ownership _{A,B}	-0.03	0.01	0.11**	0.13**	0.11*	0.09
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,076,216	8,358,272	9,323,100	9,677,034	9,677,034	9,477,612
Adjusted R-squared	0.853	0.853	0.892	0.914	0.929	0.94

Table 2.8.5: Common ownership and patent similarity convergence across time
This Table reports the correlation between common ownership and patent similarity through different time scopes. The dependent variable is the pairwise textual similarity of patent application abstracts between two firms, measured as the difference between the stated time and the period before (e.g. $T+2 = t+2 - t+1$). The main independent variable is pairwise common ownership in year t , measured using two different approaches. The beta measure in Panel A and the kappa measure in Panel B. The dyadic regression includes duplicate firm pairs (i.e., both Firm A–Firm B and Firm B–Firm A) and controls for the leading firm’s characteristics in year t , except for the patent application variable, which aggregates applications over the specified scope. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A: Beta measure					
	T+1	T+2	T+3	T+4	T+5
Common ownership _{A,B}	9.43**	7.86***	4.40***	0.98	1.42
	(4.46)	(2.50)	(2.07)	(1.68)	(1.49)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,134,066	8,268,125	9,221,029	9,571,733	9,372,494
Adjusted R-squared	0.111	0.391	0.308	0.296	0.29
Panel B: Kappa measure					
	T+1	T+2	T+3	T+4	T+5
Common ownership _{A,B}	0.11	0.24***	-0.03	-0.08*	-0.03
	(0.11)	(0.07)	(0.06)	(0.05)	(0.04)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,134,066	8,268,125	9,221,029	9,571,733	9,372,494
Adjusted R-squared	0.111	0.391	0.308	0.296	0.29

Table 2.8.6: Common ownership and patent similarity in product innovation: High and low quality
This Table reports the correlation between common ownership and product innovations patent similarity
high-quality innovation-producing firm pairs and a set of low-quality innovation-producing firm pairs.
text measure and a citation measure as described in the heading of the Table. The dependent variable
(t+1 to t+3) of patent similarity. The main independent variable is common ownership in year t, mea-
sures. Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical sig-
* for the 1%, 5%, and 10% levels, respectively.

	High Quality (Text)		High Quality (Cite)		Low Quality (Cite)	
	Beta	Kappa	Beta	Kappa	Beta	Kappa
Common ownership _{A,B}	10.25 (6.67)	0.15 (0.21)	8.66 (8.07)	-0.27 (0.26)	23.88** (11.39)	0.32 (0.2
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Pair × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	375,104	375,104	722,606	722,606	259,300	259,300
Adjusted R-squared	0.914	0.914	0.937	0.937	0.83	0.83

Causal analysis appendix²⁶

Table 2.8.7: List of eligible mergers between financial institutions

This Table from left to right reports the announcement date, acquirer name and target name of a list of mergers to exploit for my exogenous shock. The last column indicates whether the eligible merger was a case number is used in Table 2.8.8 which details the reasons behind the use and non-use of the stated

Case number	Announcement Date	Acquirer name	Target name
1	03-Dec-2006	Bank of NY Trust Co	Mellon Bank
2	07-Jul-2008	RiverSource Investments LLC ²⁷	J&W Seligman
3	23-Apr-2006	Lehman Brothers Holdings Inc	David J Greenglass
4	10-Mar-2008	Wells Fargo & Co	Wachovia Co
5	14-Sep-2008	Bank of America Corp	Merrill Lynch
6	16-Sep-2009	Blackrock Inc	Barclays Global

²⁶I exclude several merger events from Lewellen and Lowry (2021) and Bindal and Nordlund (2024) because at least one of the firms involved in the transaction does not appear in my 13F blockholding data. This is the case for both my sample firms and any other acquisitions between 2006 and 2013 include (acquirer-target): Morgan Stanley-FrontPoint Partners LLC 2006; Barclays-Goldman Sachs Group Inc-Level Global Investors 2010; Raymond James Financial Inc-Morgan Keegan &Co Inc 2012; Scotiabank Ltd 2013; Allianz Global Investors US-RCM Capital Management LLC 2013.

The 13D and 13G filing database from Schwartz-Ziv and Volkova (2024) makes some of these mergers technically eligible for my sample. The 13D and 13G filing database from Schwartz-Ziv and Volkova (2024) makes some of these mergers technically eligible for my sample. The 13D and 13G filing database from Schwartz-Ziv and Volkova (2024) makes some of these mergers technically eligible for my sample.

²⁷RiverSource Investments LLC goes by the name of Ameriprise in my 13F database

Table 2.8.8: Reasons for used versus non-used financial mergers

This Table is linked to Table 2.8.7 through the first column (Case number) which states which merger columns detail the number of unique blockholdings in the acquirer's and target's portfolios respectively, 4 and 5) state how many of the eligible firm blockholdings can be found in my sample of firms. The first merged institution for three years following the merger event to be included in my causality analysis so last column states the financial institution mergers that fit the criteria of use for this paper.

Case number	Eligible acquirers	Eligible targets	Sample acquirers	Sample targets
1	2	36	1	1
2	3	10	0	0
3	12	6	0	0
4	97	20	23	23
5	69	10	16	16
6	23	862	7	7

2.8.4 Robustness: Other factors

2.8.4.1 Baseline results

Existent relationships between commonly owned firms could be driving the correlation between common ownership and patent similarity. Table 2.8.9 captures the impact of common ownership on patent similarity while accounting for various types of relationships. In Columns 1 and 2 official relationships (customer-supplier, strategic alliance and joint ventures) between firms in year t are given a dummy value equal to one.²⁸ Columns 3 and 4 look at firm pairs that cite one another at least once in year t (cross citation takes a dummy variable of one and zero otherwise) as an indicator of an unofficial technological relationship. Columns 5 and 6 use the pairwise [Hoberg and Phillips \(2016\)](#) 10-K product similarity measure to examine competition-related relationships between firm pairs.²⁹

The positive and statistically significant association between common ownership and patent similarity persists across all iterations of firm relationships and common ownership measures in Table 2.8.9. There is also a consistent positive and statistically significant association between the different relationship types and patent similarity. However, the interactions between the different common ownership measures and the different relationship measures are statistically insignificant.

2.8.4.2 Causal results

My sample of control and treated firm pairs only have cross-citation and competition-related relationships.³⁰ Table 2.8.10 focuses on product market relationships through the [Hoberg and Phillips \(2016\)](#) measure. Column 1 looks at the full causal sample whereas Column 2 focuses on a sub-sample where firm pairs have at least some degree of product market overlap (non-zero firm-pair product similarity).

²⁸Strategic alliance and joint venture data is from Factset and customer-supplier data is from WRDS. When there is no end date to a relationship, a three-year forward time frame is assumed.

²⁹Firms that compete in similar product spaces tend to innovate along similar technological paths

³⁰[Lewellen and Lowry \(2021\)](#) also find limited firm pair relationships in their causal interpretation during the financial crisis period.

Table 2.8.9: Common ownership, firm relationships, product market overlap and firm relationships. This Table reports the correlation between common ownership and patent similarity when accounting relationships. Columns 1 and 2 look at official relationships (customer-supplier, joint-venture, strategic) at patent citation relationships, and Columns 5 and 6 look at product competition relationships using a measure. The dependent variable is the three-year forward scope (t+1 to t+3) of patent applications using firms (firm-pair level). Common ownership is measured using the beta and kappa measures. Standard errors, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, a

	Official relationships		Cross citations		Pro
	Beta	Kappa	Beta	Kappa	
$C.O_{A,B} \times Relationship_{A,B}$	47.11 (46.97)	0.42 (0.84)	-20.79* (11.61)	0.44* (0.14)	-56 (56)
$C.O_{A,B}$	17.32*** (4.88)	0.26** (0.13)	17.7*** (4.8)	0.12** (0.06)	18. (4.)
$Relationship_{A,B}$	0.88** (0.34)	0.88* (0.48)	0.8*** (0.09)	0.57*** (0.10)	6.1 (0.)
Firm controls	Yes	Yes	Yes	Yes	Y
Firm-Pair FE	Yes	Yes	Yes	Yes	Y
Industry-Pair FE	Yes	Yes	Yes	Yes	Y
Year FE	Yes	Yes	Yes	Yes	Y
Industry-Pair $\times$ Year FE	Yes	Yes	Yes	Yes	Y
Observations	9,677,034	9,677,034	9,677,034	9,677,034	9,67
Adjusted R-squared	0.914	0.914	0.914	0.914	0.9

Importantly, product market overlap does not attenuate the main results of this paper. In both Column 1 and Column 2, we continue to see common ownership increasing patenting similarity between firms through the positive and statistically significant Treatment $\times$ Post variable. After the financial mergers, product market overlap (Prod. Sim $\times$ Post) led to more similar patenting. The common ownership and product similarity interaction after an exogenous increase in common ownership continues to be statistically insignificant.

Table 2.8.10: Common ownership and patent similarity: Product competition
This Table studies the moderating role of product market similarity in the relationship between common ownership and the one-year forward patent similarity measure (dependent variable). It shows that the common ownership effect on patent similarity (Treatment $\times$ Post) persists when accounting for product market similarity. Column 1 uses the full sample from the causal analysis setting, and Column 2 uses a sub-sample where treatment firm pairs and their corresponding control firm pairs have at least some product market similarity. Product market similarity and control variables are taken in year t . Product similarity is from [Hoberg and Phillips \(2016\)](#). Standard errors, clustered at the firm-pair level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Full Sample	Similar firms
Treatment $\times$ Post $\times$ Prod. Sim	-4.49 (5.6)	-6.84 (7.09)
Treatment $\times$ Post	0.64*** (0.24)	1*** (0.40)
Prod. Sim $\times$ Post	15.6*** (4.39)	19.45*** (5.66)
Firm controls	Yes	Yes
Firm-Pair FE	Yes	Yes
Industry-Pair FE	Yes	Yes
Year FE	Yes	Yes
Industry-Pair $\times$ Year FE	Yes	Yes
Observations	42,187	21,971
Adjusted R-squared	0.746	0.735

Chapter 3

The market for climate technologies

3.1 Introduction

Climate change mitigation and adaptation technologies are viewed as essential tools in addressing the global climate crisis. The academic literature has highlighted firm valuation benefits of patenting such technologies.¹ However, the act of patenting does not necessarily imply that the firm will use the technology. Instead, climate patents may serve strategic purposes. Firms may patent climate technologies to secure future options, monetize innovations or signal environmental commitment without using the technology developed immediately. In this paper, I examine climate patent transactions between firms to assess whether financial markets value firm commitment to climate-related innovation.

Achieving net zero carbon emission goals will require substantial investment to transition from dirty production technologies to clean production technologies. The path-dependent nature of innovation makes transitioning to clean technologies difficult in the absence of strong climate policies such as carbon taxes and R&D subsidies ([Acemoglu et al., 2016](#); [Aghion et al., 2014](#)). In the U.S., the lack of pro-climate regulation weakens corporate incentives to provide cleaner products and production methods. For example,

¹See [Hege et al. \(2023\)](#), [Hege et al. \(2024\)](#), [Dechezleprêtre et al. \(2021\)](#), [Reza and Wu \(2024\)](#) and [Klausmann et al. \(2025\)](#)

Brandon et al. (2022) show that institutional investors that sign the UN Principles for Responsible Investment (UN PRI) engage in greenwashing behaviour by incorporating less ESG practices than non-UN PRI institutional investors in the U.S.² The lack of maturity in the ESG markets and lower pressure for ESG implementation in the U.S. is blamed for this outcome.

Nonetheless, the U.S. is home to some of the biggest climate patent-producing firms in the world.³ The disconnect between climate patent production and low incentives to transition to clean technologies is not necessarily incompatible. Innovation is a noisy process where the outcome can be difficult to predict (Manso, 2011). The decision to patent on this outcome does not necessarily imply that the technology will be used internally for cleaner products and production methods. Firms can also patent climate technologies to establish a market leader position and limit competition in anticipation of tighter climate regulations. Similarly, patents can be used to monetize an innovation without ambitions of internal use.

The market for technologies is often overlooked in the innovation literature. This market provides the platform for efficient reallocation of technologies. Since innovation is riddled with uncertainty, its outcome may not necessarily be a good economic prospect for the technology-producing firm. In this scenario, interest from another firm can lead to a transaction of the patented technology between the two firms. This efficient patent reallocation incentivizes firms to produce and patent innovations. Due to the buyer-driven nature of this market, traded patents tend to hold economic and scientific value. For example, Serrano (2018) show that 7.9% to 23.9% of granted patents are traded depending on the technological field. These patents are also shown to represent up to 50% of the economic value of all patented technologies.

In the context of climate patents, the market for technologies can provide valuable insight into how markets value climate patents. The academic literature which focuses on climate patent grants, has provided mixed evidence on the economic value of climate

²The UN PRI is a voluntary initiative that encourages investors to account for ESG factors in investment decision-making and ownership practices

³Data on patent production in renewable energy per country:
<https://ourworldindata.org/grapher/patents-for-renewables-by-country>

patents. On the one hand, [Hege et al. \(2024\)](#), [Dechezleprêtre et al. \(2021\)](#), [Reza and Wu \(2024\)](#) and [Klausmann et al. \(2025\)](#) show that climate patent production is positively linked to firm value. On the other hand, [Andriosopoulos et al. \(2024\)](#) and [Leippold and Yu \(2024\)](#) find that climate patent producers do not experience valuation benefits. These papers implicitly assume that climate innovation output equates to environmental commitment. In this paper, I shift the focus from climate patent producers to climate patent buyers and sellers as a more informative signal of firms’ strategic engagement with climate technologies. Unlike patenting, which may reflect option value or signalling motives, buying or selling patents requires deliberate allocation of resources and reflects concrete strategic choices. As such, transactions in the market for technologies offer a clearer window into whether firms are investing in or divesting from climate innovation. If markets reward climate engagement, we should observe a positive reaction to climate patent acquisitions and a negative reaction to climate patent sales, which could signal a retreat from future climate strategies.

To study whether climate patent sales and acquisitions impact firm value, I construct a panel dataset of U.S. publicly listed and headquartered firms that are granted or buy at least one climate patent between 2000 and 2020. This panel dataset contains novel firm-level patent transaction data that I obtain by developing cleaning and matching algorithms to match USPTO patent transaction data to Compustat firms. I use the Cooperative Patent Classification’s (CPC) “Y02” classification to identify climate patents. In two separate empirical models for patent sales and patent acquisitions, I distinguish climate from non-climate patent transactions and estimate their impact on firm value as measured by Tobin’s Q. Following the valuation framework of intangible assets by [Griliches \(1981\)](#), [Hall et al. \(2005\)](#), and [Dechezleprêtre et al. \(2021\)](#), I control for innovation related intangible assets that can impact firm value including R&D stock, granted climate patent stock, and granted non-climate patent stock.⁴ I limit endogeneity concerns in the baseline model by controlling for firm characteristics that could impact firm value, including the firm’s lagged Tobin’s Q. I also include time, firm, and year fixed effects to

⁴The notion of stock captures the idea that these innovation inputs and outputs contribute to value over time and gradually become obsolete. For example, R&D stock is R&D expense in year t for firm i plus 0.85 multiplied by firm i ’s R&D stock in year $t-1$, where the original R&D stock in year 0 is the R&D expense in year 0 discounted by 10%.

ensure that only within-firm variation in value is studied.

The baseline results reveal statistically significant and economically important associations between climate patent sales and firm value. Each climate patent sold is associated with a 2% decrease in firm value. This relationship holds when using the fraction of climate patents sold instead, where the fraction corresponds to the amount of climate patents sold scaled by the granted climate patents in stock. When using the one-year forward firm value, this relationship weakens with statistical significance at the 10% level and a discount in firm value of 0.7% following each climate patent sale. However, the fraction of climate patents sold variable holds its 1% statistical significance and economic magnitude. These results indicate that divesting climate technologies is penalized by markets. Abandoning important real options and signalling low environmental commitment by selling patents despite producing climate patents is associated with losses in market value.

Climate patent acquisitions are not associated with firm value immediately. When I use the number of climate patents acquired scaled by R&D stock, there is an economically small association with the end of year firm value of -0.03%. However, when I use the one-year forward firm value, there is a strong and positive relationship between climate patent acquisition and firm value. Each patent acquisition is associated with an increase of 0.1% in firm value. This delayed effect suggests that climate patent acquisitions increase firm value with time. This is expected because acquired technologies bring value thanks to resources spent for their implementation and their use in developing future technologies (Bowen, 2016). This is an uncertain process that can take time as observed by the consistent negative association between non-climate patent acquisition and firm value. The contrast in results between climate and non-climate patent acquisition indicates the real option value and positive signalling effect of climate patents. The delayed effect suggests that signalling the acquisition of climate options is not sufficient to increase firm value and actions to implement the technologies are also important.

Despite using a rigorous empirical methodology, endogeneity concerns may persist. Therefore, in addition to using an important amount of control variables and fixed effects, I use four different methods to ensure my results are robust.

First, I address potential omitted variable biases that may persist despite the baseline methodology. Firms may engage in patent transactions as a result of financial distress or legal disputes. [Ma et al. \(2022\)](#) show that firms can be constrained to sell important technologies in periods of bankruptcy while [Galasso et al. \(2013\)](#) show that patent reallocation impacts litigation risk. Therefore, I use the Florida-UCLA-LoPucki database to remove all Chapter 7 and Chapter 11 filing firms from my panel dataset. I also use the USPTO's patent-level district court litigation dataset to remove litigated climate patents that are transacted from my dataset. The core findings remain robust in this restricted sample.

Second, I test whether the effect of climate patent transactions varies with firms' climate exposure. I use the measure developed by [Sautner et al. \(2023\)](#), which captures the fraction of words dedicated to climate-related concerns in earnings conference calls. When interacted with climate patent sales, this measure amplifies the negative association between climate patent sales and firm value. This suggests that markets penalize climate patent sales more severely for firms where climate discourse is more prominent. The interaction between climate patent acquisitions and climate discourse is not statistically significant. This weakens the option value interpretation of climate patent acquisition. This result suggests that for climate patent acquisitions to affect firm value, firms may need to actively implement and integrate the acquired technologies rather than merely holding them as strategic options.

Third, I address potential selection bias in climate patent transactions by employing a propensity score matching (PSM) analysis. Firms that engage in climate patent sales or acquisitions may systematically differ from those that do not in ways that also influence firm value. For example, firms with high innovation capabilities but low production capabilities may pursue a business strategy that involves monetizing their technological assets through patent sales. In this case, any observed relationship between climate patent sales and firm value may reflect underlying firm characteristics rather than a causal effect. To mitigate this concern, I create two separate propensity score matching (PSM) analyses for climate patent selling and climate patent buying firms. Treated firms (those selling climate patents in the first analysis and those buying climate patents in the second analysis) are matched on a one-to-one nearest neighbour basis to control firms (non-climate

patent selling firms in the first analysis and non-climate patent buying firms in the second analysis). The matching variables include non-climate patent transaction characteristics and profitability characteristics. This matching strategy reduces differences in observable firm traits, enabling a more credible estimation of the independent effect of climate patent transactions. The results from these matched samples are consistent with the baseline findings.

Fourth, to further address potential endogeneity arising from reverse causality and omitted variable bias for climate patent sales, I implement a two-stage least squares (2SLS) estimation strategy. I instrument climate patent transactions using the interaction between state-level climate policy stringency (i.e. the number of climate policies enacted in the firm’s headquarter state) and the firm’s lagged climate patent stock. This instrument captures exogenous variation in the opportunity to transact climate patents due to increased climate technology demand from external regulatory environments conditional on the firm’s existing technological assets. This instrument survives the relevance and exclusivity criteria for climate patent sales. The climate patent sales result remains consistent with the baseline results.

To the best of my knowledge, this is the first study to examine the relationship between climate-related patent transactions and firm value. It provides novel evidence on how capital markets evaluate firms’ strategic engagement with climate technologies through their innovation-related transactions.

Existing studies focus on the consequences of patenting on climate technologies. [Dechezleprêtre et al. \(2021\)](#) find a positive correlation between clean patents and firm value. [Hege et al. \(2024\)](#) use quasi-randomly granted climate patents from lenient examiners to show that they increase stock returns, attract environmentally responsible institutional investors and enhance ESG ratings. Similarly, [Reza and Wu \(2024\)](#) and [Klausmann et al. \(2025\)](#) find that during periods of unexpected climate shocks and regulations, green patent grants are associated with a higher market reaction than non-green patent grants and more green revenue. However, [Andriosopoulos et al. \(2024\)](#) find no relationship between green patent grants and firms’ environmental scores, institutional ownership, or Tobin’s Q. [Leippold and Yu \(2024\)](#) document that climate innovation discourse in earnings calls correlates with lower expected returns. Elsewhere, recent studies

highlight the strategic behaviour of brown firms. [Cohen et al. \(2024\)](#) show that climate patent producers are predominantly brown firms. [Kwon et al. \(2024\)](#) further this observation by demonstrating that brown climate patent-producing firms simultaneously lobby for policies that maintain the regulatory status quo while accumulating climate patents as a real option strategy in anticipation of future climate policy. I contribute to this literature by shifting the focus from the production of climate patents to their reallocation through market transactions. These transactions offer an observable indicator of firms' engagement or disengagement with climate innovation. By distinguishing between climate and non-climate patent transactions and assessing their differential valuation effects, I offer an understanding of how financial markets price climate innovation beyond the act of patenting.

This paper also contributes to the market for technologies literature by being the first to show a relationship between patent transactions and firm value. In relation to corporate finance, existing studies have focused on the innovation-related outcomes of patent transactions. [Bowen \(2016\)](#) show that patent acquirers invest more in R&D, increase patent applications, and make new capital expenditure investments. [Zhang \(2024\)](#) find that patent sales lead to improved operating performance and positive stock market returns. Similarly, [Brav et al. \(2018\)](#) show that activism improves innovation efficiency through the sale of peripheral patents to increase focus on core technologies. Another strand of the literature focuses on the magnitude and mechanisms of patent reallocation. [Akcigit et al. \(2016\)](#) show that patent reallocation enhances economic growth by enabling more productive acquiring firms to implement innovations and selling firms to monetize their technological advancements. [Serrano \(2010\)](#) and [Serrano \(2018\)](#) show that the volume of patents traded and the scientific value of traded patents are large. [Arqué-Castells and Spulber \(2022\)](#) show that innovation spreads through the market for technology and not solely through unintentional knowledge spillovers. [Arqué-Castells and Spulber \(2023\)](#) and [Kwon et al. \(2022\)](#) show that product market proximity between firms limits efficient transfers of technologies. [Ma et al. \(2022\)](#) show that financial distress in the form of bankruptcy forces firms to sell important patents that are used as collateral. I contribute to this literature by examining the capital market consequences of patent transactions in the specific context of climate technologies. I show that the market for climate technologies can transmit information to investors and shape firm valuation in a way that is not

consistently observable for other types of patents.

