Does Green Die in Opportunism?

Opportunistic NPE Litigation and Green Corporate Innovation

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Abstract

This study analyses the effects of opportunistic non-practicing entity (NPE) litigation activity on green corporate innovation (GCI) strategies. Our findings highlight the detrimental effects of opportunistic litigation behaviour on a firms' innovation-related decision making. Notably, we find that immediately after being involved in a litigation event, targeted firms prioritise the reduction of GCIs, specifically, climate change mitigating (CCM) technologies. This suggests that firms sacrifice their commitments to long-term sustainability efforts to produce low-risk, less innovative technologies. Additionally, we demonstrate that firms produce green technologies that are of a lower quality and value after being targeted by an opportunistic NPE. We identify causality through the America Invents Act (AIA), which leads to an exogenous increase in opportunistic litigation exposure in the state of Texas. Consistent with our baseline results, we find firms headquartered in Texas to escalate their reduction in green innovation, following the introduction of the Act. Further to our causality testing, we demonstrate that the introduction of various state-level anti-troll laws have an insignificant effect in reducing opportunistic NPE litigation risk. We illustrate that after the introduction of these laws, firms increase their non-GCI efforts, however, make no changes to their GCI production levels. Finally, we identify the presence of various underlying mechanisms which drive our results. Notably, we find managerial short-termism, climate beliefs, and corporate culture to significantly influence the GCI-related reaction of firms in the face of opportunistic behaviour.

JEL Classification: G30, G32, K11, O31, O34, Q50.

Keywords: Climate finance; Green corporate innovation; Opportunistic NPE litigation; Climate change mitigation.

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1. Introduction

The introduction of the Paris Agreement, the establishment of various net-zero emissions targets, and the imposition of stringent regulatory requirements represent critical measures in addressing the ongoing climate crisis (*The Paris Agreement*, 2022; Sautner et al., 2020). At the micro-level, firms also assume a pivotal role in achieving these targets by offering efficient solutions for reducing greenhouse gas (GHG) emissions and environmental footprints. Hong et al. (2020) asserts that in the absence of substantial change to mitigation and adaption efforts, climate change could reduce the size of the US economy by 10% before the year 2100. In this heightened context, green corporate innovations (GCIs)[1], particularly those pertaining to climate change mitigation (CCM)[2], stand as critical tools to take concrete actions to mitigate and adapt to climate change (Hall & Helmers, 2010; Hong et al., 2020; Shang et al., 2022). Extending beyond the scope of climate change mitigation, GCIs also provide a range of additional benefits for innovators. Notably, GCI production can drive corporate carbon disclosure (Li et al., 2016), reduce regulatory risk for high-emitting firms (Cohen et al., 2020; Li et al., 2022), and improve financial health and capital attractiveness for businesses (Cheng et al., 2014; Hojnik & Ruzzier, 2017; Przychodzen & Przychodzen, 2015; Song et al., 2017; Zaman et al., 2021; Zhang, 2022). Hence, GCIs assume a crucial role not only in the context of climate change, but also within the broader spectrum of the business cycle.

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[1] We define green corporate innovations (GCIs) as patented technologies with cooperative patent classifications (CPCs) relating to environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, and climate change mitigation (Cohen et al., 2020; Li et al., 2022). Further detail on these classifications, provided by the OECD, is outlined in Haščič & Migotto (2015).

[2] We note that climate change mitigation (CCM) technologies, a category within the OECD guidelines for GCIs, refers to CCM technologies relating to energy generation, transmission and distribution, transportation, buildings, wastewater treatment and waste management, production and processing of goods, and finally, the capture, storage, sequestration and disposal of GHGs (Haščič & Migotto, 2015).

Whilst firm-level innovation should be a frictionless process, it is often squandered by the barriers of intellectual property (IP) law. Notably, innovation efforts are restricted by those that aim to profit off IP protection. Patent trolls or opportunistic non-practicing entities (NPEs) hold portfolios of patented technologies, attempting to seek rents from firms that infringe on their patent rights. Literature suggests that opportunistic NPEs have detrimental effects on firms. In fact, Bessen et al. (2011) find opportunistic litigation to be associated with a US$500 million loss of market capitalisation over a two-decade period. Further, opportunistic NPEs are found to effect corporate employment and financing opportunities (Appel et al., 2019) and drive overly conservative capital structures (Duan, 2023). However, the most dominant impact of opportunistic NPEs centres around their ability to pose extensive threats to corporate innovation. Specifically, in the face of opportunistic litigation, firms reduce innovation intensity and produce lower quality innovations in years that follow (Bessen et al., 2011; Cohen et al., 2019; Huang et al., 2022). Consequentially, this is to the detriment of a firms' ability to stimulate organic growth and enhance process efficiency.