This paper is divided as follows. Section 3.2 develops the predictions behind my research question. Section 3.3 details the sources, construction, and descriptive statistics behind the data used in this paper. Section 3.4 develops the baseline methodology applied in this paper. Sections 3.5 and 3.6 report baseline results and robustness checks respectively. Section 3.7 concludes.

3.2 Hypothesis development

Insights on the market for technologies can help us understand the expected relationship between climate patent transactions and firm value. The market for technology is a buyer-led market that brings together two parties in an exchange of patent ownership. The bilateral agreement is carried out on a set of patents concerned (often multiple per bilateral transaction), a date of transfer, and a fee. Technology transfers allow patent sellers to monetize underutilized technologies and patent buyers to strengthen their patent portfolio or tackle new technology areas. For example, [Akcigit et al. \(2016\)](#) demonstrate that a patent sale is determined by the seller’s internal productivity for the patent, the buyer’s valuation of the patent and the buyer’s comparative advantage in commercializing the patent. This means that patented technologies that are distant from the seller’s technology base and close to the buyer’s technology specialization should be transferred. In such a scenario, patent reallocations benefit both parties. [Brav et al. \(2018\)](#) and [Zhang \(2024\)](#) show that patent sales allow for more innovation efficiency due to a subsequent focus on core patents. [Serrano \(2010\)](#) and [Serrano \(2018\)](#) show that patents with high scientific value are more likely to be traded. The suggested positive outcome for firms engaging in voluntary patent transactions does not necessarily translate into enhanced firm value.⁵ Firm-level innovation is difficult to evaluate ([Hirshleifer et al., 2013](#)). Therefore, the market response to patent transactions can be noisy. This is notably the case for patent acquisitions because the value of a newly acquired patent depends on the firm’s

⁵[Ma et al. \(2022\)](#) show that firms tend to have recourse to the market for technologies to sell their core patents in times of financial distress. They study the case of firms filing for bankruptcy in particular. This relationship is said to be driven by creditor sales of collateralized patents.

ability to integrate and implement it. Therefore, in the mist of this uncertainty, we can expect mixed or negative short-term valuation effects of patent acquisitions.

The transition to climate-friendly technologies is costly for firms (Acemoglu et al., 2016; Aghion et al., 2014). This is particularly true for firms reliant on dirty technologies, which are also the main producers of climate patents today (Kwon et al., 2024; Cohen et al., 2024). The lack of policy incentives in the U.S., such as carbon taxes and green R&D subsidies, adds to the financial burden of greening production and products. In this context, we can expect a positive association between climate patent sales and firm value. As with conventional patent sales, climate patent sales provide a source of revenue while also reducing uncertainty over costly climate-friendly approaches. To the extent that markets fail to value climate technologies, we can expect a negative association between climate patent acquisition and firm value. Moreover, patent acquisitions involve an initial cost and suggest future expenses in R&D to develop and implement the technology. The required expenditures and uncertainty around innovation may lead to a negative market reaction, especially if investors do not perceive climate technologies as enhancing future firm performance..

H1.A: *Climate patent sales are positively associated with firm value.*

H1.B: *Climate patent acquisitions are negatively associated with firm value.*

At the same time, a wave of climate regulations is expected to help the U.S. meet a zero-net emissions economy target by 2050.⁶ The average number of climate mitigation or adaptation policies across U.S. states increased from 2.43 in 2015 to 6.54 in 2020.⁷ This represents a 169% increase in state-level climate policy activity over five years.

In this context, patented climate technologies embody real options. Kwon et al. (2024) argue that climate patent producers lobby for brown causes to preserve the status quo while simultaneously patenting climate technologies. This strategy enables firms to maintain their market-leading positions while delaying transition investments. As

⁶<https://climateactiontracker.org/countries/usa/>

⁷This data is from ClimateXChange’s count of climate policies enacted in each U.S. state averaged across the 46 represented states. Only 46 states are represented here because my sample firms are headquartered across 46 different U.S. states. The data can be found here: <https://www.climatepolicydashboard.org/>

such, they treat climate patents as real options. This means that these firms withhold climate technologies from the market while waiting for more favourable implementation conditions. If climate patents are perceived as valuable for future firm performance and if climate action is important for investors, one might expect climate patent sales to be penalized and acquisitions to be rewarded by the market. This asymmetry arises because climate patent sales signal low commitment and preparation for incoming climate regulations while climate patent acquisitions signal the opposite.

H2.A: *Climate patent sales are negatively associated with firm value.*

H2.B: *Climate patent acquisitions are positively associated with firm value.*

3.3 Data

3.3.1 Data construction

I create a panel dataset of U.S. headquartered firms that have at least one climate patent granted by the U.S. Patent and Trademark Office (USPTO) or that acquire at least one climate patent between 2000 and 2020. This sample of firms ensures that my main results are not driven by firms with no climate patent activity or by periods in which climate patents may not have been valued.

Patent data are gathered from PatentsView. This data is linked to my firm-year panel dataset based on the number of granted patents attributed to each firm year. I link patents to Compustat firms using the matching dataset constructed by [Dyèvre and Seager \(2023\)](#).⁸ The number of patents granted to each firm year is divided into two variables: the number of climate patents granted and the number of non-climate patents granted. The latter corresponds to all granted patents that are not climate patents.

⁸[Dyèvre and Seager \(2023\)](#) link USPTO patents to their Compustat firm owner. In doing so they extend the coverage provided for granted patents by [Arora et al. \(2021\)](#). [Dyèvre and Seager \(2023\)](#) also account for changes in patent ownership due to M&A activity by offering a dynamic match to Compustat firms. In my paper, I use their static patent to firm match which links each patent to their Compustat ultimate owner at the time of the patent grant. The end of Appendix 3.8.2 explains why I use the [Dyèvre and Seager \(2023\)](#) dataset rather than other available alternatives.

I rely on the Cooperative Patent Classification’s (CPC) “Y02” classification to identify climate patents. This classification tag was introduced in 2013 following a collaboration between the European Patent Office (EPO), the United Nations Environmental Program (UNEP), and the International Centre on Trade and Sustainable Development (ICTSD) to study the importance of climate change technologies ([Veefkind et al., 2012](#)). It has since been applied to all relevant granted patents from before the classification’s creation. This classification allows non-experts to identify climate technologies and has propelled empirical research on the importance of climate technologies. The classification is divided into two types of climate technologies. First, climate adaptation technologies labelled with the “Y02A” sub-classification tag refer to patented technologies that facilitate adaptation to the consequences of climate change. Second, climate mitigation technologies refer to technologies that tackle the climate change problem directly by reducing greenhouse gases. Climate mitigation technologies hold one of seven different classifications depending on the area they apply to. These classifications are “Y02B” (buildings), “Y02C” (capture and storage of greenhouse gases), “Y02D” (ICT aiming at the reduction of own energy use), “Y02E” (production, distribution and transport of energy), “Y02P” (industry and agriculture), “Y02T” (transportation) and “Y02W” (waste and wastewater) sub-classes. Together, all climate change adaptation and mitigation technologies form part of my climate patents granted variable. All granted patents without the “Y02” tag form part of the non-climate patents granted variable. In the Appendix, Figure [3.8.1](#) breaks down the number of climate patents granted, bought, and sold per “Y02” sub-classification while Figure [3.8.2](#) plots the fraction of climate patents granted each year between 2000 and 2020.

The USPTO Patent Assignment Dataset reports voluntarily recorded changes to patent ownership. These changes include entity (owner) name change, government interest in a patent, licensing agreements, patents used as collateral, mergers, abandonment of claims on a patent (release), and more importantly for this study, a change of assignment. Patent buyers (assignees) hold strong incentives to record patent transactions. In the instance where a transaction is not recorded and the seller (assignor) sells the patent to another firm, the recorded transaction takes priority in ownership disputes. Protection is only secured if the recording occurs within three months of the execution date or before any subsequent conflicting assignment is recorded ([Graham et al., 2015](#)).

The USPTO Patent Assignment dataset contains patent-level data, the buyer (assignee), the seller (assignor), the execution date, and the reported date along with other important administrative information. Since firms can return to the same filing and add newly acquired patents, there are some inconsistencies in the filing dates. To deal with this, I require that each transaction have an execution year that is at least on or after the year of the original patent application filing. To ensure that information about the transaction is also available to the public, I also only select patent transactions that contain the same execution and reporting year. To link this data to my firm-year panel dataset, I use a name-matching algorithm and create corporate ownership trees.⁹ This means that patent transactions reported by or to the subsidiary of a firm are attributed to the subsidiary's ultimate Compustat owner at the execution date of the transaction. A change of patent ownership because of a merger or acquisition is excluded from my sample to only focus on the consequences of climate patent transactions.

I carry out a few simplifying steps to ensure accuracy in my dataset. First, to remove any noise and incorrect recordings, I only use the first transaction recording of a patent. This means that I remove all instances of multiple transactions per patent. Second, for patent sales, I ensure that the selling firm is the original patent creator of the transacted patent. Third, I make sure that each transaction takes place between two distinct entities. This guarantees that the patent transactions studied are not polluted with instances of patent reallocation between subsidiaries of the same firm. Patents bought and sold are aggregated at the firm-year level. This forms two distinct variables that are further divided into climate and non-climate patent transactions.

Compustat data on firm characteristics complements the patent data. I require that all sample firm-years contain the relevant data necessary for calculating Tobin's Q (total assets, book value of equity, shares outstanding, and end-of-year share price). I also collect data on elements that could influence firm value in the form of Tobin's Q. They include total asset scaled R&D expense, leverage, and capital expenditure. I also use firm size as measured by the natural logarithm of the firm's market capitalization, firm age which is the difference between the current year and the initial Compustat listing year

⁹A detailed explanation of the methodology used can be found in Section 3.8.2 of the Appendix

for the firm, and a set of profitability measures. These profitability measures include earnings per share growth (one year change in EPS scaled by the previous year’s end-of-year share price), sales growth (one year change in sales scaled by the current year’s total asset), and return on assets. All firm-level data collected and transformed are described in Panel C of Table 3.8.1 in the Appendix.

3.3.2 Data description

My sample contains 1,842 unique climate patent-producing firms and 24,500 firm-years between 2000 and 2020. These firms obtained 83,056 climate-granted patents and 1,109,392 non-climate-granted patents in this time frame. Together, this covers around 54% of the patents granted to Compustat firms between 2000 and 2020 in the [Dyèvre and Seager \(2023\)](#) dataset. In this period, 11,537 climate patents and 161,999 non-climate patents are sold by my sample firms. This corresponds to 13.9% and 14.6% of these firms’ granted climate and non-climate patents between 2000 and 2020. This is in line with the previous literature on patent transactions with [Serrano \(2010\)](#) finding 7.9% to 23.9% of granted patents being sold depending on the industry. As for patent acquisitions, we have 10,585 climate patents acquired and 180,661 non-climate patents acquired. The difference between patents sold and patents bought in my sample can be explained by transactions with out-of-sample firms such as private and foreign companies. Table 3.8.2 in the Appendix provides a detailed industry-level breakdown of this data. In the Appendix, Figure 3.8.3 plots the average yearly amount of climate patents bought and sold in my sample while Figure 3.8.4 plots the average yearly amount of non-climate patents bought and sold in my sample.

Table 3.1 presents the summary statistics for the main variables used in this study. Panel A breaks down the climate patent data between the amount granted, sold, and bought. They respectively have averages of 2.04 grants, 0.22 sales, and 0.22 acquisitions per firm year. This non-winsorized distribution is right-skewed which demonstrates that climate patent activity is led by a small group of firms. There are 7,485 climate patent granting firm-years, 2,222 climate patent selling firm-years, and 2,247 climate patent buying firm-years. The climate patent transaction figures are represented by 662 unique

climate patent selling firms and 956 unique climate patent buying firms. Panel B breaks down the non-climate patent data by patents granted, sold, and bought at the firm-year level. Both transactions and the number of granted patents are more prevalent with averages of 43.68 patent grants, 4.31 patent sales, and 5.21 patent acquisitions. We can see that public firms tend to buy more non-climate patents than sell non-climate patents. This distinction does not exist for climate patents.

Panel C of Table 3.1 also reports the firm characteristics data used in this study. All firm characteristics data are winsorized at the 1% level and defined in Panel C of Table 3.8.1 in the Appendix. Firm value in the form of Tobin's Q has an average of 2.67. The average R&D expense to asset ratio is 10% while the average leverage and capital expenditure to asset ratio are 24% and 4% respectively. The average change in EPS and sales growth are positive at 1% and 7% respectively. The return on assets displays substantial dispersion. It has a mean of -14%, a median of 3%, and a first quartile of -8% which suggests that there is a sub-set of loss-making firms. This can be deemed acceptable for a sample of R&D intensive firm-years and highlights the importance of controlling for financial health in this study.

Table 3.1: Summary statistics

This Table respectively reports the first quartile, median, mean, third quartile, standard deviation, and number of firm-year observations for each of the main variables used. Panels A and B report the climate and non-climate patent variables used. Panel C reports the firm characteristics variables used. All variables are winsorized at the 1% level. In the Appendix, Table 3.8.1 details the construction of each variable and Table 3.8.3 reports the summary statistics of the other variables used in my analysis.

Panel A: Patent variables – Climate patents						
	Q1	Median	Mean	Q3	SD	Obs
Patents granted	0	0	2.04	1	7.55	25,400
Patents sold	0	0	0.22	0	0.91	25,400
Patents bought	0	0	0.22	0	0.53	25,400
Panel B: Patent variables – Non-climate patents						
	Q1	Median	Mean	Q3	SD	Obs
Patents granted	0	2	43.68	15	11,984	25,400
Patents sold	0	0	4.31	1	598.47	25,400
Patents bought	0	0	5.21	1	557.39	25,400
Panel C: Firm characteristics						
	Q1	Median	Mean	Q3	SD	Obs
Tobin's Q	1.22	1.66	2.67	2.65	3.5	25,400
R&D	0	0.03	0.1	0.11	0.18	25,400
Firm size	4.52	6.63	6.15	8.21	3	25,400
Firm age	8	17	21.09	34	15.82	25,400
Leverage	0.03	0.19	0.24	0.34	0.29	25,400
CAPEX	0.01	0.03	0.04	0.05	0.04	25,400
Δ EPS	-0.03	0.01	0.01	0.03	0.43	25,400
Sales growth	-0.02	0.03	0.07	0.13	0.25	25,400
ROA	-0.08	0.03	-0.14	0.07	0.63	25,400

3.4 Methodology

The empirical model I use to estimate how climate patent transactions influence the firm's market value is based on the methodologies of [Griliches \(1981\)](#), [Hall et al. \(2005\)](#), and [Dechezleprêtre et al. \(2021\)](#).¹⁰ The intuition behind this methodology is that the natural logarithm of scaled intangible assets regressed on the natural logarithm of Tobin's Q can indicate the impact of intangible assets on firm value. Tobin's Q serves as a forward-looking proxy for firm value, making it well-suited to assess how markets value intangible assets such as innovation inputs and outputs. My specification of the model for patent sales and patent acquisitions are as follows:

$$\begin{aligned} \log(Q_{i,t}) = & \beta_1 \text{Climate Sold}_{i,t} + \beta_2 \text{Non-Climate Sold}_{i,t} \\ & + \beta_3 \left(\frac{\text{Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) + \beta_4 \left(\frac{\text{Non-Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) \\ & + \beta_5 \left(\frac{\text{R\&D Stock}_{i,t}}{\text{Total Assets}_{i,t}} \right) + \beta' X'_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \quad (3.1)$$

$$\begin{aligned} \log(Q_{i,t}) = & \beta_1 \text{Climate Bought}_{i,t} + \beta_2 \text{Non-Climate Bought}_{i,t} \\ & + \beta_3 \left(\frac{\text{Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) + \beta_4 \left(\frac{\text{Non-Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) \\ & + \beta_5 \left(\frac{\text{R\&D Stock}_{i,t}}{\text{Total Assets}_{i,t}} \right) + \beta' X'_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \quad (3.2)$$

Equation 3.1 and Equation 3.2 respectively present the empirical models used to evaluate the impact of climate patent sales and climate patent acquisitions on market value. In both versions, the dependent variable is the natural logarithm transformation of Tobin's Q as the measure of the end-of-year market value. On the right-hand side, I

¹⁰[Griliches \(1981\)](#) developed this methodology to estimate how the market values intangible assets in the form of R&D. [Hall et al. \(2005\)](#) used this methodology to estimate how markets value patents and patent citations. [Dechezleprêtre et al. \(2021\)](#) used this methodology to estimate how markets value clean and dirty climate patents.

use the real values of my innovation measures instead of their logarithmic transformation. This choice allows for more variation in my innovation variables and works well in a setting where only around 15% (3,911 firm years involve a climate patent sale or acquisition) of the observations have a climate patent transaction.¹¹

The main independent variable is the number of climate patents sold in Equation 3.1 and the number of climate patents bought in Equation 3.2. I do not scale these variables because this paper looks to study the within-firm variation in firm value that is produced from the number of climate patents transacted. The year (λ_t) and firm fixed effects (α_i) with firm-level controls ensure this interpretation.

I also control for non-climate patent sales and patent acquisitions. This helps distinguish climate patent-specific transaction effects. These variables also help control for firms that excessively indulge in patent transactions as a business strategy (Zhang, 2024) and patent sales that arise from financial distress. I also control for the conventional innovation measures that could influence market value from Hall et al. (2005). These variables are defined as follows:

$$\text{R\&D Stock}_{i,t} = \text{R\&D Expenses}_{i,t} + 0.85 \cdot \text{R\&D Stock}_{i,t-1} \quad (3.3)$$

$$\text{Climate Stock}_{i,t} = \text{Climate Patents Granted}_{i,t} + 0.85 \cdot \text{Climate Stock}_{i,t-1} \quad (3.4)$$

$$\text{Non-Climate Stock}_{i,t} = \text{Non-Climate Patents Granted}_{i,t} + 0.85 \cdot \text{Non-Climate Stock}_{i,t-1} \quad (3.5)$$

The stock transformation of these variables reduces the variability effects of R&D expense and patent grants from year to year. They also capture the idea that these innovation inputs and outputs contribute to value over time and gradually become obsolete. In Equation 3.3, R&D stock for firm i , in year t is the firm's current R&D expense plus a 15% depreciation of its lagged R&D stock. In Equation 3.4, the climate patent stock of firm i in year t is its year t amount of granted climate patents plus a 15% depreciation of its lagged climate patent stock. In Equation 3.5 the non-climate patent stock of firm i in

¹¹Dechezleprêtre et al. (2021) also use the real value instead of a logarithmic transformation of the innovation variables.

year t is its year t amount of non-climate patents granted plus a 15% depreciation of its lagged non-climate patent stock. The original stock value is simply a 10% depreciation of the original variable (R&D expense or patent grant in year zero), assuming a 5% growth rate and a 15% depreciation value following [Bloom et al. \(2013\)](#). In my empirical models, R&D stock is scaled by total assets and the two patent stock variables are scaled by the firm's R&D stock.¹²

$X'_{i,t}$ represents a set of control variables that are described and defined in Table 3.8.1 of the Appendix. They include a set of profitability variables that could impact Tobin's Q in the form of change in earnings per share, sales growth, and ROA. A set of capital structure-related variables control for the impact investment opportunities and financial constraints may have on Tobin's Q . This includes capital expenditure and leverage variables. I also control for structural differences between firms by including firm size and firm age control variables. All empirical models also include a one-year lagged Tobin's Q control variable that helps control for pre-existing valuations and limits problems of reverse causality.

For the sake of consistency with the original methodology, I also study scaled patent transaction variables. As stated by [Hall et al. \(2005\)](#), theory does not provide insights on which weighting variables to use for the intangible assets (patent sale and acquisition in my case). Therefore, I rely on economic intuition for the scaled versions of my patent transaction variables. I choose to scale patent sale variables by the patent stock variables. This measures climate patent sale intensity for my main independent variable of interest. Patent acquisition variables are scaled by the total asset adjusted R&D stock variable (i.e. R&D stock scaled in Table 3.8.1 of the Appendix). This measures the importance of external climate activity relative to the firm's internal innovation capacity for our main buying variable of interest. A high value suggests a strategic shift toward climate innovation as patent acquisitions are followed by a period of high R&D expense and investments ([Bowen, 2016](#)). This specification of my empirical model is stated in Equations 3.6 and 3.7. Going forward, the scaled patent transaction variables will be

¹²Contrary to the empirical model in [Hall et al. \(2005\)](#) and [Dechezleprêtre et al. \(2021\)](#) I do not include patent citation variables in my study. This choice is driven by my paper's focus on the impact of climate patent transactions rather than the scientific value of patents produced.

called Fraction of climate patents sold, Fraction of non-climate patents sold, Fraction of climate patents bought, and Fraction of non-climate patents bought.

$$\begin{aligned}\log(Q_{i,t}) = & \beta_1 \left(\frac{\text{Climate sold}_{i,t}}{\text{Climate Stock}_{i,t}} \right) + \beta_2 \left(\frac{\text{Non-Climate Sold}_{i,t}}{\text{Non-Climate Stock}_{i,t}} \right) \\ & + \beta_3 \left(\frac{\text{Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) + \beta_4 \left(\frac{\text{Non-Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) \\ & + \beta_5 \left(\frac{\text{R\&D Stock}_{i,t}}{\text{Total Assets}_{i,t}} \right) + \beta' X'_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}\end{aligned}\tag{3.6}$$

$$\begin{aligned}\log(Q_{i,t}) = & \beta_1 \frac{\text{Climate Bought}_{i,t}}{(\text{R\&D Stock/Total Assets})_{i,t}} + \beta_2 \frac{\text{Non-Climate Bought}_{i,t}}{(\text{R\&D Stock/Total Assets})_{i,t}} \\ & + \beta_3 \left(\frac{\text{Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) + \beta_4 \left(\frac{\text{Non-Climate Stock}_{i,t}}{\text{R\&D Stock}_{i,t}} \right) \\ & + \beta_5 \left(\frac{\text{R\&D Stock}_{i,t}}{\text{Total Assets}_{i,t}} \right) + \beta' X'_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}\end{aligned}\tag{3.7}$$

The summary statistics of the transformed variables used in my empirical methodology are reported in Panel A, Panel B, and Panel C of Table 3.8.3 in the Appendix.

3.5 Baseline analysis

In this section, I test my hypotheses with the empirical models stated in the previous section (Section 3.4). This section presents the climate patent sale results and then the climate patent acquisition results.

3.5.1 Patent sales

I begin by studying the association between climate patent sales and firm value in Table 3.2. Columns 1 and 2 present the results for the number of climate patents sold measure while Columns 3 and 4 present the results for the fraction of climate stock sold.

All results include firm and year fixed effects with Columns 2 and 4 additionally including control variables mentioned in the methodology section (Section 3.4).

Across both measures of climate patent sales, there is a negative and statistically significant correlation with firm value at the 1% level. In Column 2, an additional climate patent sale is associated with a 2% decrease in Tobin's Q, holding other variables constant. In Column 4, a one standard deviation increase in the fraction of climate patents sold is associated with a 0.66% decline (-0.06×0.11) in firm value. These results suggest that firms that sell their climate patents are penalized by markets. As stated in hypothesis 2.A, this can be due to firms signalling a low commitment to the climate transition and being penalized for abandoning important real options which can lead to a loss in the equity premium (Ľuboř Pástor et al., 2022; Kwon et al., 2024).

Non-climate patent sales' association with firm value are statistically insignificant for the raw number measure (Columns 1 and 2) but positive and statistically significant for the fraction of non-climate patent stock measure (Columns 3 and 4). The positive effect (Columns 3 and 4) is consistent with the literature which shows that the market for technologies allows mutually beneficial transfers of technologies. This is because such transactions allow selling firms to earn revenue on technologies that they do not intend to use and remain focused on their core technologies (Akcigit et al., 2016; Brav et al., 2018; Zhang, 2024). The insignificant results for non-climate patent sales in Columns 1 and 2 suggest a mixture of positively and negatively viewed sales. The latter can occur in periods of bankruptcy where selling firms are forced to sell their important but collateralized patents by creditors (Ma et al., 2022). These results further validate the negative impact of climate patent sales.

The innovation input and output control variables are consistent across the different Columns. Firms with high R&D input have a consistent and statistically significant positive association with firm value as corroborated by the previous literature (Griliches, 1981; Hall et al., 2005; Dechezleprêtre et al., 2021). The insignificant association between climate and non-climate patent stock to firm value suggests that patent output is not necessarily positively valued. Importantly, it also indicates that climate patent-producing firms do not necessarily observe better valuation as demonstrated by Andriosopoulos et al. (2024) and Leippold and Yu (2024). The patent stock insignificance indicates that the

content (i.e. scientific value measured through patent citations) and implementation of new technologies may matter more to firm value. Variation in the number of observations when firm controls are added is due to missing out of sample lagged Tobin's Q values used as control variables.

In Table 3.3, I further the analysis by looking at how climate patent sales are associated with the one-year forward firm value. The results are consistent with the findings in Table 3.2 which demonstrates a persistent negative valuation following climate patent divestment. However, in Column 2 of Table 3.3 there is a decrease in statistical significance from the 1% level to the 10% level. This can indicate that the immediate decrease in market value observed wears out over time. Factors such as market optimism about the firm's new technological direction, the production of new climate technologies, or focused alignment on the firm's core technologies can explain this mitigation.

3.5.2 Patent acquisitions

Table 3.4 presents the correlation between climate patent acquisitions and firm value. In Columns 1 and 2, the number of climate patents acquired is statistically insignificant which indicates that climate patent acquisitions do not have an association with firm value. In Columns 3 and 4, where the R&D stock scaled measure of patent acquisitions is used, we can see a negative and statistically significant association at the 5% level without firm control variables (Column 3). This relationship is statistically significant at the 1% level with firm control variables (Column 4). Statistical significance with the scaled measure indicates uncertain implementation prospects or deviation from core technologies given the relatively weak research capabilities of the firm.

In Table 3.5, I look at the correlation between patent acquisition and one-year forward Tobin's Q. Here, the association between climate patent acquisition and firm value becomes positive and statistically significant at the 1% level across all the different regression specifications. Column 2 indicates that an additional climate patent acquisition is associated with a 0.13% increase in Tobin's Q, holding other variables constant. The lower economic value in terms of impact on firm value can be explained by patent acquisitions requiring time to be evaluated by investors. The value from acquired patent

depends on technology implementation resources, know-how, and future patent success based on the original acquisition (Bowen, 2016). As such, we can expect positive reactions due to initial climate patent acquisitions to increase with time.

Table 3.5 also shows that the acquisition of non-climate patents has an economically small but statistically significant negative association with firm value across all specifications. The contrast to the acquisition of climate patent result further supports hypothesis 2.B. and its prediction of a positive relationship between climate patent acquisition and firm value. This is because the contrasting results suggest that climate patent acquisitions signal clear strategic value by showing engagement towards climate goals. Therefore, using climate patents as options in a more pro-climate business environment is valued. For non-climate patent acquisitions, we instead have a potential signal of dispersion from the firm's core technologies. The benefits from non-climate patent acquisitions may require even more time until it is reflected in the firm value. Substantial investments and costs may be necessary to put forward the benefits of such acquisitions. In the case of climate patent acquisitions, its benefits reside in its signalling value, future option value, and perhaps less uncertain implementation.

Table 3.2: Climate patents sales and firm value

This Table reports the regression where the dependent variable is the natural logarithmic transformation of Tobin's Q and the main independent variables are measures of the amount of climate patents sold. Columns 1 and 2 use the raw number of climate patents sold and Columns 3 and 4 use the number of climate patents sold scaled by the stock of climate patents (fraction of climate patents sold). Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included in Columns 2 and 4. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Sold	-0.02*** (0.005)	-0.02*** (0.004)		
Non-Clim. Sold $\times$ 100	0.0002 (0.02)	0.01 (0.02)		
Fraction Clim. Sold			-0.1*** (0.03)	-0.06*** (0.02)
Fraction Non-Clim. Sold			0.14*** (0.03)	0.05*** (0.02)
Clim. Stock Scaled	0.02 (0.12)	0.1 (0.08)	0.03 (0.12)	0.1 (0.08)
Non-Clim. Stock Scaled	-0.001 (0.01)	-0.01 (0.01)	0.003 (0.14)	-0.01 (0.01)
R&D Stock Scaled	0.14*** (0.01)	0.06*** (0.01)	0.14*** (0.01)	0.06*** (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	25,336	24,588	25,336	24,588
Adjusted R-squared	0.655	0.738	0.656	0.738

Table 3.3: Climate patent sales and future firm value

This Table reports the regression where the dependent variable is the one-year forward natural logarithmic transformation of Tobin's Q and the main independent variables are measures of the amount of climate patents sold. Columns 1 and 2 use the raw number of climate patents sold and Columns 3 and 4 use the number of climate patents sold scaled by the stock of climate patents (fraction of climate patents sold). Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included in Columns 2 and 4. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Sold	-0.01*** (0.005)	-0.007* (0.004)		
Non-Clim. Sold	-0.0001 (0.0002)	-0.0001 (0.0001)		
Fraction Clim. Sold			-0.09*** (0.03)	-0.07*** (0.023)
Fraction Non-Clim. Sold			0.11*** (0.03)	0.06*** (0.02)
Clim. Stock Scaled	0.08 (0.1)	0.09 (0.07)	0.09 (0.11)	0.09 (0.07)
Non-Clim. Stock Scaled	-0.006 (0.01)	-0.01 (0.01)	-0.002 (0.015)	-0.008 (0.01)
R&D Stock Scaled	0.12*** (0.01)	0.04*** (0.012)	0.12*** (0.013)	0.04*** (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	24,471	24,471	24,471	24,471
Adjusted R-squared	0.661	0.72	0.662	0.719

Table 3.4: Climate patent acquisitions and firm value

This Table reports the regression where the dependent variable is the natural logarithmic transformation of Tobin's Q and the main independent variables are measures of climate patents acquired. Columns 1 and 2 use the raw number of climate patents bought and Columns 3 and 4 use the number of climate patents bought divided by the scaled R&D stock (fraction of climate patents acquired). Innovation input and output controls are included across all regression models (non-climate patents bought, fraction of non-climate patents bought, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). The fraction of non-climate patents bought coefficients are multiplied by 1,000 for readability. Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included in Columns 2 and 4. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Bought	0.0003 (0.0004)	0.0003 (0.0005)		
Non-Clim. Bought	-0.0002*** (0.00004)	-0.0001*** (0.0001)		
Fraction Clim. Bought			-0.0003** (0.0001)	-0.0004*** (0.0001)
Fraction Non-Clim. Bought $\times$ 1,000			0.0002 (0.0005)	0.0002 (0.0004)
Clim. Stock Scaled	0.02 (0.12)	0.09 (0.08)	0.02 (0.12)	0.1 (0.08)
Non-Clim. Stock Scaled	-0.002 (0.014)	-0.008 (0.01)	-0.002 (0.14)	-0.01 (0.01)
R&D Stock Scaled	0.14*** (0.013)	0.06*** (0.01)	0.14*** (0.13)	0.06*** (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	25,336	24,588	25,336	24,588
Adjusted R-squared	0.655	0.738	0.655	0.738

Table 3.5: Climate patent acquisitions and future firm value

This Table reports the regression where the dependent variable is the one-year forward natural logarithmic transformation of Tobin's Q and the main independent variables are measures of climate patents acquired. Columns 1 and 2 use the raw number of climate patents bought and Columns 3 and 4 use the number of climate patents bought divided by the scaled R&D stock (fraction of climate patents acquired). Innovation input and output controls are included across all regression models (non-climate patents bought, fraction of non-climate patents bought, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included in Columns 2 and 4. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Bought	0.0012*** (0.0005)	0.0013*** (0.0004)		
Non-Clim. Bought	-0.0002*** (0.00004)	-0.0001*** (0.00003)		
Fraction Clim. Bought			0.0005*** (0.0001)	0.0005*** (0.0001)
Fraction Non-Clim. Bought			-0.00006*** (0.00002)	-0.00004*** (0.00002)
Clim. Stock Scaled	0.08 (0.1)	0.09 (0.07)	0.08 (0.1)	0.09 (0.07)
Non-Clim. Stock Scaled	-0.06 (0.015)	-0.01 (0.01)	-0.005 (0.015)	-0.01 (0.01)
R&D Stock Scaled	0.12*** (0.013)	0.04*** (0.01)	0.12*** (0.013)	0.04*** (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	24,471	24,471	24,471	24,471
Adjusted R-squared	0.661	0.719	0.661	0.72

3.6 Robustness

In this section, I address endogeneity concerns. In the baseline results (Section 3.5) I account for reverse causality by controlling for a lagged firm value variable. Nonetheless, endogeneity through omitted variable bias and selection bias remains a problem. I tackle these endogeneity concerns by using a more robust sample of firms, introducing a mediating variable, using propensity score matching, and using an instrumental variable approach.

3.6.1 Bankruptcy and patent litigation

To reduce the risk of omitted variable bias, I restrict my sample to a set of firms that do not experience bankruptcy between 2000 and 2020. I also remove litigated climate patents from the climate patent transaction variables. [Ma et al. \(2022\)](#) show that under a bankruptcy procedure, innovative firms are forced to sell their more important patents which tend to be used as collateral. This can mean that firms under financial distress are simultaneously obliged to sell their climate patents and face negative market valuation due to financial troubles. Moreover, [Galasso et al. \(2013\)](#) show that patent trades reduce the risk of patent litigation. Excluding transactions of litigated climate patents shows that the results are not simply capturing legal resolution effects or litigation-related uncertainty. Together, these exclusions strengthen the identification of climate patent transactions as strategic choices rather than reactive measures driven by financial or legal distress.

I use the Florida-UCLA-LoPucki database to exclude all companies that have filed for a chapter 7 or chapter 11 bankruptcy procedure between 1980 and 2023.¹³ This database covers large firm bankruptcies, that report assets of over \$100 million in 1980 dollars and around \$355 million in 2022 dollars. This accounts for around two-thirds of my panel dataset. I exclude 86 firms and 1,212 firm-year observations that file for a bankruptcy procedure in my sample. These firms are responsible for 8% (6,614/83,056) of the climate patents granted, 19% (2,189/11,537) of all climate patents sold, and 3% (299/10,585) of

¹³The data can be found here: <https://lopucki.law.ufl.edu/index.php>

all climate patents acquired. Around 5% (1,212/25,400) of bankruptcy-concerned firm-year observations in my sample are disproportionately responsible for 20% of climate patent sales.

The patent litigation dataset from the USPTO reports patent level district court litigation.¹⁴ I exclude litigated climate-transacted patents that appear in this USPTO dataset. This reduces the climate patents sold in my sample by an additional 150 patents and the climate patents acquired by 311 patents.¹⁵

Table 3.6 reports the results for climate patent sales using the end-of-year firm value in Columns 1 and 2 and the one-year forward end-of-year firm value in Columns 3 and 4. In Columns 1 and 2, the coefficients report the same economic decrease in firm value and statistical significance as the baseline results. This association continues to be observed with the one-year forward measure of firm value (Columns 3 and 4). The higher statistical significance for the climate patent sale scaled by the climate patent stock measure (Column 4) compared to the raw count of the amount of climate patents sold (Column 3) suggests that the relative amount of climate patents sold has a lasting impact on firm value. Firms that divest a higher fraction of their climate patents send a stronger signal of climate disengagement and loss of options in case of regulation implementation, thereby leading to a lasting impact on firm value. Removing financially troubled but important climate patent contributors from my sample does not change the original interpretation of the baseline results.

Next, in Table 3.7 I report the results for climate patent acquisitions using the end-of-year firm value in Columns 1 and 2 and the one-year forward end-of-year firm value in Columns 3 and 4. In Columns 1 and 2, the statistically insignificant association between climate patent acquisitions and Tobin's Q persists from the baseline result. The

¹⁴The data can be found here: <https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-litigation-docket-reports-data>

¹⁵In an extreme scenario where I remove all firms that transact at least one litigated patent, I drop 167 unique firms from my sample which account for 2,515 firm years. These firms are responsible for 44,007 climate patents, which accounts for around 53% of all climate patents granted in my sample. They are also responsible for around 49% (541,404/1,109,392) of non-climate patents, 54% (6224/11,537) of climate patent sales, and 50% (5,241/10,585) of climate patent acquisitions. In this extreme version, the climate patents sold variable has the same coefficient and a statistical significance at the 5% level at the very least. The climate patents bought variables struggle a bit more with significance thresholds.

positive and statistically significant relationship between climate patent acquisitions and the one-year forward Tobin's Q also persists in Column 3. This is not the case for the R&D stock scaled version of climate patent acquisition in Column 4. This suggests that acquiring climate technologies signals a forward-looking strategy or responsiveness to future regulatory changes, which investors reward with a lag. However, once acquisition activity is scaled by normalized R&D stock (Column 4), the signal becomes noisier. This may reflect instances where climate patent acquisitions represent an unusual or potentially inefficient allocation of resources given previous R&D activity. In such cases, markets may not interpret these acquisitions as credible or as likely to be successfully developed and commercialized.¹⁶

By removing firms and patents involved in bankruptcies or litigation from the analysis, I focus on entities whose climate patent sales and acquisitions are more plausibly driven by strategic considerations rather than restructuring, liquidation, or litigation processes. This restriction helps isolate the relationship between climate patent transactions and firm value under normal operating conditions, thereby strengthening the causal interpretation of the empirical findings. In summary, I find results that are consistent with the baseline results.

¹⁶I rerun this regression with subsets of firm exclusions. The initial correlation reported in Table 3.5 holds when only the firms that file for bankruptcy are excluded from the sample (positive and statistically significant effect for both climate acquisition measures). This is not the case when the firms that indulge in litigation-related climate patent transactions are excluded from the sample.

Table 3.6: Climate patent sales excluding litigated patents and bankruptcies
This Table reports the regression for the sample where the set of firms used have not been involved in bankruptcy filings and litigated climate patent transactions are excluded. The dependent variable is the natural logarithmic transformation of Tobin's Q (Columns 1 and 2) or the one-year forward natural logarithmic transformation of Tobin's Q (Columns 3 and 4). The main independent variables are measures of the amount of climate patents sold. Columns 1 and 3 use the raw number of climate patents sold and Columns 2 and 4 use the number of climate patents sold scaled by the stock of climate patents (fraction of climate patents sold). Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Tobin' Q		Future Tobin's Q	
	(1)	(2)	(3)	(4)
Clim. Sold	-0.016*** (0.004)		-0.008* (0.005)	
Non-Clim. Sold	-0.00002 (0.0002)		-0.0001 (0.0002)	
Fraction Clim. Sold		-0.06*** (0.03)		-0.09*** (0.03)
Fraction Non-Clim. Sold		0.05*** (0.02)		0.07*** (0.02)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	23,342	23,342	23,262	23,262
Adjusted R-squared	0.74	0.74	0.72	0.72

Table 3.7: Climate patent acquisitions excluding litigated patents and bankruptcies
This Table reports the regression for the sample where the set of firms used have not been involved in bankruptcy filings and litigated climate patent transactions are excluded. The dependent variable is the natural logarithmic transformation of Tobin's Q (Columns 1 and 2) or the one-year forward natural logarithmic transformation of Tobin's Q (Columns 3 and 4). The main independent variables are measures of the amount of climate patents bought. Columns 1 and 3 use the raw number of climate patents bought and Columns 2 and 4 use the number of climate patents bought divided by the scaled stock of R&D (fraction of climate patents acquired). Innovation input and output controls are included across all regression models (non-climate patents bought, fraction of non-climate patents bought, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Tobin' Q		Future Tobin's Q	
	(1)	(2)	(3)	(4)
Clim. Bought	0.0004 (0.0004)		0.001*** (0.0004)	
Non-Clim. Bought	-0.0001*** (0.00004)		-0.0002*** (0.00003)	
Fraction Clim. Bought		-0.0003 (0.0003)		-0.000002 (0.000003)
Fraction Non-Clim. Bought		0.00004 (0.00002)		-0.00004*** (0.00002)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	23,342	23,342	23,262	23,342
Adjusted R-squared	0.74	0.74	0.72	0.72

3.6.2 Channel of influence

I also use firms' climate-related discourse to tackle endogeneity. Specifically, I interact the climate patent sale and acquisition variables with a firm-year level measure of climate exposure in earnings calls developed by [Sautner et al. \(2023\)](#). The measure developed by [Sautner et al. \(2023\)](#) counts the relative frequency of climate-related bigrams in quarterly earnings calls averaged out to a yearly measure. This measure is also broken down into relative frequencies of climate-related opportunities, regulations, and physical risk. In Panel C of Table 3.8.3 in the Appendix, I report the summary statistics of these variables. I use the one plus logarithmic transformation of this value in my analysis following [Sautner et al. \(2023\)](#), however, using the real value of the measure produces similar results. Due to missing values for certain firm-year observations in the variables from [Sautner et al. \(2023\)](#), my sample size is reduced to 16,789 observations.

I report the results in Table 3.8 and Table 3.9. I focus on firm value at the end of year t because firms facing climate scrutiny are likely to exhibit an immediate market response to the announcement of climate patent transactions. Each column uses a different variable for climate exposure ranging from overall climate exposure, opportunity-related exposure, regulatory exposure, and physical exposure.

Table 3.8, shows that the negative association between climate patent sales and firm value deepens when the selling firm has a higher level of climate exposure. This effect is driven by firms that sell their climate patents when they are associated with climate-related opportunities in their business (Column 2). Column 3 shows a negative but statistically insignificant interaction coefficient with regulatory exposure. Factors such as long-term innovation implementation versus near-term regulatory requirements can explain the insignificance here. In Column 4, we have a statistically significant and positive interaction between climate patent sales and physical climate exposure. This result implies that firms facing risks from physical climate events may be rewarded by the market for divesting climate patents. One potential explanation is that investors may perceive these firms as reallocating resources toward more immediate adaptation strategies rather than long-term mitigation strategies.

Table 3.9 does not show an amplification of the positive association between climate

patent acquisitions and firm value when buying firms discuss climate topics in conference calls. This finding also persists when I use future firm value in unreported results. This outcome likely reflects the uncertainty and long-term horizon involved in realizing value from acquired climate technologies, even for firms under immediate climate-related scrutiny. Nonetheless, Column 4 of Table 3.9 indicates a positive interaction between climate patent acquisitions and physical climate exposure that is statistically significant at the 10% level. This suggests that firms more exposed to tangible climate risks may benefit slightly in market valuation when acquiring climate technologies.

In all, climate discourse amplifies the market's negative interpretation of climate patent sales but does not meaningfully affect the market's reaction to climate patent acquisitions. These results demonstrate that the observed negative association between sales and firm value is not only driven by endogenous bias. The effect persists among firms more engaged in climate discourse, where such transactions are more salient and scrutinized. This is not the case for patent acquisitions. This may not only imply an endogenously driven climate acquisition effect on firm value because for firms with significant climate exposure, the real value derived from deploying these technologies may matter more than their potential option value. As a result, climate patent acquisitions may not serve as a sufficiently strong signal of future value creation unless accompanied by credible commitments to implementation. Therefore, the positive association could be obtained over a longer time frame, once implementation and development of the climate technologies acquired have been demonstrated.

Table 3.8: Climate patent sales and climate exposure

This Table presents how climate change exposure ($\log(1+\text{variable})$ transformation) interacted with the number of climate patent sales impacts end of year t Tobin's Q (dependent variable). Columns 1 to 4 respectively use the following exposure variables from [Sautner et al. \(2023\)](#): overall climate exposure, opportunities related to climate change, regulatory exposure, and physical exposure. Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q , firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Sold $\times$ Exposure	-2.57** (1.31)	-7** (2.8)	-16.7 (17)	18.93*** (7.02)
Clim. Sold	-0.01** (0.004)	-0.01** (0.004)	-0.01*** (0.001)	-0.01*** (0.001)
Climate Exposure	3.94** (1.97)			
Opportunity Exposure		5.16 (3.13)		
Regulatory Exposure			37.2** (17.27)	
Physical Exposure				12.04 (32.95)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,506	16,506	16,506	16,506
Adjusted R-squared	0.741	0.741	0.741	0.741

Table 3.9: Climate patent acquisitions and climate exposure

This Table presents how climate change exposure ($\log(1+\text{variable})$ transformation) interacted with the number of climate patent acquisitions impacts end of year t Tobin's Q (dependent variable). Columns 1 to 4 respectively use the following exposure variables from [Sautner et al. \(2023\)](#): overall climate exposure, opportunities related to climate change, regulatory exposure, and physical exposure. Innovation input and output controls are included across all regression models (non-climate patents bought, fraction of non-climate patents bought, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q , firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Clim. Bought $\times$ Exposure	1.01 (1.36)	3.2 (2.3)	-1.96 (9.59)	25.31* (15.32)
Clim. Bought	-0.005 (0.004)	-0.005 (0.003)	-0.003 (0.003)	-0.003 (0.003)
Climate Exposure	3.54* (1.92)			
Opportunity Exposure		3.89 (3.26)		
Regulatory Exposure			37.09** (17.7)	
Physical Exposure				11.72 (33.95)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,506	16,506	16,506	16,506
Adjusted R-squared	0.741	0.741	0.741	0.741

3.6.3 Propensity score matching

Next, I implement a propensity score analysis to address selection bias and potential confounding. Firms do not sell and acquire climate patents randomly. This decision likely depends on observable firm characteristics such as firm size, profitability, or innovation intensity. Propensity score matching (PSM) allows me to construct a more comparable control group by matching treated firms (those that sold or acquired climate patents) with non-treated firms exhibiting similar characteristics. The PSM approach aims to simulate a quasi-experimental setting in which the only difference between the two groups is the treatment itself.