In this paper we examine the impact of opportunistic NPE litigation on GCI strategies. Apriori, the relationship between NPE litigation and GCI remains unclear. The existing literature suggests that firms decrease the intensity of their patent production (Bessen et al., 2011; Cohen et al., 2019; Bernard et al., 2022) as well as R&D expenditure (Cohen et al., 2016) after an opportunistic NPE litigation. Therefore, it is natural to assume that the effects of opportunistic NPE are likely to be negative on GCIs. However, we argue that managerial short-termism, differences in climate beliefs, and the diverse nature of corporate culture may drive firms to prioritise a reduction in their future GCIs over non-GCI technologies. In other words, firms are likely to cut their green innovation more deeply than non-green innovation following an opportunistic NPE litigation.

Prior studies show that managerial short-termism impede firms' long-term innovation investments (He & Tian, 2013). Therefore, it is plausible to argue that managers, under greater pressure to meet interim financial targets, are likely to opt to preserve their non-green, operation-centric innovations, over GCIs. Existing studies also demonstrate that executives view corporate culture as the most important factor that contributes to long-term firm value (Graham et al., 2022). More importantly, firms with strong corporate culture are shown to withstand adversity more effectively and therefore, endeavour to continue in pursuing their long-term goals, in comparison to those with a weaker culture (Graham et al., 2018; Li et al., 2021a; Fang et al., 2023). Hence, we argue that firms with weaker culture are likely to cut their GCIs, which are more long-term in nature, than non-GCIs when facing opportunistic NPE litigation. Finally, since climate change is not universally accepted and such beliefs play a significant role in decisions involving green technologies (Hong et al., 2020), we argue that firms located in regions where climate change beliefs are not as strong are more likely to cut their GCIs more than non-GCIs when facing opportunistic NPE litigation.

Alternatively, it is also evident that GCIs have demonstrated their significance and continue to be of paramount importance to firms. Several prior studies suggest that GCIs promote, among others, competitive advantages and bottom-line profitability (Cheng et al., 2014; Hojnik & Ruzzier, 2017; Przychodzen & Przychodzen, 2015; Song et al., 2017), as well as long-term financial sustainability (Przychodzen & Przychodzen, 2015; Zaman et al., 2021). More importantly, firms have an incentive to maintain GCIs to not only avoid penalties associated with environmental standards and regulations (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013), but also to improve social perception. This argument becomes even more compelling when considering the fact that the largest green innovators tend to be firms with poorer emission and pollution credentials (Cohen et al., 2020; Zhang et al., 2020; Li et al., 2022).

Hence, we alternatively hypothesise that firms will preserve their GCIs while reducing their non-GCIs following an opportunistic NPE litigation.

To examine the impact of opportunistic NPE litigation activity on GCI strategies, we collect data from: (1) the Stanford NPE Litigation Database, (2) Kogan et al. (2017)'s USPTO utility and citation dataset, (3) Compustat, and (4) the Centre for Research in Security Prices (CRSP) database. After identifying opportunistic NPE litigation events, we construct our primary opportunistic independent variable, a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, *t*. Our main dependent variables are a firms' future total, green, and non-green innovation output. Our sample, which spans from 2000 to 2020, holds 69,211 firm-year observations for 7,408 unique US public firms.

Our baseline empirical findings corroborate the established perception of opportunistic NPE litigations having harmful consequences on firm-level innovation strategies. More importantly, we find that firms prioritise the reduction of GCIs over non-GCIs in the years following a NPE litigation event. Furthermore, we find that this decrease in green technologies is driven by a reduction in explorative green patents and CCM technologies. This evidence indicates that NPE litigation negatively impacts the development of 'ground-breaking' green innovations that could contribute significantly to emissions mitigation. Additionally, we find that firms reduce the quality and value of their green innovations in the years following an opportunistic litigation event.