To implement this, I estimate the propensity score using a logistic regression model where the treatment indicator is regressed on a set of firm-level covariates. I carry out two different propensity score analyses. One, where firms that sell at least one climate patent obtain treatment throughout the sample and all other firms are controls. Another, where firms that buy at least at least one climate patent obtain treatment throughout the sample and all other firms are controls. Matching is performed on a one-to-one nearest-neighbour basis without replacement, using a caliper of 0.01 to restrict poor matches. In Table 3.8.4 of the Appendix, I present the variables used for the matching procedure for climate patent selling firms (Panel A) and climate patent buying firms (Panel B). The Table also shows the difference in means before and after the matching procedure.

In Panel A of Table 3.8.4 climate patent selling firms tend to sell more non-climate patents, produce more climate and non-climate patents, be older, bigger, and have a higher ROA. Whereas firms that do not sell their climate patents have a higher value (Tobin's Q) and sales growth. After the matching procedure, the only difference in covariates remaining is the two-and-a-half-year difference in firm age between the two groups of firms. The tight matching procedure means that only 423 out of the 662 climate patent-selling firms find a match. This reduces the number of climate patents sold from 11,537 to 1,578 in the propensity score matching analysis.

Panel B of Table 3.8.4 shows that climate patent buying firms tend to buy more non-climate patents than firms that do not buy climate patents. Climate patent buying firms also tend to produce fewer patents, invest less in R&D, and have a lower valuation while

being bigger, and more profitable (higher ROA). After the matching procedure, firms that do not buy climate patents have a slightly bigger firm size and firm age. Out of the 956 climate patent buying firms, only 486 are matched. The matched sample only contains 2,269 climate patent acquisitions in comparison to 10,858 in the full sample.

Table 3.10 reports the matched sample results for climate patent selling firms. Selling climate patents continues to be associated with a decrease in Tobin's Q at the 5% significance level using both measures of climate patent sales (i.e. the raw measure in Column 1 and the scaled measure in Column 2). The raw climate patents sale effect on Tobin's Q disappears when I use the one-year forward Tobin's Q measure (Column 3). However, the scaled climate patent sale measure continues to be negative and statistically significant at the 5% level (Column 4). This shows that climate patent sales have a significant and immediate effect on firm value. This effect dissipates in the long-run unless an important fraction of the firm's climate patents are sold. This paper's results concerning climate patent sales hold even when accounting for observable differences between firms that sell their climate patents and firms that do not sell their climate patents.

Table 3.11 reports the matched sample results for climate patent buying firms. The results are consistent with the original analysis. In Columns 1 and 2, both measures of climate patent acquisition display a statistically insignificant association with end-of-year Tobin's Q. This relationship becomes positive and statistically significant at the 5% level when using the one-year forward Tobin's Q measure and the raw value of climate patents bought (Column 3). However, the scaled measure of climate patents acquired continues to produce a statistically insignificant result. This continues to suggest that climate patent acquisition has a positive association with future firm value, however, this effect is dependent on the firm's historical innovation success (i.e. R&D stock).

Table 3.10: Climate patent sale - PSM

This Table reports the results for the propensity score matching sample of firms that sell (treatment group) and firms that do not sell (control group) their climate patents. The dependent variable is the natural logarithmic transformation of Tobin's Q (Columns 1 and 2) or the one-year forward natural logarithmic transformation of Tobin's Q (Columns 3 and 4). The main independent variables are measures of the amount of climate patents sold. Columns 1 and 3 use the raw number of climate patents sold and Columns 2 and 4 use the number of climate patents sold scaled by the stock of climate patents (fraction of climate patents sold). Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Tobin' Q		Future Tobin's Q	
	(1)	(2)	(3)	(4)
Clim. Sold	-0.021** (0.009)		-0.01 (0.01)	
Non-Clim. Sold	-0.002** (0.0009)		-0.002** (0.001)	
Fraction Clim. Sold		-0.07** (0.03)		-0.07** (0.03)
Fraction Non-Clim. Sold		0.1*** (0.03)		0.12*** (0.04)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,164	12,121	12,059	12,059
Adjusted R-squared	0.69	0.72	0.67	0.67

Table 3.11: Climate patent acquisitions - PSM

This Table reports the results for the propensity score matching sample of firms that buy (treatment group) and firms that do not buy (control group) climate patents. The dependent variable is the natural logarithmic transformation of Tobin's Q (Columns 1 and 2) or the one-year forward natural logarithmic transformation of Tobin's Q (Columns 3 and 4). The main independent variables are measures of the amount of climate patents bought. Columns 1 and 3 use the raw number of climate patents bought and Columns 2 and 4 use the number of climate patents bought divided by the scaled stock of R&D (fraction of climate patents acquired). Innovation input and output controls are included across all regression models (non-climate patents bought, fraction of non-climate patents bought, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). The fraction of non-climate patents bought's coefficients are multiplied by 10,000 for readability. Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included across all regression models. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Tobin' Q		Future Tobin's Q	
	(1)	(2)	(3)	(4)
Clim. Bought	-0.002 (0.002)		0.002** (0.001)	
Non-Clim. Bought $\times$ 10,000	-0.9 (2.28)		-0.001** (0.0003)	
Fraction Clim. Bought		0.62 (1)		-0.75 (0.98)
Fraction Non-Clim. Bought		0.00001 0.00003		0.00002 (0.00003)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,604	13,604	13,522	13,522
Adjusted R-squared	0.74	0.74	0.72	0.714

3.6.4 Instrumental variable approach

To further address endogeneity problems that can arise from unobservable variables, I implement an instrumental variable approach. This method aims to isolate exogenous variation in climate patent transactions that arise from exogenous state-level climate policy and the firm’s past exposure to climate technologies. More precisely, I use an interaction variable that is formed from the firm’s headquartered state’s number of climate policies enacted and the firm’s climate patent stock. This variable and the firm control variables are lagged by one year for the first stage regression model. This model includes the same fixed effects as the OLS model presented in Section 3.4. Data for the number of climate policies enacted per state and year are obtained from ClimateXChange.¹⁷

The intuition behind this instrument is that state-level climate policies enacted generate demand for climate technologies. As such, firms that are headquartered in states with more climate policies face a demand shock in the market for climate technologies. The firm’s previous climate patent stock also plays a critical role here since it determines firms’ recourse to the market for climate technologies. The interaction of these two variables captures exogenous variation in the likelihood of a firm engaging in climate patent transactions. This interaction serves as a plausible instrument because it reflects the firm’s exposure to localized policy-driven demand shocks for climate technologies, conditional on its existing innovation capacity. Lagging the interaction variable helps satisfy the exclusion restriction. For example, without the lag, the instrument could directly influence Tobin’s Q if investors immediately adjust firm valuations in response to new climate policies, regardless of any patent transaction activity.

Table 3.12 presents the first-stage regression results for both climate patent sales (Columns 1 and 2) and climate patent acquisitions (Columns 3 and 4) as dependent variables. The lagged instrumental variable’s (IV) coefficients are multiplied by 100 for readability. For the climate patent sale regression models (Columns 1 and 2), the IV is statistically significant at the 1% level with coefficients of 0.6 in both models (Columns 1 and 2). For the climate patent acquisition regression models (Columns 3 and 4), the IV is insignificant, with a coefficient of 0.02 in both models. This suggests that the IV is

¹⁷<https://www.climatepolicydashboard.org/>

more relevant in explaining the variation in climate patent sales than acquisitions. The F-statistics in the first stage regression provide insight into the strength of the instruments. For the climate patent sale regression models, the F-statistic increases from 14.19 to 15.1 after including lagged firm control variables. This indicates that the instruments pass the weak instrument threshold of 10. For the climate patent acquisition regression models, the F-statistics of 1.75 and 1.7 suggest weak instruments. Therefore, I only study the instrumented climate patents sold instance in the second stage.¹⁸

Additional validity tests are provided in the Appendix. Table 3.8.5 supports the exclusion criteria by showing no significant relationship between the instrument and Tobin's Q (main dependent variable) in its logarithmic transformation and natural form. Table 3.8.6 shows that the exclusivity criteria are respected by demonstrating that there is no significant correlation between the instrument and the set of control variables included in the regression models.¹⁹

Table 3.13 reports the two-stage least squares (2SLS) regression model using the predicted values of climate patent sales ($\widehat{\text{Clim. Sold}}$) from the first-stage estimation. The dependent variable is the natural logarithm of Tobin's Q in Columns 1 and 2 and the one-year forward natural logarithm of Tobin's Q in Columns 3 and 4. In Column 1, where firm control variables are excluded, the coefficient of -0.007 with a statistical significance at the 1% level suggests that an exogenous increase in climate patent sales is associated with a decline in firm value. When I include firm control variables to this model in Column 2, this effect becomes more pronounced (-0.06) with a statistical significance at the 5% level. In Columns 3 and 4, where the dependent variable is the one-year forward Tobin's Q, the negative effect persists. In Column 3, the coefficient of -0.004 is statistically significant at the 10% level, while in Column 4 which includes firm control variables the estimate remains negative (-0.004) but becomes statistically insignificant. Overall, these results support the hypothesis that divesting climate patents negatively affects firm value, at

¹⁸I attempt to instrument climate patent acquisitions through other variables such as federal and state R&D tax incentives, climate disasters, innovator location, and local green project financing but they fail the F-statistics test for weak instruments.

¹⁹One caveat concerns the potential correlation between states that adopt stringent climate policies and the types of firms they host. This could imply a non-random geographic allocation of environmentally proactive firms, possibly affecting the exogeneity of the instrument. However, replacing climate policy data with climate disaster data from the NOAA NCEI database produces similar results for climate patent sales.

least in the short term.

Table 3.12: Instrumental approach - First stage regression

This Table presents the first-stage regression results for the climate patent sale (Columns 1 and 2) and climate patent acquisitions (Columns 3 and 4) endogenous variables. The main independent variable is the instrumental variable (IV) which is the interaction between the one-year lagged state climate policies in firm i 's headquarter and the one-year lagged firm climate patent stock. All IV outputs are multiplied by 100 for readability. Firm and innovation control variables are lagged by one year and used in Columns 2 and 4. They are defined in Panel C of Table 3.8.1 in the Appendix. The one-year lagged control variables used in Columns 2 and 4 include Tobin's Q, firm size, firm age, change in EPS, sales growth, ROA, CAPEX, leverage, climate patent stock scaled, non-climate patent stock scaled, and R&D stock scaled. For climate patent sales (Column 2), I include non-climate patent sales as a control variable and for climate patent acquisitions (Column 4), I include non-climate patent acquisitions as a control variable. F-statistics measuring weak instruments are reported. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Clim. Sold		Clim. Bought	
	(1)	(2)	(3)	(4)
$IV_{t-1} \times 100$	0.6*** (0.2)	0.6*** (0.1)	0.02 (0.01)	0.02 (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-Stats	14.19	15.1	1.75	1.7
Observations	25,295	22,945	25,295	22,945
Adjusted R-squared	0.31	0.32	0.18	0.2

Table 3.13: Climate patent sales - 2SLS

This Table reports the results for the second stage regression where the main independent variable is the instrumented climate patents sold variable ($\widehat{Clim.Sold}$). The dependent variable is the natural logarithmic transformation of Tobin's Q (Columns 1 and 2) or the one-year forward natural logarithmic transformation of Tobin's Q (Columns 3 and 4). Innovation input and output controls are included across all regression models (non-climate patents sold, fraction of non-climate patents sold, climate patent stock scaled, non-climate patent stock scaled, R&D stock scaled). Firm control variables (ROA, change in EPS, sales growth, lagged Tobin's Q, firm size, firm age, leverage, capital expenditure) are included in Columns 2 and 4. Variables are defined in Table 3.8.1 in the Appendix. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Tobin' Q		Future Tobin's Q	
	(1)	(2)	(3)	(4)
$\widehat{Clim. Sold}$	-0.007*** (0.003)	-0.06** (0.03)	-0.004* (0.0025)	-0.004 (0.0027)
Non-Clim. Sold $\times$ 1,000	-0.2 (0.2)	-0.2 (0.2)	-0.2 (0.2)	-0.2 (0.2)
Clim. Stock Scaled	0.06 (0.11)	0.08 (0.1)	0.08 (0.1)	0.08 (0.1)
Non-Clim. Stock Scaled	-0.005 (0.01)	-0.01 (0.01)	-0.003 (0.02)	-0.008 (0.01)
R&D Stock Scaled	0.14*** (0.01)	0.07*** (0.01)	0.12*** (0.01)	0.07*** (0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	22,935	22,935	22,107	22,107
Adjusted R-squared	0.68	0.7	0.67	0.68

3.7 Conclusion

This paper provides the first empirical evidence that climate patent transactions transmit distinct signals to financial markets. The negative market reaction to climate patent sales suggests that divesting from climate technologies is interpreted as a withdrawal from future-oriented climate innovation and environmental commitment. Conversely, the positive delayed effect of climate patent acquisitions indicates that markets recognize their potential to create long-term value. This is, however, contingent on its effective implementation which suggests that climate patents are not solely valued on their option value.

These findings highlight the importance of distinguishing between the act of patenting and the strategic use of climate technologies through market transactions. By focusing on patent transactions rather than patent grants this paper provides new evidence on how firms' engagement with climate innovation is perceived by investors. These results call for a reevaluation of how firm-level climate innovation is measured and assessed. They also suggest that the market for technologies plays an important role in shaping the financial implications of the green transition.

This study has both managerial and policy implications. It suggests that markets are anticipating important climate-related transitions that will require the development and deployment of new technologies. Therefore, firms should be cautious about selling climate patents, as it may signal disengagement and harm firm valuation. In contrast, acquiring climate patents, even for future strategic use, can enhance long-term value when implemented effectively. These firm-level implications may unintentionally encourage climate patent hoarding. In this scenario, firms retain climate technologies (in the absence of incentives to transition to clean products and processes) without deploying them which restricts the diffusion of climate-related innovations that are crucial for addressing the global climate crisis. To counteract this risk, policymakers should consider elaborating mechanisms that facilitate the dissemination of critical climate technologies such as patent pools, open innovation frameworks, or targeted incentives to ensure that climate patent-selling firms are rewarded for their contribution to societal utility.

The findings in this paper open new avenues for research on climate patenting. Future research can test whether climate patent transactions indicate signals of firms' climate commitment by measuring their impact on green revenue, carbon emissions, ESG, and more. Further work is also needed to understand the drivers of these transactions. For instance, whether institutional investors through the use of pro-climate shareholder proposals influence firms' decisions to buy or sell climate patents. In addition, replicating this paper's analysis in a European context, where more advanced climate regulations may provide credible exogenous shocks, could help establish a stronger causal relationship between climate patent transactions and firm value.

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3.8 Appendix

3.8.1 Data description and summary statistics

Table 3.8.1: Definition of variables

This Table presents all the data used in this paper. Firm characteristics data are from Compustat, patent data is from the USPTO, and the sources of all other forms of data are mentioned in the Table below. This Table is broken down as follows: Panel A describes the main dependent variable, Panel B describes the innovation variables, Panel C describes the firm characteristics, and Panel D describes all other variables used.

Panel A: Dependent variable	
Variable	Definition
Tobin's Q	Measure of firm value (stock value) following Dechezleprêtre et al. (2021) . This measure is the natural log transformation of: (total assets minus book value of equity plus market value of equity) divided by total assets. The lagged version used as a control variable takes the non-logarithmic form and is winsorized at the 1% level.
Panel B: Innovation variables	
Variable	Definition
Climate patents	Number of climate patents granted by the USPTO to firm i in year t . Climate patents are defined by the "Y02" CPC codes.
Non-Climate patents	Number of patents granted by the USPTO to firm i in year t that are not climate patents.
R&D	R&D expense scaled by the firm i 's total assets. Winsorized at the 1% level.
R&D stock	$R\&D \text{ expense in year } t + 0.85 * R\&D \text{ stock in year } t-1$. The initial R&D stock is the R&D expense in year 0 discounted by 10%, following Bloom et al. (2013) . Winsorized at the 1% level.

R&D stock scaled	(R&D expense in year $t + 0.85 \times$ R&D stock in year $t-1$) scaled by total assets in year t . The initial R&D stock is the R&D expense in year 0 discounted by 10%, following Bloom et al. (2013) . Winsorized at the 1% level.
Patent stock	Patents granted in year $t + 0.85 \times$ Patent stock in year $t-1$. The initial patent stock is the number of patents granted in year 0 discounted by 10%. Climate and non-climate patent stock form two different variables. Winsorized at the 1% level.
Patent stock scaled	Patent stock scaled by R&D stock. Climate and non-climate patent stock scaled form two different variables. Winsorized at the 1% level.
Patents sold	Patents that are initially attributed (at application at least) to firm i in year t and are sold to another firm according to the USPTO patent assignment dataset. The execution and recording year of the patent sale have to be the same, and must not occur before the year of the original patent application filing. Climate and non-climate patent sales form two different variables. Winsorized at the 1% level.
Patents bought	Patents that are bought by firm i in year t from another firm according to the USPTO patent assignment dataset. The execution and recording year of the patent transaction have to be the same, and must not occur before the year of the original patent application filing. Climate and non-climate patents bought form two different variables. Winsorized at the 1% level.
Fraction of patents sold	The number of patents sold by firm i in year t scaled by the raw patent stock of firm i in year t . Fraction of climate and non-climate patents sold form two different variables that are scaled by climate and non-climate patent stock separately. Winsorized at the 1% level.

Fraction of patents bought	The number of patents bought by firm i in year t divided by the total assets scaled R&D stock (R&D stock scaled) of firm i in year t . Fraction of climate and non-climate patents bought form two different variables that are scaled by the same R&D stock scaled value. Winsorized at the 1% level.
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Panel C: Firm characteristics

Variable	Definition
Firm size	$\text{Log}(\text{Sale})$. Winsorized at the 1% level.
Firm age	Current year minus the firm's first appearance on Compustat. Winsorized at the 1% level.
Leverage	Book value of debt (long-term and short-term) divided by total assets. Winsorized at the 1% level.
CAPEX	Capital expenditure scaled by total assets. Winsorized at the 1% level.
Δ EPS	Change in earnings per share. $(\text{EPS}_t \text{ minus } \text{EPS}_{t-1})$ divided by end of year $t-1$ share price. Winsorized at the 1% level.
Sales growth	$(\text{Sales}_t \text{ minus } \text{sales}_{t-1})$ scaled by total assets in year t . Winsorized at the 1% level.
ROA	Return on assets. Profitability measure. Earnings before extraordinary items divided by total asset. Winsorized at the 1% level.

Panel D: Other variables

Variable	Definition
Lagged Climate stock	One of the two variables used for the interacted instrumental variable. The measure is Climate patents granted to firm i in year $t + 0.85 \times \text{Climate patent stock of firm } i \text{ in year } t-1$. The initial Climate patent stock is the climate patents granted in year 0 discounted by 10%. The one year lag of this variable is used.

No. green policies	One of the two variables used for the interacted instrumental variable. The measure is the number of climate related policies enacted in the headquarter of firm i in year t at the U.S. state level. The one year lag of this variable is used. The data is from Climate XChange.
Climate exposure	Relative frequency of climate change words in earnings conference calls constructed by Sautner et al. (2023) . The following transformation is used for this paper's analysis: $\text{Log}(1 + \text{Climate exposure})$.
Opportunity exposure	Relative frequency of climate change opportunities related words in earnings conference calls constructed by Sautner et al. (2023) . The following transformation is used for this paper's analysis: $\text{Log}(1 + \text{Opportunity exposure})$.
Regulatory exposure	Relative frequency of climate change related regulatory shock words in earnings conference calls constructed by Sautner et al. (2023) . The following transformation is used for this paper's analysis: $\text{Log}(1 + \text{Regulatory exposure})$.
Physical exposure	Relative frequency of climate change related physical shock words in earnings conference calls constructed by Sautner et al. (2023) . The following transformation is used for this paper's analysis: $\text{Log}(1 + \text{Physical exposure})$.

Table 3.8.2: Industry breakdown

This Table breaks down the number of firms (Firms), climate patents granted (C. Pat), non-climate patents sold (C. Sold), climate patents bought (C. Bought), non-climate patents sold (NC. Sold), a Bought) in each industry (two-digit SIC code in Column 1) from my sample.

SIC	Industry	Firms	C. Pat	NC. Pat	C. Sold	C
1	Agriculture	3	378	4090	11	5
2	Fishing	1	1	0	0	0
10	Metal Mining	5	62	65	6	2
12	Coal Mining	2	49	84	43	3
13	Oil & Gas	33	1,066	2,474	140	7
14	Nonmetallic Minerals	3	15	166	3	3
15	General Building Contractors	1	2	5	0	0
16	Heavy Construction	9	54	10	19	2
17	Special Trade Contractors	5	0	8	1	1
20	Food Products	28	139	5,754	15	4
21	Tobacco Products	3	51	2,348	8	5
22	Textile Mill Products	4	47	721	2	7
23	Apparel Products	4	4	539	1	3
24	Lumber & Wood	4	68	487	11	5

Table 3.8.2: Continued from previous page

SIC	Industry	Firms	C. Pat	NC. Pat	C. Sold	C
25	Furniture	7	213	6,298	7	1
26	Paper & Allied	18	142	8,285	32	3
27	Printing & Publishing	5	12	430	3	3
28	Chemicals	452	6,443	78,338	955	1
29	Petroleum	15	1,957	7,456	175	1
30	Rubber & Plastics	17	195	14,718	16	2
31	Leather	2	31	85	0	2
32	Stone, Clay, Glass	12	474	3,510	55	4
33	Primary Metals	27	163	2,018	52	4
34	Fabricated Metal Products	33	251	9,903	55	1
35	Machinery & Equipment	183	7,324	146,134	731	9
36	Electrical Equipment	298	19,555	247,386	2,620	2
37	Transportation Equipment	70	21,309	83,279	2,722	6
38	Instruments	142	2,954	76,423	363	5
39	Miscellaneous Manufacturing	16	113	5,157	7	2
40	Railroad Transportation	2	7	24	0	1

Table 3.8.2: *Continued from previous page*

SIC	Industry	Firms	C. Pat	NC. Pat	C. Sold	C
41	Local Transit	2	3	429	1	8
42	Trucking & Warehousing	5	12	1,322	2	7
44	Water Transportation	2	1	9	0	3
45	Air Transportation	5	64	290	6	1
47	Transportation Services	1	3	59	0	0
48	Communications	39	1,539	38,881	176	3
49	Electric, Gas & Sanitary Services	56	330	1,045	46	1
50	Wholesale Trade – Durable Goods	9	18	122	2	1
51	Wholesale Trade – Nondurable Goods	15	18	573	1	1
53	General Merchandise Stores	3	66	2,722	35	3
54	Food Stores	1	0	71	0	1
55	Automotive Dealers	3	9	21	2	0
58	Eating & Drinking Places	4	4	230	1	2
59	Miscellaneous Retail	8	408	16,408	8	2
60	Depository Institutions	12	6	1,357	3	2
61	Non-depository Institutions	4	31	2,046	2	4

Table 3.8.2: Continued from previous page

SIC	Industry	Firms	C. Pat	NC. Pat	C. Sold	C
62	Security & Commodity Brokers	12	24	576	2	1
63	Insurance Carriers	12	12	465	0	1
64	Insurance Agents	2	1	16	0	3
65	Real Estate	3	3	9	4	2
67	Holding & Other Investment Offices	28	514	6,867	41	3
70	Hotels & Lodging	1	0	0	0	1
73	Business Services	147	6,863	255,242	1,587	1
75	Auto Repair	1	1	80	0	0
78	Motion Pictures	1	3	250	0	0
79	Amusement & Recreation	4	7	173	0	7
80	Health Services	11	37	518	0	3
81	Legal Services	1	4	15	2	2
82	Educational Services	4	5	56	5	2
87	Engineering & Management	32	89	1,148	31	8
99	Non-classifiable Establishments	10	9,902	49,925	1,527	5
Total		1,842	83,056	1,109,392	11,537	1

Figure 3.8.1: Climate patent distribution
This Figure presents the distribution of climate patents by CPC subclass. The number of climate patents presented by CPC subclass category.

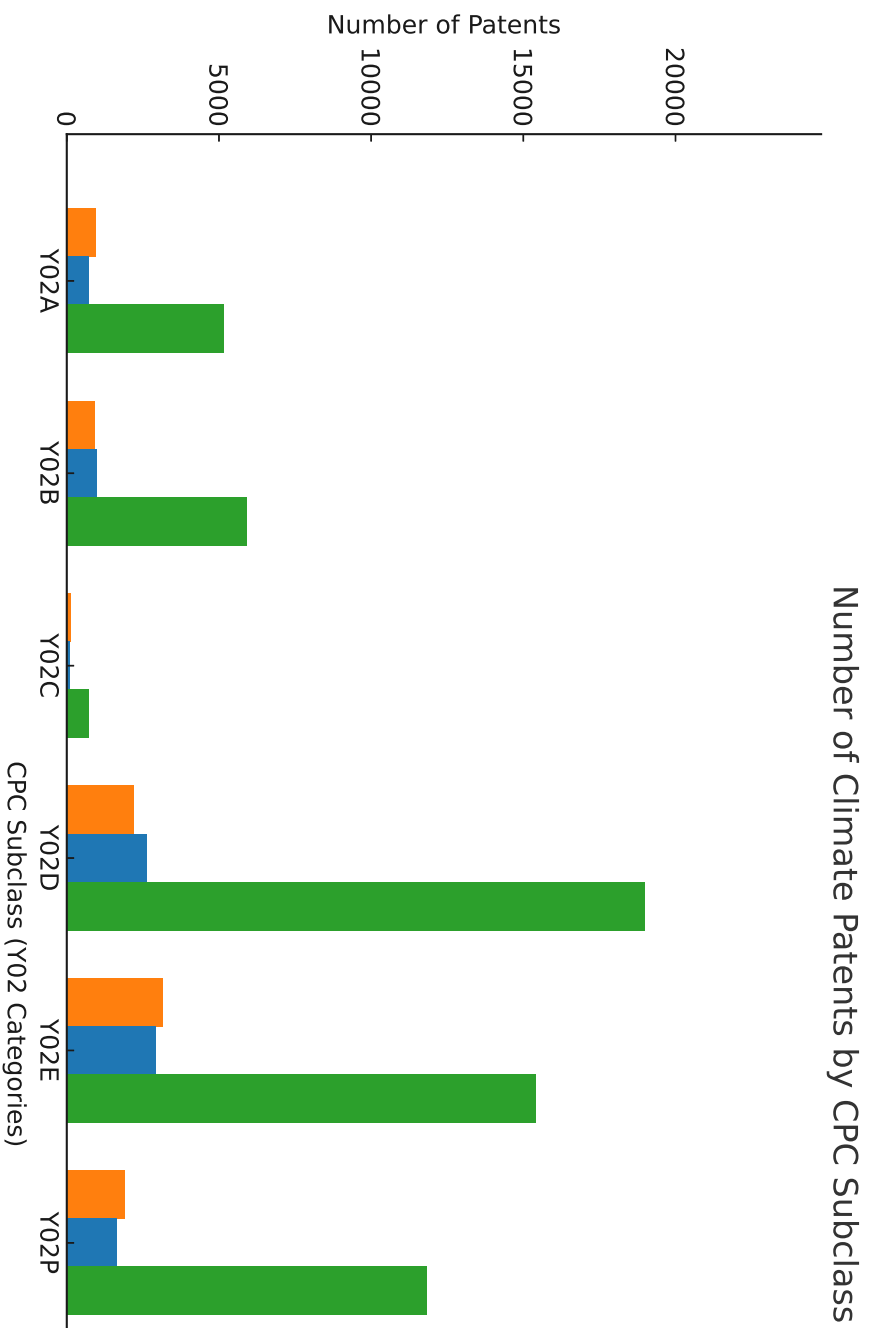


Figure 3.8.2: Fraction of climate patents granted

This Figure presents the average yearly amount of climate patents granted as a fraction of all granted patents in my sample.

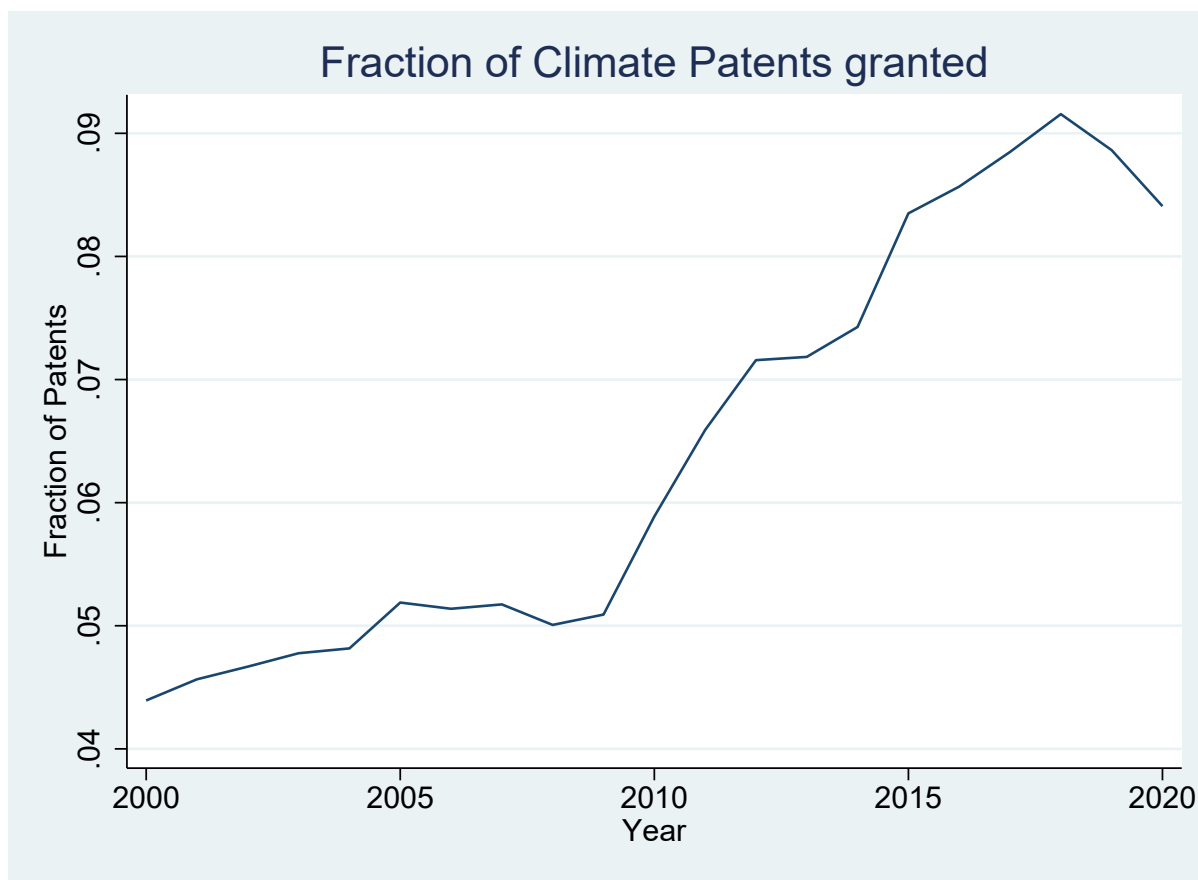


Figure 3.8.3: Average climate patents bought and sold

This Figure presents the average amount of climate patents bought (blue) and sold (red) each year in my sample.

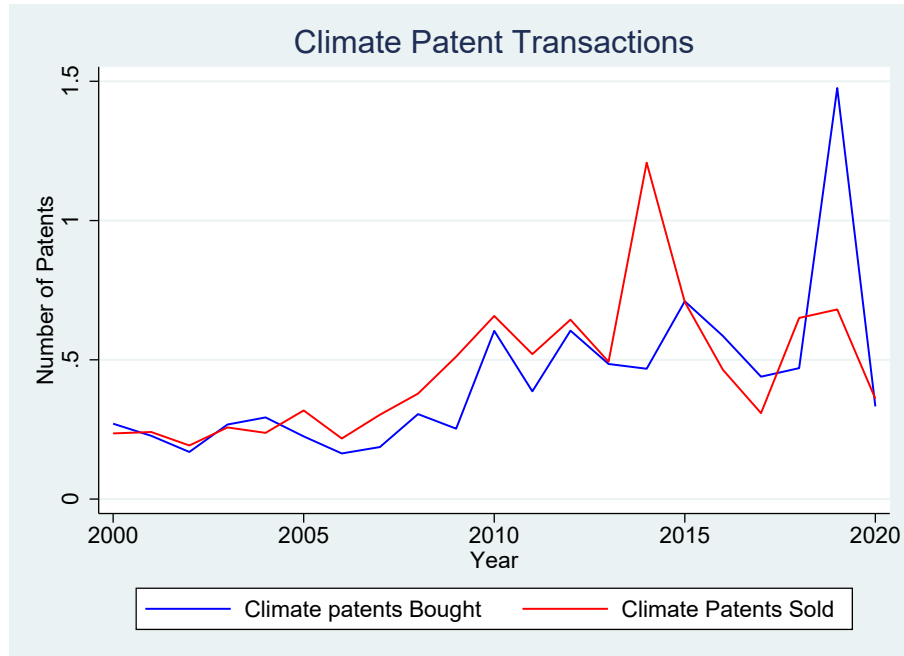


Figure 3.8.4: Average amount of non-climate patent transactions

This Figure presents the average amount of non-climate patents bought (blue) and sold (red) each year in my sample.

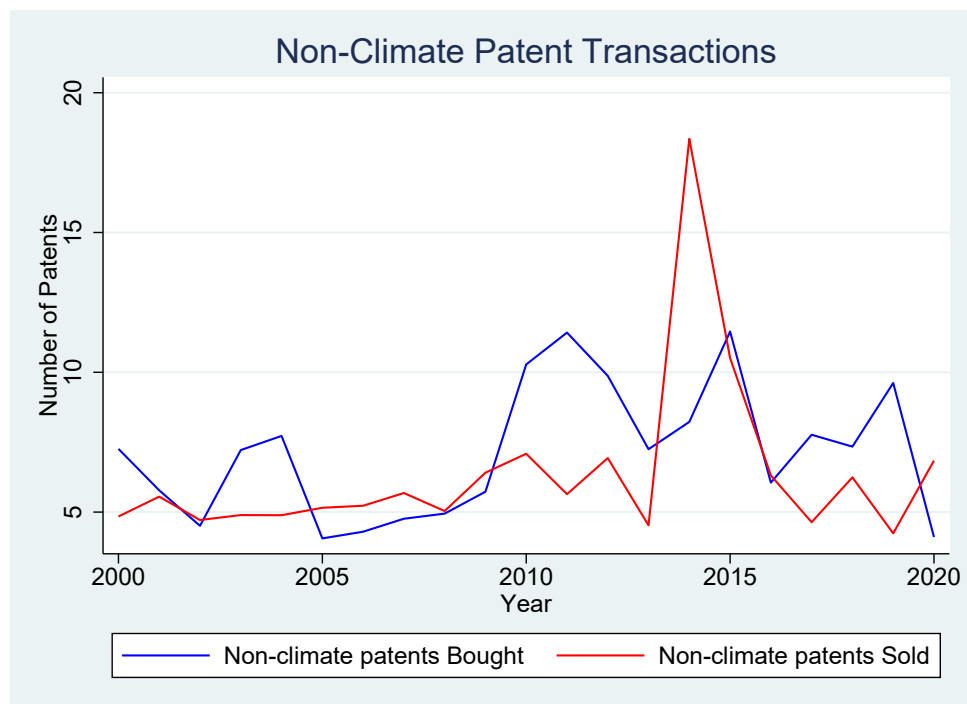


Figure 3.8.5: Fraction of climate patents sold

This Figure presents the average amount of climate patents sold as a fraction of climate patent stock each year from my sample.

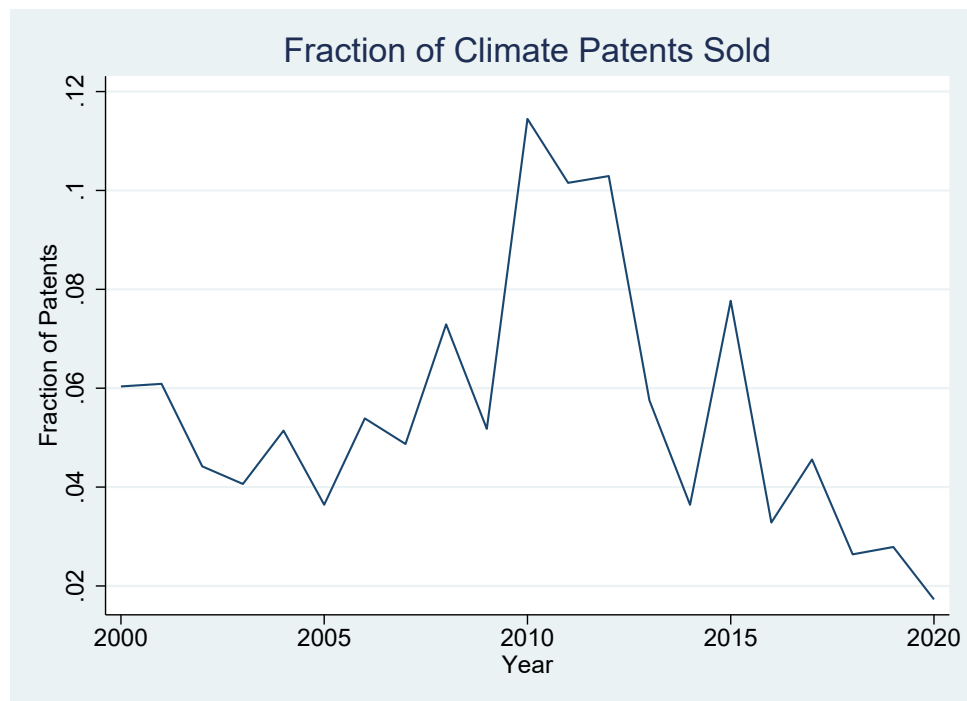


Table 3.8.3: Summary statistics of transformed and other variables

This Table respectively reports the first quartile, median, mean, third quartile, standard deviation, and number of firm-year observations for a set of the transformed variables (Panels A, B and C) and relative climate change references in earnings calls from [Sautner et al. \(2023\)](#) (Panel D) used in this study. The climate change exposure coefficients in panel D are multiplied by 1,000 and winsorized at the 1% level. Panel D data also reports the real values of the variables rather than their logarithmic transformation as used in the analysis and reported in Table 3.8.1 of the Appendix. Panels A, B, and C data are described and defined in Panels A and B of Table 3.8.1 in the Appendix. Panel D data is described in Panel D of Table 3.8.1 in the Appendix.

Panel A: Climate patents						
	Q1	Median	Mean	Q3	SD	Obs
Patent stock Scaled	0	0	0.04	0.01	0.14	25,400
Fraction sold	0	0	0.02	0	0.11	25,400
Fraction bought	0	0	0.001	0	0.005	25,400
Panel B: Non-climate patents						
	Q1	Median	Mean	Q3	SD	Obs
Patent stock Scaled	0	0.1	0.39	0.33	1.06	25,400
Fraction sold	0	0	0.22	0.12	0.4	25,400
Fraction bought	0	0	35.24	2.98	150.98	25,400
Panel C: Firm variables						
	Q1	Median	Mean	Q3	SD	Obs
Log (Tobin's Q)	0.2	0.51	0.68	0.98	0.71	25,377
R&D stock Scaled	0.01	0.16	0.71	0.59	1.66	25,377
Panel D: Climate change exposure $\times$ 1,000						
	Q1	Median	Mean	Q3	SD	Obs
Climate exposure	0.16	0.4	1.41	1.12	3.19	16,789
Opportunity exposure	0	0	0.45	0.23	1.55	16,789
Regulatory exposure	0	0	0.07	0	0.33	16,789
Physical exposure	0	0	0.02	0	0.15	16,789

3.8.2 Data construction

The USPTO Patent Assignment Dataset reports voluntarily recorded changes to patent ownership. This dataset is based on voluntary patent transaction filings. Recording a transaction is highly incentivised because doing so provides legal protection against patent ownership conflicts. Despite limited real-world proof, in the event of a dispute over ownership, courts can rely on the USPTO Patent Assignment Dataset as authoritative evidence of ownership ([Graham et al., 2015](#)).

The type of transactions recorded include entity (owner) name change, government interest in a patent, licensing agreements, patents used as collateral, mergers, abandonment of claims on a patent (release) and change of assignment. This study focuses on the change of assignment of the patents. I do not use licensing and mergers-related patent ownership data. This is because patent transactions due to mergers will create noise in the firm value effect of patent transactions. Also, ownership change due to mergers and licensing agreements are reputed for being incomplete on the USPTO Patent Assignment Dataset. Previous studies such as [Arqué-Castells and Spulber \(2023\)](#) use datasets from professional vendors for this reason.

Before September 2012, patents were issued to a human inventor and then legally re-assigned to an employer. I exclude these assignments by only studying firm-to-firm transactions. This is done thanks to a dummy variable in the USPTO dataset that indicates if an employee was involved in the transaction.

Once the correct type of transactions (i.e. change of ownership) is selected and employee-related transactions are removed, I proceed by matching the patent acquiring and selling firm names in each filing to Compustat firms by using the firm GVKEY identifier. There are three challenges to consider in carrying out this task.

First, firms can change names and therefore all possible names should be accounted for during the matching process. I deal with this by using the historical list of firm names in the CRSP database and linking them to unique GVKEYs.

Second, firms can carry out patent transactions within their different subsidiaries for tax or other purposes. Firms can also buy or sell patents via subsidiaries. Therefore,

I create corporate trees linking Compustat firms to all their subsidiaries and acquired or merged firms for the active years of the relationship. I do this with the WRDS subsidiary database and the Refinitiv M&A database. In this scenario, a patent transacted by an acquired firm of a Compustat entity is only attributed to the Compustat entity if the patent acquisition occurs the year of or after the acquisition of the firm. All merged, acquired, or subsidiary firms are given the ultimate owner's GVKEY for the years concerned.

Third, the names recorded in the USPTO database are not necessarily the same as the names in the CRSP database. USPTO-recorded firm names may even contain mistakes. Therefore I use a name-matching algorithm that standardizes the firm names in the USPTO dataset and my GVKEY to name linked database. The name standardization algorithm is inspired by [Dyèvre and Seager \(2023\)](#). The matching between the two datasets is based on an initial clean match and then a fuzzy match using the Fuzzy-Wuzzy python package and Levenstein distance score on unmatched patent applications. Levenstein distance scores propose a match based on the similarity between two string variables. Text similarity depends on the amount of character manipulations required to have a match between two string variables. This step is followed by a manual verification of the matches proposed. I remove all matches with a score lower than 40% and manually validate all other matches. The 40% level is taken due to subsidiary firms such as Boeing (cleaned name being BOEINGCO) having Boeing Air Borne Surveillance Enterprise (cleaned name BOEINGAIRBORNESURVEILLANCEENT) as a subsidiary which produces a low matching score. Most valid manual matches occur for Levenstein scores that are superior to 92% (where 100% represents a perfect match).

After matching USPTO entity names to CRSP entity names separately for patent acquisitions and sales, I validate transactions based on dates. All transactions attributed to the ultimate owner are validated. Transactions by subsidiaries and M&A linked firms are only included if they occur between the dates where a relationship exists. This is the starting date of the subsidiary relationship and the effective date of the M&A. I then link patent-level transaction data and remove all instances where the ultimate owner (unique GVKEY) is identical between the buyer and the seller.

An additional concern for the patent transaction data is that firms can update pre-

vious filings with new transactions. This is a problem because identifying the correct transaction date is important for my study. Due to this concern, I only keep patent transactions that occur during or after the patent application filing year. I also demand that the execution date and recording date reported occur in the same year. This ensures that the filing was made close to the real transaction date. This data restriction reduces eligible climate patent transactions by half for both buying and selling instances.

To avoid potential mistakes that could arise from data manipulation and to remain consistent with the previous literature using this database ([Serrano, 2018](#)), I only use the first transaction of each transacted patent. This means that subsequent transactions of a patent that has already been transacted once are excluded. In the same line, for the sake of consistency, I ensure that patent sales data correctly match with patent grant data. This ensures that the dataset I built functions correctly. Since I only look at first transactions, all patent sale entities should match with patent grant entities for the transacted patents. I carry out this procedure by using the [Dyèvre and Seager \(2023\)](#) granted patents to Compustat firms dataset. I use their dataset because they extend the [Arora et al. \(2021\)](#) dataset by quantity and date by going up to 2020 granted patents. I also prefer the [Dyèvre and Seager \(2023\)](#) dataset to the [Kogan et al. \(2017\)](#) patent-to-firm dataset because the latter incorrectly attributes patent grant data to patent acquirers instead of patent producers in some cases. This is notably the case when the patent acquisition takes place before the patent is granted.

It should also be noted that [Arqué-Castells and Spulber \(2022\)](#) develop a similar database which they provide for public use. There are, however, a few major contextual differences that push me to create a new dataset. First, their dataset ends in 2012 whereas a big part of climate patent transactions occur after this date. Secondly, their rich access to external datasets makes replicating and thereby extending their dataset impossible. For example, they use OSIRIS and SDC Platinum to build corporate trees which accounts for partial ownership stakes between firms.