Next, we try to establish causality by considering how firms headquartered in the state of Texas react to the introduction of the America Invents Act (AIA) of 2011. Notably, Love & Yoon (2017) find the Eastern District of Texas to remain relaxed in their enforcement of the AIA, a federal law aimed at curbing opportunistic patent trolls. Therefore, opportunistic NPEs are seen to refocus their litigation efforts on Texas, where they benefit from lower litigation costs. Based on two-stage least squares (2SLS) regression analysis, we first find that opportunistic litigation activity in Texas increases after the AIA is introduced. Then, we demonstrate that firms headquartered in Texas significantly reduce their green innovation output over their non-green innovation output after being targeted by an opportunistic NPE. Economically, these results are consistent with our baseline findings, establishing causality.

Next, we examine the mechanisms driving our results. We identify managerial short-termism, climate beliefs, and corporate culture to all play significant roles in a firm's GCI-related decision-making following a litigation event. Specifically, we find firms with heightened levels of managerial short-termism, weak climate beliefs, or a poor corporate culture to prioritise the reduction of GCI output after being targeted by an opportunistic NPE. Through our identification of these three underlying mechanisms, we find robust evidence in support of our baseline findings and in our first hypothesis. In a wider context, these results also provide novel insights into the role of these characteristics on a firm's commitment to climate change mitigation.

In additional tests we investigate the effectiveness of various state-level anti-troll legislation changes introduced after the AIA. Following Appel et al. (2019), we infer that firms could be misled by these laws. Specifically, whilst we find firms to improve their total and non-green innovation output after these laws are enacted, we do not observe any decrease in opportunistic litigation activity. This suggests that firms consider themselves to be less exposed to litigation risk, when in fact they bear the same risk as before. Further, we find no changes in future green innovation production, suggesting that despite a perception of lower litigation exposure, firms still prioritise non-green innovations over green innovations. Finally, we find no evidence to suggest that opportunistic litigation forces firms to be more financially constrained.

Our paper makes several contributions to literature. Firstly, this paper is the first study to investigate the effects of opportunistic NPE litigation on GCI strategies. Whilst confirming pre-existing findings on the harmful effects that opportunistic NPEs have on firm-level innovation, our study unveils the intensified influence of this activity on a firms' willingness towards prospective future GCI investments. Specifically, we demonstrate that after being targeted, firms significantly alter their green innovation strategies to produce fewer green innovations of both lower quality and value. These innovations are also less explorative in nature.

Secondly, our paper contributes to the climate finance literature by identifying a significant impediment to effective climate change mitigation. Notably, Hong et al. (2020)'s review of existing climate finance literature finds valuable research into the impediments of climate-related corporate innovation to be limited. However, Hong et al. (2020) highlight the importance of forward-thinking GCIs to meet long-term climate and sustainability targets. Our findings unveil the harmful effects of opportunistic NPEs on explorative green patents and CCM technologies, which gravely restricts a firms' ability to contribute positively to climate action. To tangibly meet sustainability targets in the future, firms must have confidence that they are not punished for risk-taking behaviour in their CCM strategies. Thus, our contribution sets a basis for future improvements in IP legislation related to green and CCM-specific technologies.

Our paper is organised as follows. In Section 2, we develop our hypotheses while Section 3 describes our dataset and variable construction. Sections 4 shows the summary statistics and Sections 5-7 presents all empirical analysis. We conclude our paper in Section 8.

2. Hypothesis Development

Existing literature suggests that firms change their corporate innovation strategies following a litigation event. Notably, Bessen et al. (2011), Cohen et al. (2019), Bernard et al. (2022), and Huang et al. (2022) find that firms reduce the intensity of their patent production in the years after being targeted by an opportunistic NPE. Further, Cohen et al. (2016) demonstrate that firms also reduce their R&D expenditure, a proxy for innovation output, in similar circumstances. Hence it is natural to argue that the effects of opportunistic NPE behaviour on future green innovation will also be negative. Regardless, an interesting question relates to whether the impacts of such litigation provoke greater or fewer reductions in green innovation, relative to other general innovations. In the following paragraphs we develop arguments and hypotheses to suggest the stronger and weaker impacts of opportunistic NPE litigation on green innovation. Initially, we first hypothesise that GCIs will follow a similar but more significant trend, driven by four channels.