3.8.3 Propensity score matching: matching statistics

Table 3.8.4: PSM before and after comparison of Firm characteristics and innovation for the firms that do not sell their climate patents (control group) and the firms that sell their climate patents (control group) and the firms that do not buy climate patents (control group) and the firms that buy climate patents (treatment group).

Panel A: Climate patent selling	Full sample			
	Non-selling	Selling	Diff. t-stat	Non-selling
Non-Clim Sold	0.55	9.08	-10.29***	1.24
Clim Stock Scaled	0.03	0.07	-4.83***	0.06
Non-Clim Stock Scaled	0.3	0.5	-4.55***	0.44
R&D Stock Scaled	0.98	0.83	1.88*	0.93
Firm age	14.47	20.98	-9.22***	17.31
ROA	-0.25	-0.16	-3.36***	-0.21
Leverage	0.24	0.24	-0.11	0.24
Δ EPS	0.02	0.02	0.04	0.02
Sales growth	0.08	0.06	2.45***	0.07
Lagged Q	3.19	2.78	2.43***	3
Firm size	5.22	6.25	-7.09***	5.48
CAPEX	0.04	0.04	-0.59	0.04
Firms	1,180	662		423

Table 3.8.4 – Continued from previous page

Panel B: Climate patent buying				
	Full sample			
	Non-buying	Buying	Diff. t-stat	Non-buying
Non-Clim Bought	0.92	9.76	-12.59***	1.44
Clim Stock Scaled	0.06	0.03	5.99***	0.03
Non-Clim Stock Scaled	0.5	0.26	5.51***	0.27
R&D Stock Scaled	1.32	0.56	10.67***	0.62
Firm age	14.14	19.28	-7.54	18.48
ROA	-0.33	-0.11	-8.38***	-0.18
Leverage	0.24	0.25	-0.59	0.24
Δ EPS	0.03	0.01	2.23**	0.02
Sales growth	0.07	0.07	-0.67	0.08
Lagged Q	3.42	2.7	4.48***	2.91
Firm size	4.59	6.51	-14.3***	5.86
CAPEX	0.04	0.04	-0.55	0.04
Firms	886	956		486

3.8.4 Instrumental variable

Table 3.8.5: First stage regressions - Exclusion restriction on dependent variable
This Table presents the first-stage regression results for the main dependent variable (Tobin's Q) to demonstrate that the exclusion restriction is respected. Column 1 uses the logarithmic transformation of Tobin's Q and Column 2 uses the real value of Tobin's Q winsorized at the 1% level as the dependent variable. The main independent variable is the instrumental variable (IV) which is the interaction between the one-year lagged number of state climate policies in firm i's headquarter and the one-year lagged firm climate patent stock. All IV outputs are multiplied by 10,000 for readability. Standard errors, clustered at the firm level, are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Log(Q)	Q
IV _{t-1} × 10,000	-0.3 (0.2)	-0.8 (0.7)
Firm controls	No	No
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	25,272	25,272
Adjusted R-squared	0.65	0.59

Table 3.8.6: First stage regressions - Exclusion restriction on control

This Table reports the regression results of the lagged instrumental variable (lagged climate patent level climate policies in firm i's headquarter) on a set of control variables at time t . The coefficient by 100 for readability. The columns have the following variables as the dependent variable: Sold in (2), climate stock scaled (3), non-climate stock scaled (4), R&D stock scaled (5), age (6), ROA (7) sales growth (10), firm size (11), and scaled capital expenditure (12). Standard errors, clustered at theses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IV_{t-1} \times 100$	0.55 (0.59)	0.02 (0.3)	0.0005 (0.0001)	0.001 (0.002)	0.002 (0.01)	0.007 (0.005)	0.00006 (0.00004)	0.002 (0.001)
Firm controls	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,295	25,295	25,295	25,295	25,272	25,295	25,295	25,295
Adj R-squared	0.63	0.31	0.65	0.72	0.66	0.99	0.59	0.5

Chapter 4

Long-termism in Dual-Class Firms: Evidence from accruals and variation in R&D

4.1 Introduction

Dual-class structures, a nemesis of the one share-one vote principle that allows certain agents to control a public firm without owning a majority of the firm's equity, have seen their popularity grow in the U.S. over the last few years. The data shows as many as 21.1% of U.S. firms in 2021 opting for a dual-class structure at their IPO.¹ Whereas much of the finance literature has focused on the positive and negative consequences of employing this structure, few have looked into why they are being employed in the first place. This paper looks to test a longstanding anecdotal argument for pro-dual-class share firms. Claims for the increased use of dual-class shares is often justified by the long-term vision argument. Prominent companies using dual-class structures often reiterate the necessity of retaining this structure. For example, along with waving the merit of a dual-class structure, Google constantly iterate the importance of their CEO and founders

¹Data source from Professor Jay Ritter's website: <https://site.warrington.ufl.edu/ritter/files/IPOs-Dual-Class.pdf>

for the value of the firm and its business strategy in order to justify utilizing a dual-class structure.² A section of their IPO filing is dedicated to this purpose:

“Our future success depends in a large part upon the continued service of key members of our senior management team. In particular, our CEO Eric Schmidt and our founders Larry Page and Sergey Brin are critical to the overall management of Google as well as the development of our technology, our culture and our strategic direction.”

Moreover, in their original letter to shareholders, the founders of Google stated:

“As a private company, we have concentrated on the long-term, and this has served us well. As a public company, we will do the same. In our opinion, outside pressures too often tempt companies to sacrifice long-term opportunities to meet quarterly market expectations. Sometimes this pressure has caused companies to manipulate financial results in order to ‘make their quarter’. In Warren Buffett’s words, ‘We won’t ‘smooth’ quarterly or annual results: If earnings figures are lumpy when they reach headquarters, they will be lumpy when they reach you.’ If opportunities arise that might cause us to sacrifice short-term results but are in the best long-term interest of our shareholders, we will take those opportunities. We would request that our shareholders take the long-term view. Many companies are under pressure to keep their earnings in line with analysts’ forecasts. Therefore, they often accept smaller, but predictable, earnings rather than larger and more unpredictable returns.”

Nearly 20 years later, Google continues to refer to this original letter to justify the use of a dual-class structures in their latest compulsory financial reporting documents.³

Due to scarce empirical evidence on these statements, I test whether dual-class firms sacrifice short-term targets to focus on long-term goals. More precisely, this paper investigates whether dual-class structures are more likely to maintain their long-term objectives when facing short-term pressure in two steps. First, I study whether dual-class firms manipulate their earnings less than one share one vote firms (i.e. single-class structures).

²Google’s IPO filing:

<https://www.sec.gov/Archives/edgar/data/1288776/000119312504073639/ds1.htm>

³Google’s latest 10-k filing:

<https://www.sec.gov/ix?doc=/Archives/edgar/data/0001652044/000165204423000016/goog-20221231.htm>

Second, I study if dual-class firms that manage their earnings are more or less inclined to do so by manipulating long-term investments.

To conduct this study, I build a dataset of dual-class and single-class firms that captures the recent rise in founder-led dual-class firms. Founder-led dual-class firms are companies that have at least one founder who has an important management role at the firm and detains effective control of the firm through super-voting shares. In this paper, I focus on founder-led dual-class firms because founders should be more committed to the firm's original vision, potentially placing greater emphasis on long-term innovation and value creation. They are also less susceptible to short-term market pressures due to their concentrated control. On the contrary, non-founder-led dual-class firms are more susceptible to agency problems. The separation of ownership and management in these cases can lead to an entrenched single-class type arrangement where meeting short-term targets matters more than long-term value creation.

In the first part of the study, I use discretionary accruals, a measure initially modelled by [Jones \(1991\)](#), to capture whether firms comply with short-term performance expectations. Discretionary accruals highlight strategic manipulation of reported earnings by management to achieve certain financial outcomes. In the second part of this study, I compare how this short-term pressure compliance measure may impact absolute variation in R&D expenses for dual-class and single-class firms. [Terry \(2023\)](#) shows that varying R&D in order to meet short-term targets such as earnings per share targets has a negative impact on firm value in the long run. To mitigate endogeneity concerns such as self-selection into dual-class status, I use two instrumental variables. These instruments include the average use of dual-class structures in the firm's industry and the number of anti-takeover laws in the state where the firm was incorporated at the time of its IPO.

I find that founder-led dual-class structures are positively linked to discretionary accruals in comparison to single-class structures. This suggests that, contrary to expectations, founder-led dual-class structures are more responsive to short-term market pressures. A potential explanation lies in the presence of short-term incentives in founder-led dual-class governance structures. For instance, Meta Platforms has faced activist pressure during periods of underperformance, which has resulted in enforced changes to its governance structure. Moreover, early investors and founders sell super-voting shares

a few years after the IPO. This boosts founder-led dual-class firm incentives to inflate short-term value by meeting market expectations. Surprisingly, I also find that founder-led dual-class firms engaging in earnings management are no less likely than single-class firms to rely on R&D reductions to do so. Therefore, dual-class structures also compromise long-term firm value when faced with short-term market pressures. These results remain unchanged in a sample where both founder-led and non-founder-led dual-class firms are used.

Together these results show that founder-led dual-class shares are not immune to short-term market pressures nor do they focus on long-term firm value. Therefore, founder-led dual-class structures appear to function primarily as an entrenchment mechanism, much like their non-founder-led counterparts.

The remainder of this paper is organised as follows. Section 4.2 reviews the literature and states the contributions of this paper. Section 4.3 details the hypotheses tested. Section 4.4 defines the data collection process and provides initial insights through summary statistics. Section 4.5 details the methodologies used throughout this study. Sections 4.6 and 4.7 report the results for the founder-led and full (i.e. founder and non-founder-led) dual-class firm samples. Section 4.8 concludes.

4.2 Background and related literature

The dual-class shares literature has mainly compared dual-class structures to single-class structures to show the costs and benefits associated with the former. Grossman and Hart (1988) theoretically show one share-one vote structures to be optimal in maximizing shareholder value thanks to its disciplinary effects on management and efficiency in facilitating value increasing takeovers.⁴ Moreover, the earlier literature also looked at a plethora of principal-agent conflicts that are related to the topic of dual-class shares today. For example, Burkart et al. (1997) show that shareholder control can be negative for managerial incentives and discretion which can reduce managers' ability to correctly

⁴Burkart and Lee (2008) provide an overview on theoretical papers related to the one share-one vote topic.

select firm value improving projects. My paper uses these earlier theoretical frameworks as a basis and applies them to the current empirical context of dual-class structures.

Elsewhere, [Bebchuk \(2019\)](#) theoretically argue that dual-class structures can be beneficial in the short-term thanks to their protection mechanisms and their ability to allow insiders to lay out their vision. [Arugaslan et al. \(2010\)](#) find that dual-class structures often allow insiders to keep control of their company while allowing them to diversify their wealth. This diversification is carried out through a gradual conversion of the super-voting shares to normal shares that are sold to the public on financial markets. This allows dual-class firms to keep at least effective control of the firm while reducing their cash flow to as low as they sometimes can.⁵ With such trends, [Bebchuk and Kastiel \(2018\)](#) argue that the agency problems created from this wedge destroy any potential benefits associated with dual-class structures as time passes. [Cremers et al. \(2024\)](#) and [Kim and Michaely \(2019\)](#) show dual-class structures to be beneficial in terms of firm value and voting premia in the short term. However, the observed premia begins to disappear seven years post-IPO. I contribute to this literature by building on the idea of a life cycle effect within dual-class firms. By using discretionary accruals, I show that dual-class firms are associated with short-term behaviour. This can explain the short-term dual-class premia observed in the literature. Moreover, I test the insider vision argument of the literature by observing whether dual-class firms keep long-term resources stable in difficult periods.

Dual-class structures are also linked with multiple agency cost proxies (higher CEO compensation, cash holdings, and lower capital expenditures) ([Masulis et al., 2009](#)), better returns and performance post unification ([Dittmann and Ulbricht, 2008](#); [Pajuste, 2005](#)), and lower firm value as the wedge increases ([Gompers et al., 2010](#)). On a more positive note, dual-class structures are argued to reduce managerial myopia, increase takeover premiums, increase human-specific capital, and increase riskier innovation ([Smart and Zutter, 2003, 2008](#); [Jordan et al., 2016](#); [Cao et al., 2020](#)).

⁵A concrete example can be taken with the case of 10X Genomics, which went public with a dual-class structure in 2019. Initially, the insiders of the company controlled around 78% of the firm's total shares outstanding, including both the publicly traded class A shares and the privately held super-voting 10 votes to 1 class B shares giving them around 97% of the company's total votes. This structure gave them a wedge (difference between voting power and cash-flow rights) of only 20%. One year later, the wedge had increased to around 50% with the total voting power being around 70% while the total amount of shares held by the insiders dropped down to 20% of the firm's shares outstanding.

My paper is closely related to [Nguyen and Xu \(2010\)](#) and [Jordan et al. \(2016\)](#). [Nguyen and Xu \(2010\)](#) states that dual-class firms between 1995 and 2006 are less likely to participate in negative earnings management than one share-one vote firms. [Jordan et al. \(2016\)](#) show that dual-class structures are more likely to be adopted by firms with high investment and growth opportunities as proxied by R&D intensity and sales growth. [Jordan et al. \(2016\)](#) also state that dual-class firms face lower short-term pressure in comparison to one share-one vote firms because of a lower association with short-term institutional investors and less analyst coverage. I build on this literature in two ways. First, I focus on a more recent sample to study the novel founder-led dual-class technology firm trend.⁶ Second, my paper attempts to add a short-term, long-term trade-off to this literature by showing whether dual-class firms are more or less likely to amputate long-term resources to meet short-term pressures.

This paper also relies on empirical facts from [Terry \(2023\)](#), [Edmans et al. \(2017\)](#), and [Belot et al. \(2023\)](#). [Terry \(2023\)](#) shows that firms that are in the earnings management grey area are more likely to vary their R&D expenses in absolute terms. Although in most cases these extreme changes in R&D are shown to move back to their original value, initial and constant variations are shown to negatively impact long-term firm and economic value. Similarly, [Edmans et al. \(2017\)](#) show that vesting equity, an exogenous measure of short-term incentives, leads to lower R&D growth and lower long-term investments. [Belot et al. \(2023\)](#) exploit the exogenous adoption of loyalty shares in France to show that strengthening long-term shareholder incentives leads to an increase in R&D expenditures. I contribute to this literature by studying dual-class firm-specific short-term and long-term incentives.

⁶[Aggarwal et al. \(2020\)](#) is to my knowledge the only other paper that studies founder-led dual-class firms. They show that founder bargaining power due to more available private capital is responsible for the surge in dual-class IPOs in the U.S. [Aggarwal et al. \(2020\)](#) also find that among 613 dual-class IPOs in the US between 1994 and 2019 (foreign and U.S. firms included), only 281 of them were founder controlled.

4.3 Hypotheses

To what extent are dual-class structures used to lighten, if not alleviate, short-term market pressures? There are two forces at play.

On the one side, we may expect dual-class structures to indulge less in discretionary accruals to meet short-term market expectations. A part of the literature argues that the demand for earnings management is primarily led by the principal's inability to observe the firm's real output (Dye, 1988; Sankar and Subramanyam, 2001). Instead of contracting on the firm's performance or actual earnings measures, they are obliged to reward managers on reported earnings. As argued by the CEO compensation literature, constant contracts are not optimal as they tend to induce the lowest amount of effort from managers. Compensation attached to short-term targets therefore provides incentives to carry out actions that are in the best interest of the shareholders (Dye, 1988; Stein, 1989; Sankar and Subramanyam, 2001; Ewert and Wagenhofer, 2011). Moreover, career concerns along with personal tenure objectives are often entangled with short-term targets set out by the principals in these models. Contrary to this literature, the principal-agent view does not hold for dual-class structures as the insiders find themselves to be the owners and managers of these firms. Since founder-led dual-class firms lack a separation between ownership and control, they are less likely to engage in earnings management intended to mislead shareholders. Moreover, lower dismissal risk, the ability to set their own compensation, and a strong personal commitment to the firm provide founder-led dual-class firms with additional autonomy and long-term orientation. Furthermore, the mean-reverting nature of earnings management should reduce incentives to manipulate earnings in founder-led dual-class firms since their management tends to be in control over long-term horizons. Additionally, following Chemmanur and Jiao (2012), dual-class structures may be optimally used by some firms with a visionary leader that looks to implement uncertain but high-paying projects. Since such firms are expected to deviate from analyst forecasts, they should have little incentive to engage in earnings management that could erode investor trust.

On the other side, the same theoretical model by Chemmanur and Jiao (2012) eludes to dual-class structures being used by opportunistic firms as a protection mechanism to

extract private value from shareholders. The lack of management oversight in dual-class firms creates incentives for earnings management to cover potential poor performances. Moreover, short-term compensation incentives also exist in dual-class firms. Founder-led dual-class firms have management that are often idiosyncratically linked to the firm, which has risky wealth implications ([Arugaslan et al., 2010](#)). The average wedge, which is calculated as the average insider voting power minus the average insider cash-flow rights, increases by around 12% between the IPO year and two years after the IPO in my sample. This period, which is responsible for nearly 40% of my dual-class firm years, shows a decrease in stock ownership by insiders of around 24%. By meeting short-term pressures to increase the firm's market value, founder-led dual-class insiders can sell their super-voting shares at a high value. Furthermore, recent pressures from institutional investors have increased the pressure on dual-class firms to meet short-term market targets. The Council of Institutional Investors pushed for more transparency concerning dual-class structures in 2017 while also encouraging the SEC to instate obligations for a sunset provision within these firms, meaning that dual-class structures last a few years at most unless explicitly asked to continue by a majority of the shareholders. Moreover, proxy advisors' recommendations to vote against dual-class structures have dramatically increased since 2010 as a sign of protest against this structure.

Hypothesis 1a: *Dual-class structures help insiders overlook short-term pressures and are thus less likely to manage earnings.*

Hypothesis 1b: *Wealth and compensation incentives exist in dual-class structures, notably in the short-term. Therefore, dual-class structures are expected to manage earnings more than single-class firms.*

Next, I investigate how dual-class structures change variables that relate to their long-term firm value in comparison to single-class shares when they manage earnings. Managing short-term market pressures is shown to negatively impact long-term firm value and innovation due to cuts in R&D. For example, firms have been shown to get penalized for overinvesting in R&D projects when faced with high short-term pressures in the form of the number of analyst coverage ([Guo et al., 2019](#)).

[Edmans et al. \(2017\)](#) find managerial short-term incentives to lead to lower long-term

investments. I expect the same result. As the firm's earnings management increases, the more their long-term investments vary (R&D variation). However, dual-class structures may vary their long-term investments less. Long-term sacrifices should not be expected because insiders' hold on dual-class structures weakens as time goes on (i.e. due to the sell-off effect). Similarly, as the insiders within these firms are heavily tied up with the company's outcome, reputation concerns could lead them to avoid sacrificing long-term value when preoccupied with the short-term. The theoretical model developed by [Jiang and Xin \(2022\)](#) demonstrates that a combination of low short-term pressure and moderate managerial discretion leads to optimal investment efficiency. Given that founder-led dual-class structures operate under low short-term pressure and retain managerial discretion, I expect their long-term investment decisions to remain unaffected by short-term market pressures.

Hypothesis 2: *Earnings management in dual-class structures are less likely to come at the cost of long-term value in comparison to single-class firms, thus supporting the long-term vision argument.*

Moreover, I expect firms with founder-led dual-class shares to behave differently to non-founder-led dual-class firms. This is mainly because the latter is associated with a higher agency problem. Owner-manager separation and the lack of management attachment in non-founder-led dual-class structures should lead to more earnings management ([Aggarwal et al., 2020](#)). In such firms, managers are more likely to receive compensation packages that emphasize short-term performance targets, while owners may be more inclined to pursue near-term exits, thereby amplifying the incentive to engage in earnings manipulation. Similarly, I expect these firms to finance short-term earnings management through any means possible. While I argue that founder-led dual-class firms have incentives to care more about the long-term value of the firm, which means they borrow less from long-term resources to satisfy short-term demands, this is not necessarily true for non-founder-led dual-class firms. Therefore, demand to satisfy short-term targets is as likely to come from long-term resources as current resources for these firms.

Hypothesis 3: *Founder-led dual-class firms engage in less earnings management and place greater emphasis on long-term value creation than non-founder-led dual-class firms.*

4.4 Data

4.4.1 Sample

The sample is constructed from 2000 to 2020 to focus on the recent upward trend in dual-class structures. Also, electronic filings on SEC Edgar became the norm in 2000 which facilitates data collection. I use Compustat for firm characteristics data. I only use publicly listed and U.S. headquartered firms in my sample. Following the literature ([Jordan et al., 2016](#); [Nguyen and Xu, 2010](#); [Arugaslan et al., 2010](#); [Gompers et al., 2010](#)), I remove dual-class structures installed for tax purposes, spin-offs, real estate investment trusts (which commonly use dual-class structures), ADRs (American Depositary Receipts), financial (SIC codes 6000-6999) and utilities firms (SIC codes 4900-4999). In addition, I eliminate limited liability companies because of the difficulty in tracking their ownership information. After accounting for missing firm characteristics data, I have a sample size of 27,321 firm-years.

I identify dual-class structures through three different methods. The first consists of matching my sample with Professor Jay Ritter’s publicly available dataset that identifies dual-class firms at their IPO. I supplement this dataset with the Council of Institutional Investors’ data on firms employing a dual-class structure. The Compustat and CRSP databases can also be exploited to identify dual-class structures at the firm-year level. The former reports all shares issued by firms while the latter only reports publicly traded shares ([Howell, 2017](#); [Jordan et al., 2016](#)). This divergence is useful because dual-class structures’ super-voting shares are not publicly traded. Therefore, following [Jordan et al. \(2016\)](#), I identify firms with a difference of at least 5% between their shares outstanding in the Compustat dataset and the CRSP dataset. I then use yearly 10-k filings to see if these firms use a dual-class structure and correct any mistakes in my dataset. I account for 24 out of 135 dual-class structure unifications and 6 out of 75 founder-led dual-class structure unifications in my dataset. Unifications represent an abandonment of the dual-class structure to revert to a one share-one vote structure. Founder-led identification is given to firm-years where at least one founder has super-voting shares and is in an important management position according to yearly 10-K filings.

My final panel dataset consists of 26,453 one share-one vote and 868 dual-class firm-year observations. Only 456 of these dual-class firm-year observations are founder-led.

4.4.2 Variables

I use three different [Jones \(1991\)](#) inspired discretionary accruals measures to study how dual-class structures behave in light of short-term pressures. The measures are the real value of discretionary accruals (as described in [section 4.5](#)), the absolute value of this proxy, and a dummy variable that takes the value of 1 for positive values of this proxy.

Discretionary accruals are a proxy for accounting adjustments made by a company's management that are not directly related to the company's operating performance but are instead used to manipulate earnings. Positive values are said to be linked with an upward push of earnings numbers while a negative value is associated with underplaying real earnings. The latter may be produced in firms that are satisfied with just beating the benchmark set by analysts in order to have more flexibility with their numbers in a worse future state ([Nguyen and Xu, 2010](#)). Another often popular explanation for negative accruals stems from the notion of a big bath. Here, firms profit off knowing they will not meet forecasts by massively undercutting expectations to be in a better position for future earnings forecasts.

Absolute discretionary accruals is the most important measure I will use. Both negative and positive discretionary accruals can be used to smooth out earnings results over a certain period. Moreover, both types of earnings management can have similar impacts on R&D spending. R&D expenses are more likely to be cut no matter the direction of the discretionary accruals. What matters is the strength of the accruals. A firm looking to downplay earnings will vary R&D as much as a firm seeking to exaggerate earnings because over time both will find themselves on each side of the discretionary accruals measure in an attempt to smooth earnings and meet the market's expectations. This is due to the reversing nature of earnings management ([Dye, 1988](#); [Sankar and Subramanyam, 2001](#); [Terry, 2023](#)).

The third measurement concentrates on positive discretionary accruals, synonymous

with an artificial amplification of earnings figures by having a dummy that is equal to one for all firms that have a discretionary accruals number that is bigger than zero.

The proxy used for long-term focus is R&D variation in absolute terms. This measure has been linked with positive firm and economic value in the long-term (Terry, 2023). I do not use the real value of R&D variation or a dummy variable for R&D expense cuts for interpretation related issues. For example, in the latter, a very small negative variation is considered as a cut in R&D expenses.

The main variable of interest is the dual-class structure dummy which is explained in Section 4.4.1.

All the variables used in this paper are defined in Table 4.9.1. The control variables used differ depending on which part of the study is being tackled. The justification for the control variables used is explained in Section 4.5.

4.4.3 Summary statistics

Table 4.1 reports the summary statistics for my full sample (i.e. including founder and non-founder-led dual-class firms). All continuous variables in this paper are winsorized at the 1% level to avoid outliers. R&D has a mean scaled value of 14% and a median of 10%. R&D change is slightly negative on average with a mean of -1% while the absolute value of this variable has a mean of 3% and a standard deviation of 0.03. The mean discretionary accruals is 0.08. Its large standard deviation of 0.36 suggests that this variable is extremely variable across firms. Firm age, leverage, cash, capital expenditure, and net property, plant, and equipment (PPE) hold reasonable distributions. ROA is extremely negative across the whole sample with an average of -14% thus indicating highly negatively skewed data for the whole sample. Elsewhere, the relatively high standard deviation of the firm size measurement, Tobin's Q, and the K-Z index indicates that the sample is highly dispersed on these variables.

Table 4.2 provides summary statistics comparing founder-led dual-class firms and one share-one vote firms. Surprisingly, one share-one vote companies have a significantly higher R&D expense in comparison to dual-class firms with 14% in comparison to 10%.

One would expect dual-class firms to have a higher R&D expense given that they often operate in R&D intensive and innovative sectors. R&D change, although negative for dual-class firms, is also negative and larger for single-class firms. This can be taken as an initial indication of more R&D stability among the former. R&D absolute change further supports this intuition by showing that dual-class firms vary their R&D expenditure less. On average dual-class structures are shown to have a higher level of discretionary accruals in comparison to single-class structures. This can be interpreted as dual-class structures having to comply to short-term pressures despite their entrenchment mechanism. A simple explanation for this barely significant comparison can be suggested by the fact that dual-class structures face more scrutiny despite previous findings showcasing the opposite through an association with lower analyst coverage ([Jordan et al., 2016](#)).

Elsewhere, dual-class structures are bigger, younger, and have higher capital expenditure and Tobin's Q ([Gompers et al., 2010](#); [Aggarwal et al., 2020](#); [Arugaslan et al., 2010](#); [Smart and Zutter, 2003](#)). The only divergence from the literature comes in the form of PPE, which proxies for tangible assets. Its average is surprisingly higher for dual-class firms that predominantly develop in the tech and cloud industry. Moreover, the highly negative return on asset average in the overall sample is driven by single-class structures with an average of -14.22% versus -2.91%. Dual-class structures also seem to be less financially constrained and less reliant on external financing as measured by the slightly higher value of the KZ index. There are no significant differences in leverage and cash between these two structures. Previous studies have shown dual-class structures to hold less cash due to entrenchment ([Gompers et al., 2005](#); [Masulis et al., 2009](#)) and have a higher recourse to leverage for financing ([Cremers et al., 2024](#); [Kim and Michaely, 2019](#)).

4.5 Methodology

The methodology used in this paper can be broken into three parts: discretionary accruals calculation, instrumenting my dual-class variable due to potential endogenous effects, and the use of two empirical models to answer the two parts of this study.

As previously defined, discretionary accruals are accounting adjustments made by a

company's management that are not directly related to the company's operating performance but are instead used to manipulate earnings. I calculate discretionary accruals by using the proxy developed by Jones (1991)⁷. The first step of this estimation consists of calculating the total accruals which is simply the income before extraordinary items minus the net operating cash-flow normalized by the firm's previous total assets as observed in Equation 4.1.

$$Total\ accruals_{i,t} = \frac{IB_{i,t} - OANCF_{i,t}}{AT_{i,t-1}} \quad (4.1)$$

Total accruals represent a proxy for the overall level of non-cash adjustments made to a company's financial statements. Discretionary accruals represent a proxy for the portion of total accruals that are likely influenced by earnings management or manipulation. Next, I run the regression model in Equation 4.2 to obtain the coefficient estimates. In Equation 4.2, $AT_{i,t-1}$ is the total asset of the firm in the preceding year while $\Delta Sales_{i,t}$ represents the difference in sales between the preceding year and the current year, and $PPE_{i,t}$ is simply the net property, plant and equipment. The coefficient estimates from Equation 4.2 are then used in a similar regression model in Equation 4.3 to obtain the estimated non-discretionary accruals ($\widehat{Non\ Discretionary\ accruals}_{i,t}$). Non-discretionary accruals (accruals that do not reflect manipulated earnings from managers) are a component of total accruals that is likely driven by the firm's operations. As shown in Equation 4.4, firm-year discretionary accruals is the firm-year total accruals value (calculated in Equation 4.1) minus the firm-year non-discretionary accruals value (estimated in Equation 4.3).

$$Total\ accruals_{i,t} = \alpha + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t} \quad (4.2)$$

$$\widehat{Non\ Discretionary\ accruals}_{i,t} = \hat{\alpha} + \hat{\beta}_1 \frac{1}{AT_{i,t-1}} + \hat{\beta}_2 \frac{\Delta Sales_{i,t}}{AT_{i,t-1}} + \hat{\beta}_3 \frac{PPE_{i,t}}{AT_{i,t-1}} \quad (4.3)$$

⁷This is a popular proxy for discretionary accruals in the earnings management literature as demonstrated by Ecker et al. (2013).

Table 4.1: Summary statistics

This Table reports the descriptive statistics including the 25th percentile, the median, the mean, the 75th percentile, and the number of observations of my dataset which includes all dual-class firms (i.e. found in both the 1% and 10% dual-class firms). All continuous variables are winsorized at the 1% level.

	Q1	Median	Mean	Q3	S
R&D	0.04	0.10	0.14	0.22	0
R&D change	-0.04	-0.00	-0.01	0.01	0
R&D absolute change	0.00	0.02	0.03	0.07	0
Discretionary accruals	-0.16	0.03	0.08	0.32	0
Absolute discretionary accruals	0.01	0.22	0.29	0.47	0
Firm size	3.84	5.46	5.40	6.93	2
Firm age	1.61	2.20	2.07	2.77	0
ROA	-0.37	-0.06	-0.14	0.05	0
Leverage	0.00	0.07	0.12	0.29	0
Cash holdings	0.12	0.32	0.38	0.60	0
Capex	0.01	0.02	0.03	0.04	0
PPE	0.04	0.09	0.14	0.18	0
Tobin's Q	1.35	2.12	2.57	3.72	1
KZ index	-26.22	-6.66	-11.04	-0.73	1

Table 4.2: Summary statistics: Single-class vs founder-led dual-class firms. This Table reports descriptive statistics for founder-led dual-class (DCS) and single-class firms. It includes (N), the mean, the standard deviation (SD), and the Welch two-sample t-test comparing the means across 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Summary Statistics					
Variable	Founder-led DCS			Single-cla	
	N	Mean	SD	N	Mean
R&D	456	0.10	0.10	26,500	0.14
R&D change	456	-0.02	0.17	26,500	-0.09
R&D absolute change	456	0.04	0.17	26,500	0.12
Discretionary accruals	456	0.17	0.30	26,500	0.07
Absolute discretionary accruals	456	0.27	0.22	26,500	0.29
Firm size	456	8.05	1.01	26,500	5.32
Firm age	456	1.62	1.01	26,500	2.08
ROA	456	-0.03	0.16	26,500	-0.14
Leverage	456	0.13	0.12	26,500	0.12
Cash	456	0.39	0.23	26,500	0.38
Capex	456	0.04	0.02	26,500	0.03
PPE	456	0.16	0.12	26,500	0.14
Tobin's Q	456	3.08	1.56	26,500	2.56
KZ index	456	-8.89	9.93	26,500	-11.13

$$Discretionary\ accruals_{i,t} = Total\ accruals_{i,t} - \widehat{Non\ Discretionary\ accruals_{i,t}} \quad (4.4)$$

Next, I describe the steps taken to minimize endogeneity issues related to the adoption of dual-class shares.⁸ The issues include self-selection bias (firms expecting to face more investor scrutiny choosing to insulate management from pressure), reverse causality (opting for a dual-class structure because of potential short-term pressures in a particular industry), and omitted variable bias (corporate practices and ownership structures impacting both the choice to have a dual-class structure and the choice to manipulate earnings).

Due to in-existent natural experiments on the adoption of dual-class structure, I follow the [Cao et al. \(2020\)](#) two-step instrumental variable methodology to tackle endogeneity. They instrument dual-class shares using the average amount of firms having a dual-class structure within the same industry over the last five years and a state-level measure for the amount of anti-takeover laws instated. I calculate the first variable by looking at a full sample of public Compustat firms that I code with a dummy that is equal to 1 if the firm is a dual-class firm and 0 otherwise. The Compustat-CRSP difference in shares outstanding method to further identify dual-class structures is used as described in the above data section. I then proceed to regroup companies by their three-digit SIC codes before calculating a previous five-year rolling average of dual-class structure use per industry for each firm-year. The second instrumental variable is built upon the initial work by [Bebchuk and Cohen \(2003\)](#). They build a state anti-takeover index whereby each state gets an overall score between 0 and 5 depending on the strength of their anti-takeover laws. The higher this value, the more the firms that incorporate in this state benefit from potential takeover threat protections. The laws looked at are: the control share acquisition statute, fair price statute, business combination statute, poison pill endorsement statute, and constituencies statute. Whenever a state has one of these statutes, they are coded with a 1. In the scenario where a state has all 5 statutes, they receive a 1 for each variable thus adding up to a total state anti-takeover score of 5 as

⁸I report the OLS results in Appendix [4.9.2](#).

has been the case for Nevada since 2001. On the polar opposite, not having any of these statutes means that firms are not protected enough in this state and a state anti-takeover provision score of 0 is obtained in this case. The data made publicly available by [Bebchuk and Cohen \(2003\)](#) only spans the period from 1986 to 2001. I manually complete this dataset by assigning each firm a state-level anti-takeover provision score, based on the year of its initial public offering and the state of incorporation at that time.

Although not completely exogenous, these two instrumental variables provide good alternatives to an exogenous shock. On the one hand, the adoption of dual-class structures is linked with an increase in firms' bargaining power against venture capitalists and initial investors. As previously mentioned, [Aggarwal et al. \(2020\)](#) shows this increase in bargaining power to be due to technological advances while [Grinapell \(2020\)](#) show it to be due to visionary and convincing founders or members of management. Therefore, evidence of this proxy for the popularity and bargaining power of dual-class firms has been shown to directly influence the upward trend observed in the use of this structure. However, while not being completely exogenous to discretionary accruals and R&D variation, there is no evidence pointing towards an association between the first instrumental variable and the main dependent variables of interest. Elsewhere, dual-class structures have also often been linked to takeovers and the protection that they offer in the case of a hostile takeover bid. Moreover, the use of the state anti-takeover variable can be motivated by dual-class structures being an extreme version of an anti-takeover provision thus pushing firms that are incorporated in low-provisioned states to use them. In the Appendix, Tables [4.9.7](#) and [4.9.8](#) show that there is no relationship between my instrumental variables and the main dependent variables studied in this paper.

$$Dual\ class_{i,t} = Probit(\alpha + \beta_1 DCS\%_{i,t} + \beta_2 State\ ATP_{i,t} + \beta' Controls_{i,t} + \gamma_t + \delta_j + \epsilon_{i,t}) \quad (4.5)$$

Equation [4.5](#) describes the first stage regression model. A dual-class structure dummy variable is used as the dependent variable in a probit regression with two instrumental variables: the rolling average of public dual-class firms in the last 5 years per industry and the state anti-takeover index score for the state where the firm was incorporated at the time of their IPO. Industry (δ_j) and year (γ_t) fixed effects are used to ensure that

industry-specific shocks or time-specific trends do not drive the estimates.

The last step of my methodology consists of answering the main research questions through linear regression models. Equation 4.6 is used to observe whether dual-class firms are more or less likely to manage their earnings. Three different dependent variables are used to proxy for earnings management: discretionary accruals, the absolute value of this measure, and a dummy variable that is equal to one when this measure is positive. The main independent variable of interest is dual-class classification which has been estimated from the first stage probit regression model ($\widehat{DCS}$). I also include the inverse Mills ratio (IMR) in this regression model, which is a tool used to correct for persistent selection bias after the first stage regression (Cao et al., 2020). The control variables include firm size, firm age, profitability, cash holding, PPE, capital expenditure, leverage, Tobin's Q, and the K-Z index. These variables have been previously shown to play a role in relation to earnings management and are defined in Table 4.9.1. I also include time (γ_t) and industry (δ_j) fixed effects.

$$EM\ proxy_{i,t} = \alpha + \beta_1 \widehat{DCS}_{i,t} + \beta_2 IMR_{i,t} + \beta' Control\ variables_{i,t} + \gamma_t + \delta_j + \epsilon_{i,t} \quad (4.6)$$

To study if dual-class firms stay fixated on their long-term objectives, I attempt to observe whether they finance short-term market pressure via R&D variation. Equation 4.7 details the regression model used. The dependent variable is the total asset scaled absolute variation of R&D from the preceding year to the current year. As previously mentioned, the use of this variable relies on Terry (2023) who finds constant variation in R&D spending to be negative for future firm and economic value. The main independent variable is the estimated dual-class shares value ($\widehat{DCS}$) interacted with my earnings management proxies (EM). This tells us how a dual-class firm changes its R&D spending in light of earnings management. The earnings management proxies used are again: discretionary accruals, the absolute value of discretionary accruals, and a dummy variable that is equal to 1 for positive values of discretionary accruals. The inverse Mills ratio (IMR) is also used in this set of regressions. The control variables used include firm size, firm age, profitability, cash holding, current level of R&D, and the amount of leverage. I also include time (γ_t) and industry (δ_j) fixed effects.

$$\begin{aligned}
R\&D\ Variation_{i,t} = \alpha + \beta_1 \widehat{DCS}_{i,t} \times EM_{i,t} + \beta_2 \widehat{DCS}_{i,t} + \beta_3 EM_{i,t} \\
&+ \beta_4 IMR_{i,t} + \beta' \text{Control Variables}_{i,t} + \gamma_t + \delta_j + \epsilon_{i,t}
\end{aligned} \tag{4.7}$$

4.6 Main results

4.6.1 First stage regression

In the Appendix, Column 1 of Table 4.9.6 shows the results from the first stage probit regression model for the founder-led dual-class sample. As expected, both the bargaining power or popularity argument and state anti-takeover provisions drive the use of dual-class structures. Firms are more likely to use a dual-class structure when their industry peers use it. Firms are also less likely to use a dual-class structure when its incorporation state at IPO has provisions against takeovers. Both values are statistically significant at the 1% level and are relatively strong instruments with F-statistics of 14.88. The full dual-class sample in Column 2 has similar results.

4.6.2 Earnings manipulation

In this section, I will be looking at the direct association between having a dual-class share structure and managing earnings.

Table 4.3 displays the results. The dependent variables take different earnings management proxies as displayed in the first row of the Table. All of the different regression models use the same control variables and include industry and year fixed effects. The main independent variable is the estimated probability of being a dual-class firm from the first stage probit regression ($\widehat{DCS}$).

The results for the main independent variable support the wealth incentives and vulnerability hypothesis. The positive value on the estimated dual-class variable in Column 1 of Table 4.3 indicates that dual-class firms are more likely to be associated with earnings management than single-class firms. Column 3 confirms these results by showing that

firms with a dual-class structure are more likely to exaggerate numbers to meet short-term market targets. The inverse Mills ratio is a function of the first-stage predicted values and captures the correlation between the independent variable and the error term in the model. Including the inverse Mills ratio in the second stage regression corrects the remaining self-selection-related endogeneity bias in the estimated dual-class structure independent variable. The inverse Mills ratio in both Columns 1 and 3 of Table 4.3 are positive and statistically significant, thus indicating that endogeneity is still potentially an issue and is driving the results upwards. Nonetheless, the main results continue to hold without the inclusion of the inverse Mills ratio.

Column 2 uses the absolute value of discretionary accruals as the proxy for earnings management. The main result here is statistically insignificant. Therefore, dual-class structures are either positively associated with earnings management or in a situation where there are no effects captured by the proxy.

The wealth and compensation incentive hypothesis for dual-class structures whereby founder-led dual-class firms manage earnings more than single-class firms trumps the short-term market pressure protection hypothesis. This is particularly relevant because founder-led dual-class observations are concentrated in the later years of my sample. This may be amplifying the incentives to meet short-term targets to be able to sell super-voting shares at a high price. Moreover, dual-class scrutiny due to their increasing popularity can explain the short-term view of some dual-class firms. As dual-class firms are now more popular and have become more vulnerable to attacks from institutional investors; complying with short-term targets may allow these firms to maintain a dual-class structure. Cases of forced dual-class unification when things do not pan out in the short term are further anecdotal proof for said arguments. This was the case for Zynga, a video game company that was forced to abandon its founder-led dual-class structure following poor stock market performances.

Elsewhere, the control variables are consistent throughout the different regression models and move in the expected direction. As expected, larger, older, and less financially dependent firms are less likely to engage in earnings management. However, firms with more cash holding, tangible assets (PPE), capital expenditure, leverage, and investment opportunities as measured via Tobin's Q are more likely to indulge in earnings

management. This is theoretically consistent as these measures show a higher ability and sometimes need to manage earnings to meet investment standards or attain lender covenants ([Ewert and Wagenhofer, 2011](#)).

4.6.3 Manipulation and long-term vision

Table 4.4 shows whether dual-class structures are forward-looking by observing if they modify their R&D to meet short-term financial targets. This Table contains three separate regressions where the dependent variable is the absolute variation in R&D. The main independent variable is the probability of having a dual-class structure interacted with a proxy representing earnings management. The proxy used for the different Columns can be observed in the first row of the Table. They are discretionary accruals, the absolute value of discretionary accruals and a dummy variable that is equal to 1 for a positive level of discretionary accruals, respectively.

The results are mostly statistically insignificant. The interaction term, which is the main variable of interest, is always negative but only statistically significant for the absolute discretionary accruals earnings management proxy in Column 2. Therefore, my second hypothesis stating that dual-class firms are more likely to focus on their long-term targets despite compliance with short-term pressures holds weak evidence. Earnings management is positively linked to a higher level of R&D fluctuation thus showing that when firms manage their earnings they manipulate and fluctuate their research and development figures. Firms that avoid manipulating their numbers can be expected to have a more stable year-to-year R&D expense rate.

Although the results are inconclusive in two of the earnings management proxies, absolute discretionary accruals show weak evidence that when dual-class firms do manage their earnings they are less likely to do it through changes in their R&D investments in comparison to single-class firms.

Table 4.3: 2SLS: Founder-led DCS firms and earnings management

This Table presents the two-stage least squares (2SLS) results comparing earnings management between founder-led dual-class firms and single-class firms. The dependent variables are three earnings management measures: (1) discretionary accruals, (2) absolute discretionary accruals, and (3) a dummy equal to one for positive discretionary accruals. The main independent variable is the instrumented probability of being a dual-class structure ($\widehat{DCS}$). Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	DA	Absolute DA	Positive DA
$\widehat{DCS}$	0.52*** (0.091)	−0.06 (0.068)	1.05*** (0.138)
IMR	0.12*** (0.013)	0.003 (0.009)	0.21*** (0.019)
Firm size	−0.02*** (0.001)	−0.03*** (0.001)	−0.03*** (0.001)
Firm age	−0.04*** (0.002)	−0.03*** (0.001)	−0.03*** (0.003)
Profitability	0.79*** (0.009)	0.10*** (0.007)	0.86*** (0.014)
Cash	0.07*** (0.008)	−0.07*** (0.006)	0.03*** (0.013)
PPE	1.01*** (0.016)	0.61*** (0.009)	0.92*** (0.024)
CAPEX	2.00*** (0.093)	0.66*** (0.068)	3.26*** (0.141)
Leverage	0.10*** (0.015)	0.04*** (0.011)	0.09*** (0.023)
Tobin's Q	0.04*** (0.001)	0.03*** (0.001)	0.06*** (0.002)
KZ index	−0.005** (0.0002)	−0.003*** (0.0001)	0.003*** (0.0003)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.43	0.23	0.33
N	26,901	26,901	26,901

Table 4.4: 2SLS: Founder-led DCS and R&D variation

This Table examines whether dual-class structures borrow wealth from the future in the form of R&D changes following earnings management, in comparison to single-class structures. The dependent variable is the absolute variation in R&D. The main independent variable is earnings management (EM) interacted with the instrumented probability of being a dual-class structure ($\widehat{DCS}$). Earnings management (EM) takes three different values, as specified in the first row. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	EM: DA	EM: Abs. DA	EM: Pos. DA
$\widehat{DCS} \times EM$	-0.02 (0.56)	-1.4* (0.8)	-0.05 (0.37)
$\widehat{DCS}$	0.1 (0.25)	0.47* (0.26)	0.12 (0.39)
EM	0.07*** (0.02)	0.4*** (0.02)	0.05 (0.01)
IMR	0.03 (0.031)	0.028 (0.031)	0.028 (0.031)
Firm size	-0.02*** (0.002)	-0.01*** (0.002)	-0.02*** (0.002)
Firm age	-0.004 (0.004)	0.01 (0.01)	-0.01 (0.01)
Profitability	-0.16*** (0.03)	-0.12*** (0.02)	-0.16*** (0.03)
Cash	0.14*** (0.02)	0.16*** (0.02)	0.14*** (0.02)
R&D	0.79*** (0.05)	0.8*** (0.05)	0.79*** (0.05)
Leverage	0.33*** (0.04)	0.3*** (0.04)	0.33*** (0.04)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.05	0.06	0.05
N	26,901	26,901	26,901

Table 4.5: Summary statistics: Single-class vs all dual-class firms

This Table reports descriptive statistics for dual-class and single-class firms, including the number of observations, the number of firms, the mean, standard deviation (SD), and the Welch two-sample t-test comparing means across groups. The full sample is split into founder-led and non-founder-led firms. Statistical significance at the 1%, 5%, and 10% levels is denoted by *, **, and *** respectively.