Building upon Hong et al. (2020), we first argue that the impact of opportunistic NPE litigation on GCI is more pronounced in comparison to other innovation activities due to financial constraints, managerial short-termism, and climate beliefs. Firstly, it is well established that litigation events incur significant costs for firms (Bessen et al., 2011; Cohen et al., 2019). At the same time, Xu & Kim (2021) find firms to actively divert their environmental efforts when experiencing financial constraints. From this, we argue that added financial pressure, associated with opportunistic litigation, will divert a firms' attention away from their environmental efforts. Notably, we hypothesis that following an opportunistic litigation event, firms will be less incentivised to produce GCI technologies over non-GCI technologies.

Secondly, He & Tian (2013) find managerial short-termism to impede a firm's long-term innovation investments. Specifically, managers with increased analyst coverage tend to face greater pressure to meet interim financial targets. Consequently, these firms sacrifice their long-term innovation efforts, diverting their focus to near-term activities. We hypothesise that GCIs will be most impacted in the presence of managerial short-termism. Notably, green innovations, especially those that are CCM technologies, tend to be less important to a firms' daily operations, driving long-term ESG strategy (Li et al., 2022). Therefore, we theorise that firms will opt to preserve their non-green, operation-centric innovations, over their green innovations when facing managerial short-termism. We expect this effect to be more pronounced in the face of opportunistic litigation, as targeted firms experience immediate financial and legal pressure. This limits their ability to meet the short-term expectations of their shareholders, and consequently drives short-termism.

Thirdly, Hong et al. (2020) note that climate beliefs play a significant role in a firms' desire to produce green technologies. The perception of climate risk and strategy in firms is still divided amongst key stakeholders. For instance, Krueger et al. (2019) find institutional investors to rank climate-risk below financial, legal, and operational-risk. Further, Li et al. (2022) find relaxed environmental policy to limit climate beliefs, incentivising lower levels of future GCI production. This alone confirms GCI strategy to be sensitive to climate beliefs. Additionally, opportunistic NPE litigation is known to immediately add pressure to a firm's financial, legal, and operational position (Bessen et al., 2011; Cohen et al., 2019). Therefore, we theorise that post-litigation, firm's climate beliefs, or lack thereof, will play a significant role in their innovation decision-making. That is, firms will sacrifice their future GCI strategy, specifically in the form of a reduction in CCM technologies, to focus on innovations deemed more critical to the immediate future.

Finally, corporate culture could also play a significant role in a firm's GCI-related decision-making following an opportunistic litigation event. Notably, Graham et al. (2018) and Graham et al. (2022) suggest that corporate culture is a significant mechanism that drives a firm's long-term decision-making. Additionally, Li et al. (2021b) demonstrate that strong corporate culture is attributed with a lessened focus on short-term earnings and performance. This implies that firms with strong corporate culture are more long-term focused, and hence, will be less likely to deviate from their existing GCI strategy after being targeted by an opportunistic NPE. Strong corporate culture is also found to improve diversity within firms (Li et al., 2021b). Further, existing literature finds greater diversity to enhance emissions disclosure (Liao et al., 2015), reduce corporate environmental violations (Lui, 2018), and overall, reduce GHG emissions (Altunbas et al., 2022; Konadu et al., 2022). Therefore, we postulate that strong corporate culture, through factors such as diversity, drives the positive uptake of climate-related investments. Finally, Li et al. (2021a) highlight that corporate culture can be a driver of business resilience in difficult times. Li et al. (2021a) demonstrate that firms with strong corporate culture outperformed their peers in terms of stock and operating performance during the COVID-19 pandemic, and hence, had greater opportunities to exhibit corporate social responsibility. Therefore, we infer that in a similar event that poses uncertainty on a firm's future, strong cultured firms targeted by opportunistic NPEs will be more resilient. This will lead them to still view their GCIs, specifically their CCM technologies, as important to their long-term strategy. Collectively, this leads to our first hypothesis.

> **Hypothesis 1:** Following an opportunistic NPE litigation event, firms prioritise the reduction of their future GCI production over their non-GCI production, with this change driven by CCM technologies.