Summary Statistics					
Variable	Dual-class shares			Single-class	
	N	Mean	SD	N	Mean
R&D	868	0.09	0.09	26,453	0.14
R&D change	868	−0.02	0.17	26,453	−0.09
R&D absolute change	868	0.02	0.02	26,453	0.03
Discretionary accruals	868	0.18	0.29	26,453	0.07
Absolute discretionary accruals	868	0.27	0.21	26,453	0.29
Firm size	868	7.73	1.89	26,453	5.32
Firm age	868	1.86	1.04	26,453	2.07
ROA	868	−0.10	0.15	26,453	−0.14
Leverage	868	0.15	0.12	26,453	0.12
Cash	868	0.31	0.23	26,453	0.38
Capex	868	0.03	0.02	26,453	0.03
PPE	868	0.16	0.12	26,453	0.14
Tobin's Q	868	2.76	1.46	26,453	2.56
KZ index	868	−7.62	9.29	26,453	−11.15

4.7 Extension: All dual-class firms

It could be argued that the results witnessed are simply due to sample selection choices. Therefore, the non-founder-led dual-class firms, that are not spin-offs, made for tax purposes, REITs, ADRs, or limited liability firms (due to traceability), are included in this set of analysis. Studying how the results fluctuate from the previous analysis can provide insight into the differences between founder and non-founder-led dual-class firms.

This sample nearly doubles the dual-class firm sample size from 456 to 868 firm years. Table 4.5 displays the summary statistics and differences in means between dual-class and single-class firms for this sample. One major difference observed with the founder-led dual-class sample is that the differences between firm structures are more pronounced in this sample. Additionally, new insights are observed with dual-class structures having a higher level of leverage in comparison to single-class shares but less cash holdings.

In the Appendix, Column 2 of Table 4.9.6 shows the first stage probit regression for the full dual-class sample. The results are similar to the founder-led dual-class sample presented in Column 1 and discussed in Section 4.6. The slightly lower statistical significance at the 5% level instead of the 1% level for the state anti-takeover provisions score can suggest that non-founder-led dual-class firms are slightly less likely to use dual-class structures for protection purposes. This can hint towards the use of dual-class structures for entrenchment and agency reasons.

Table 4.6 studies the relationship between dual-class structures and the likelihood of managing earnings. The results show that dual-class firms have a strong positive and statistically significant relationship with discretionary accruals across all discretionary accruals measures. In the founder-led dual-class sample (Table 4.3), dual-class structures had a statistically insignificant relationship with absolute discretionary accruals. This suggests that dual-class firms manage earnings more than single-class firms and non-founder-led dual-class structures manage earnings more than founder-led dual-class structures.

Table 4.7 studies whether the full sample of dual-class firms varies R&D when faced with short-term pressure. The results are similar to those observed in Table 4.4. Columns

1 and 3 remain statistically insignificant for the main interaction variable which indicates that dual-class firms are just as likely to manipulate R&D figures due to earnings management as single-class firms.

Together this set of results continues to validate hypothesis 1b which states that dual-class firms manage earnings more than single-class firms. However, there is little proof of dual-class firms maintaining a long-term vision when faced with market pressure. There are also no distinctions between the founder-led sample and the full sample of dual-class firms. Therefore, hypotheses 2 and 3 are not validated by my analysis.

Table 4.6: 2SLS: All DCS firms and earnings management

This Table presents the 2SLS regression of the relationship between dual-class structures (instrumented DCS indicator) and three measures of earnings management: discretionary accruals, absolute discretionary accruals, and a dummy equal to 1 if discretionary accruals is positive. The sample used includes both founder-led and non-founder-led dual-class firms. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	DA	Abs. DA	Positive DA
$\widehat{\text{DCS}}$	0.61*** (0.06)	0.14*** (0.04)	1.10*** (0.09)
IMR	0.19*** (0.02)	0.05*** (0.01)	0.31*** (0.02)
Firm size	-0.02*** (0.001)	-0.02*** (0.001)	-0.03*** (0.001)
Firm age	-0.04*** (0.002)	-0.03*** (0.001)	-0.03*** (0.003)
Profitability	0.79*** (0.01)	0.08*** (0.01)	0.86*** (0.01)
Cash	0.08*** (0.01)	-0.07*** (0.01)	0.04*** (0.01)
PPE	1.12*** (0.02)	0.65*** (0.01)	1.00*** (0.02)
CAPEX	2.03*** (0.09)	0.62*** (0.07)	3.26*** (0.14)
Leverage	0.11*** (0.02)	0.05*** (0.01)	0.10*** (0.02)
Tobin's Q	0.04*** (0.001)	0.03*** (0.001)	0.06*** (0.002)
KZ Index	-0.00001 (0.0002)	-0.004*** (0.000)	0.003*** (0.000)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.459	0.239	0.346
N	27,321	27,321	27,321

Table 4.7: 2SLS: All DCS firms and R&D variation

This Table examines whether dual-class structures borrow wealth from the future in the form of R&D changes following earnings management, in comparison to single-class structures. The dependent variable is absolute variation in R&D. The main independent variable is earnings management (EM) interacted with the instrumented probability of being a dual-class structure ($\widehat{DCS}$). Earnings management (EM) takes three different values, as specified in the first row. The sample used includes both founder-led and non-founder-led dual-class firms. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, ** and * for the 1%, 5%, and 10% levels, respectively.

	EM: DA	EM: Abs. DA	EM: Pos DA
$\widehat{DCS} \times EM$	−0.008 (0.008)	−0.02* (0.01)	−0.001 (0.006)
$\widehat{DCS}$	0.013** (0.006)	0.022*** (0.006)	0.011 (0.008)
EM	0.006*** (0.001)	0.018*** (0.001)	0.004*** (0.001)
IMR	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Firm size	−0.001*** (0.0004)	−0.001*** (0.0004)	−0.001*** (0.0005)
Firm age	−0.003*** (0.0005)	−0.003*** (0.0005)	−0.003*** (0.0006)
Profitability	−0.023*** (0.001)	−0.019*** (0.001)	−0.022*** (0.001)
Cash	0.017*** (0.001)	0.018*** (0.001)	0.018*** (0.001)
R&D	0.112*** (0.002)	0.112*** (0.001)	0.112*** (0.002)
Leverage	0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.46	0.54	0.52
N	27,321	27,321	27,321

4.8 Conclusion

The popularity of founder-led dual-class firms in recent years, notably but not only in tech firms, has renewed concerns on this topic. In this paper, I test the often argued short-term versus long-term trade-off that may come with a dual-class structure. To study this idea I build a new sample of dual-class firms to understand the modern-day trends. First, I study the relationship between dual-class structures and short-term market pressure proxies. Then, I study if dual-class firms facing short-term pressures manipulate their numbers by cutting R&D (i.e. destroying long-term value). I find that founder-led dual-class structures are more likely to manage earnings than single-class structures. I also find that dual-class firms are just as likely as single-class structures to cut R&D expenses (i.e. destroy long-term value) when they face short-term market pressure. These results persist when I use a complete sample of dual-class firms instead of just founder-led dual-class firms.

This paper shows that despite all the scrutiny, dual-class structures are not immune to short-term pressures. Unlike commonly perceived, dual-class structures comply with short-term targets to satisfy investors. This is also perhaps done for entrenchment purposes as dual-class share owners look to sell off super-voting shares at a high value for their own wealth. Moreover, dual-class firms are just as likely to manage earnings by sacrificing areas that can potentially yield value in the future. The story behind dual-class shares being able to curb short-term pressures and focus on the long-term is therefore not directly verifiable in the data. Short-term targets still need to be attained and long-term resources are used to attain them. These results highlight that recent founder-led dual-class structures are not inherently long-termist, but rather remain vulnerable to the same short-term incentives that affect conventional governance models.

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4.9 Appendix

4.9.1 Variable definition

Table 4.9.1: Variable Definitions
This Table defines all the variables used in this study.

Variable	Definition
R&D	Research and development expenditures scaled by total assets.
R&D change	Year-on-year change in R&D expenditures scaled by total asset
R&D absolute change	Absolute value of the R&D change variable.
Discretionary accruals	Proxy for earnings management. Accounting adjustments made linked to operational performance.
Absolute discretionary accruals	Absolute value of discretionary accruals.
Positive discretionary accruals	Dummy variable equal to 1 if discretionary accruals are positive
Firm size	Natural logarithm of market capitalization (price $\times$ shares out
Firm age	Natural logarithm of the number of years since the firm's IPO.
ROA	Return on assets: net income divided by total assets. Proxy fo
Leverage	Book value of total debt (short-term and long-term) divided by
Cash	Fiscal year-end cash holdings divided by total assets.
Capex	Capital expenditures scaled by total assets.
PPE	Net property, plant, and equipment scaled by total assets. Pro

Table 4.9.1 – *Continued from previous page*

Variable	Definition
Tobin's Q	Proxy for firm value and investment opportunities: (market value of equity – deferred taxes) divided by total assets.
KZ index	Proxy for financial constraints: $-1.002 \times \text{Cash Flow} + 0.283 \times 39.368 \times \text{Dividends} - 1.315 \times \text{Cash}$, where all components are

4.9.2 OLS results

Table 4.9.2: OLS: Founder-led DCS and Earnings Management

This Table reports the OLS results that show the difference between single-class and dual-class structures concerning discretionary accruals (earnings management). Dependent variables are different measures of earnings management (discretionary accruals, absolute value of discretionary accruals, and a dummy equal to 1 for positive discretionary accruals). The main independent variable of interest is the dual-class shares dummy variable (DCS). The founder-led dual-class sample is used here. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, ** and * for the 1%, 5%, and 10% levels, respectively.

	DA	Abs. DA	Pos. DA
DCS	0.05*** (0.02)	0.03** (0.02)	0.09*** (0.03)
Firm size	0.01*** (0.002)	−0.02*** (0.001)	0.01*** (0.002)
Firm age	−0.001* (0.001)	−0.001*** (0.0003)	0.0003 (0.001)
Profitability	0.1*** (0.01)	0.03*** (0.004)	0.12*** (0.01)
Cash	0.02 (0.015)	−0.07*** (0.009)	−0.03 (0.019)
PPE	0.89*** (0.03)	0.57*** (0.02)	0.75*** (0.04)
Capex	2.15*** (0.15)	0.53*** (0.09)	3.45*** (0.19)
Leverage	−0.24*** (0.02)	0.027* (0.02)	−0.31*** (0.03)
Tobin's Q	0.02*** (0.002)	0.014*** (0.001)	0.04*** (0.003)
KZ index	0.004*** (0.0004)	−0.003*** (0.0002)	0.008*** (0.0004)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.36	0.27	0.3
N	26,901	26,901	26,901

Table 4.9.3: OLS: Founder-led DCS and R&D variation

This Table examines whether dual-class structures borrow wealth from the future in the form of R&D changes following earnings management, in comparison to single-class structures. The dependent variable is the absolute variation in R&D. The main independent variable is earnings management (EM) interacted with the dual-class structure (DCS) variable. Earnings management (EM) takes three different values, as specified in the first row. The founder-led dual-class sample is used here. Standard errors clustered at the firm level are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	EM: DA	EM: Abs. DA	EM: Pos. DA
DCS $\times$ EM	−0.001 (0.0046)	0.0019 (0.006)	−0.0003 (0.0026)
DCS	0.0028 (0.0018)	0.0015 (0.0023)	0.0027 (0.0023)
EM	−0.0023*** (0.0006)	0.0147*** (0.0009)	−0.0006 (0.0004)
Firm size	−0.0043*** (0.0001)	−0.004*** (0.0001)	−0.0044*** (0.0001)
Firm age	−0.0002*** (0.00002)	−0.0002*** (0.00002)	−0.0002*** (0.00002)
Profitability	−0.0074*** (0.0005)	−0.0081*** (0.0005)	−0.0075*** (0.0005)
Cash	0.0186*** (0.0012)	0.0196*** (0.0011)	0.0186*** (0.0012)
PPE	−0.0032 (0.0023)	−0.0137*** (0.0024)	−0.0048** (0.0023)
CAPEX	0.0438*** (0.0102)	0.0309*** (0.0102)	0.0408*** (0.0102)
Leverage	0.0218*** (0.0018)	0.022*** (0.0018)	0.0222*** (0.0018)
Tobin's Q	0.0028*** (0.0002)	0.0025*** (0.0002)	0.0027*** (0.0002)
KZ index	−0.0002*** (0.00001)	−0.0002*** (0.00001)	−0.0002*** (0.00001)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.4611	0.4701	0.4606
N	26,901	26,901	26,901

Table 4.9.4: OLS: All DCS Firms and Earnings Management

This Table reports the OLS results that show the difference between single-class and dual-class structures concerning discretionary accruals (earnings management). Dependent variables are different measures of earnings management (discretionary accruals, absolute value of discretionary accruals, and a dummy equal to 1 for positive discretionary accruals). The main independent variable of interest is the dual-class shares dummy variable (DCS). The full dual-class sample is used here (i.e. founder-led and non-founder-led). Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, ** and * for the 1%, 5%, and 10% levels, respectively.

	DA	Absolute DA	Positive DA
DCS	0.043*** (0.015)	0.043*** (0.01)	0.094*** (0.025)
Firm size	0.008*** (0.002)	−0.023*** (0.001)	0.008*** (0.002)
Firm age	−0.001* (0.0004)	−0.001*** (0.0003)	0 (0.001)
Profitability	0.1*** (0.008)	0.034*** (0.004)	0.12*** (0.009)
Cash	0.016 (0.015)	−0.067*** (0.009)	−0.027 (0.019)
PPE	0.888*** (0.032)	0.577*** (0.021)	0.75*** (0.036)
CAPEX	2.13*** (0.147)	0.533*** (0.093)	3.437*** (0.187)
Leverage	−0.234*** (0.022)	0.026* (0.015)	−0.308*** (0.032)
Tobin's Q	0.022*** (0.002)	0.014*** (0.001)	0.038*** (0.003)
KZ index	0.004*** (0.0004)	−0.003*** (0.0002)	0.007*** (0.0004)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.3604	0.2676	0.3002
N	27,312	27,312	27,312

Table 4.9.5: OLS: All DCS Firms and R&D variation

This Table examines whether dual-class structures borrow wealth from the future in the form of R&D changes following earnings management, in comparison to single-class structures. The dependent variable is the absolute variation in R&D. The main independent variable is earnings management (EM) interacted with the dual-class structure (DCS) variable. Earnings management (EM) takes three different values, as specified in the first row. The full dual-class sample is used here (i.e. founder-led and non-founder-led). Standard errors clustered at the firm level are in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and * respectively.

	EM: DA	EM: Abs. DA	EM: Pos. DA
DCS $\times$ EM	0.003 (0.004)	0.001 (0.004)	0.001 (0.002)
DCS	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)
EM	-0.002*** (0.001)	0.015*** (0.001)	-0.001 (0.0004)
Firm size	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)
Firm age	-0.0002*** (0.00003)	-0.0002*** (0.00003)	-0.0002*** (0.00003)
Profitability	-0.007*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)
Cash	0.019*** (0.001)	0.020*** (0.001)	0.019*** (0.001)
PPE	-0.003 (0.002)	-0.014*** (0.002)	-0.005** (0.002)
CAPEX	0.045*** (0.010)	0.033*** (0.010)	0.043*** (0.010)
Leverage	0.022*** (0.002)	0.022*** (0.002)	0.022*** (0.002)
Tobin's Q	0.003*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0002)
KZ index	-0.00025*** (0.00002)	-0.00021*** (0.00002)	-0.00025*** (0.00002)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.4643	0.4734	0.4639
N	27,312	27,312	27,312

4.9.3 Instrumental variable

Table 4.9.6: First stage regression of dual-class shares

This Table presents the first stage regression results for the dual-class firm instrumental variables. The dependent variable is a dummy equal to one if the firm has a dual-class structure. Column 1 restricts the sample to founder-led dual-class firms while Column 2 includes all dual-class firms. F-statistics measuring weak instruments are reported for the instrumental variables. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Founder-led	Full DCS
DCS industry mean – Past 5 years	0.81*** (0.312)	1.24*** (0.240)
State anti-takeover provisions	−0.003*** (0.001)	−0.002** (0.001)
F-statistics	14.88	14.71
Firm controls	Yes	Yes
Firm FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.18	0.23
N	26,901	27,312

Table 4.9.7: Exclusion criteria: Founder-led dual-class sample

This Table shows that my instrumental variables are not correlated with my main dependent variables, thereby respecting the exclusion criteria. The sample used is the founder-led dual-class sample. The main dependent variables are discretionary accruals in Column 1 and absolute R&D variation in Column 2. F-statistics measuring weak instruments are reported for the instrumental variables. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	DA	R&D
DCS industry mean – Past 5 years	0.007 (0.100)	0.001 (0.200)
State anti-takeover provisions	0.0001 (0.001)	0.002 (0.002)
F-statistics	0.01	0.38
Firm controls	No	No
Firm FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.10	0.02
N	26,901	26,901

Table 4.9.8: Exclusion criteria: Full dual-class sample

This Table shows that my instrumental variables are not correlated with my main dependent variables, thereby respecting the exclusion criteria. The complete dual-class firm sample is used here (i.e. founder-led and non-founder-led). The main dependent variables are discretionary accruals in Column 1 and absolute R&D variation in Column 2. F-statistics measuring weak instruments are reported for the instrumental variables. Standard errors, clustered at the firm level, are in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	DA	R&D
DCS industry mean – Past 5 years	0.002 (0.090)	0.050 (0.160)
State anti-takeover provisions	-0.0002 (0.001)	0.002 (0.003)
F-statistics	0.01	0.27
Firm controls	No	No
Firm FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.11	0.02
N	27,312	27,312

Abstract

This thesis studies how three modern departures from traditional corporate finance principles affect corporate innovation. The first study employs a NLP technique using patent abstracts to show that common ownership increases technological similarity between firms. This relationship is driven by firms that produce low-quality innovations and is confined to patents aimed at product development rather than process improvements. Commonly owned firms therefore patent excessively within each other's fields, leading to knowledge fragmentation and potentially increased product market concentration. For common owners, product market concentration combined with non-competitive pricing strategies can enhance profits, while the reduction in breakthrough innovations induced by knowledge fragmentation helps preserve stable returns from portfolio firms. These results nuance the previously highlighted positive impact of common ownership on innovation. Causality is established using exogenous variation from financial mergers. The second study investigates the relationship between climate-related patent transactions and firm value. The results reveal that climate patent sales are associated with an immediate and persistent negative market reaction. However, climate patent acquisitions are linked to a delayed but positive market reaction that is evident one year after the transaction. These results survive a wide range of robustness checks that mitigate endogeneity concerns. This study provides new evidence suggesting that markets penalise firms for divesting from potentially valuable climate technologies and reward firms that build technological options for future climate regulation. These findings highlight that climate patent transactions serve as credible signals of a firm's strategic orientation toward the climate transition. The third study shows that dual-class firms are more likely to manage their earnings than single-class firms, as proxied by discretionary accruals. Additionally, when dual-class firms manage their earnings, they are just as likely as single-class firms to do so through changes in R&D expense. These results suggest that dual-class firms are not necessarily immune to short-term market pressure. In response to such pressures, dual-class firms appear equally willing as single-class firms to compromise long-term value drivers.

Keywords: Innovation, Common ownership, Corporate governance, Sustainable finance, Ownership structure

Résumé

Cette thèse étudie comment trois évolutions récentes par rapport aux principes traditionnels de la finance d'entreprise affectent l'innovation au sein des entreprises. La première étude utilise une technique de traitement du langage naturel appliquée aux résumés de brevets, pour montrer que l'actionnariat commun augmente la similarité technologique entre les entreprises. Cette relation est portée par les entreprises produisant des innovations de piètre qualité et se limite aux brevets orientés vers le développement de produits plutôt que l'amélioration des processus. Les entreprises ayant des actionnaires communs ont ainsi tendance à breveter excessivement dans les mêmes domaines, ce qui entraîne une fragmentation des connaissances et une concentration accrue des marchés de produits. Pour les actionnaires communs, la concentration du marché, combinée à des stratégies de tarification non-concurrentielles, peut accroître leurs profits, tandis que la réduction d'innovations de haute qualité induite par la fragmentation des connaissances contribue à garantir des rendements stables au sein de leur portefeuille d'entreprises. Ces résultats nuancent l'effet positif précédemment mis en avant de l'actionnariat commun sur l'innovation. La causalité est établie en exploitant des variations exogènes issues de fusions d'institutions financières. La deuxième étude examine la relation entre les transactions de brevets liés au climat et la valeur de l'entreprise. Les résultats montrent que les ventes de brevets climatiques sont associées à une réaction négative immédiate et persistante du marché. En revanche, les acquisitions de brevets climatiques sont liées à une réaction positive différée, observable un an après la transaction. Ces résultats résistent à un large éventail de tests visant à atténuer les préoccupations d'endogénéité. Cette étude apporte de nouveaux éléments montrant que les marchés pénalisent les entreprises qui se désengagent de technologies climatiques et récompensent celles qui construisent des options technologiques en vue de réglementations climatiques futures. Ces résultats soulignent que les transactions de brevets climatiques constituent des signaux crédibles de l'orientation stratégique d'une entreprise en matière de transition climatique. La troisième étude montre que les entreprises à droit de vote multiple sont plus susceptibles de manipuler leurs résultats comptables que les entreprises à droit de vote unique. De plus, lorsqu'elles manipulent leurs résultats, les entreprises à droit de vote multiple sont tout aussi susceptibles que les entreprises à droit de vote unique de le faire en modifiant leurs dépenses de recherche et développement. Ces résultats suggèrent que les entreprises à droit de vote multiple ne sont pas nécessairement à l'abri des pressions de court terme du marché. En réponse à ces pressions, elles semblent tout aussi disposées que les entreprises à droit de vote unique à compromettre les stratégies de croissance durable de l'entreprise.

Mots clés: Innovation, Actionnariat commun, Gouvernance d'entreprise, Finance durable, Structure de propriété des sociétés