Alternatively, we hypothesise that despite the negative consequences of litigation on innovation output, GCIs are of upmost importance to firms, especially those that are active green innovators. Firstly, multiple studies suggest that GCI production can promote competitive advantages and bottom-line profitability in firms (Cheng et al., 2014; Hojnik & Ruzzier, 2017; Przychodzen & Przychodzen, 2015; Song et al., 2017). Secondly, GCI production can relieve financial constraints (Zhang et al., 2020), improving long-term financial sustainability (Przychodzen & Przychodzen, 2015; Zaman et al., 2021) and increasing the capital attractiveness of firms (Zaman et al., 2021; Zhang et al., 2020). Hence, we hypothesise that GCI production is an essential driver of future business performance, thus incentivising firms to preserve these innovations when facing the consequences of a litigation event.

Furthermore, Cohen et al. (2020), Zhang et al. (2020), Li et al. (2022), and Xu & Kim (2021) all find the largest green innovators to be firms with poorer emission and pollution credentials. Notably, Cohen et al. (2020) find green innovating firms to primarily operate in the oil, gas, and energy industries, and further, find these firms to produce GCIs of a higher quality. GCI production is essential for these firms to drive tangible carbon emission reduction, and further, to accelerate long-term industry change. For instance, Cohen et al. (2020) finds green innovators to be the first movers in many innovation categories including those that are sustainability related.

Additionally, firms are incentivised to continue their GCI production to avoid penalties associated with environmental standards and regulations. As Aguilera-Caracuel & Ortiz-de-Mandojana (2013) conclude, green innovating companies tend to operate in areas with stricter environmental regulations. With GCI production being important for mitigating regulatory risks and improving social perception (Li et al., 2022), we postulate that firms are reluctant to reduce their GCI production in order to maintain regulatory and social compliance. To support this, Li et al. (2022) find increased financial constraints within high-emitting firms to result in a reduction in non-GCI production, not GCI production. This infers that when facing added financial pressure, such as the legal costs associated with a litigation event, firms are likely to adjust their non-GCI strategies whilst sustaining their GCI technologies. This difference is likely to be driven by the improved regulatory and abatement efficiencies that result from investing in green technologies for GCI-intensive, high-emitting firms (Cohen et al., 2020; Li et al., 2022). Therefore, the overall importance of green corporate innovation for firms, is driven by both financial and environmental abatement benefits, leading to our second hypothesis.

> **Hypothesis 2:** Following an opportunistic NPE litigation event, firms preserve their future GCI production, whilst reducing their non-GCI production.

3. Dataset & Variable Construction

3.1 Dataset

Our study uses the following three databases to test our hypotheses: (1) the Stanford NPE Litigation Database, (2) the USPTO utility patent and citation dataset, as constructed by Kogan et al. (2017) and updated by Woeppel (2021), and (3) the Compustat and CRSP databases as accessed through WRDS. Compustat and CRSP provide fundamental financial and security data for all public US companies. We focus our paper on NPE litigation events that target public firms and utility patents due to the availability of firm-level and patent-level financial and innovation data.

First, we use patent litigation data from the Stanford NPE Litigation Database to extract individual litigation events from 2000 to 2020. Each litigation event has a patent asserter, an NPE or PE who sues a firm for infringing on their patent rights, and an alleged infringer, a firm who is being sued for infringing on the patent asserter's rights. As explained in Miller (2018) and further outlined in Table A.2, each patent asserter is assigned a category from 1 to 13, which determines whether the asserter is a PE, opportunistic-NPE, or non-opportunistic NPE. Of the thirteen categories, opportunistic-NPEs are acquired patents (category 1), corporate heritage (category 4), and individual-inventor started companies (category 5). The Stanford NPE Litigation Database also includes filing dates, case numbers, and USPTO patent numbers for all litigation events in the last 20 years. It should be noted that patents referenced in the Stanford NPE Litigation Database refer to patents owned by the patent asserter, not the alleged infringer. We focus on publicly listed alleged infringers, and further, include litigation events that involve both public and private patent asserters. Whilst this limits our accessibility to patent-level characteristics of infringed technologies, it poses no limitations to our study given that we focus on the characteristics of targeted firms (alleged infringers), not targeting firms (patent asserters).

The Stanford NPE Litigation Database is one of the most comprehensive and functional IP-related litigation databases (Miller, 2018). Its ability to separate opportunistic litigation events from non-opportunistic litigation events is a feature that has not been widely replicated to such detail. Our use of this database follows Bernard et al. (2022) and Huang et al. (2022), who both use the database to identify litigation events related to NPE activity. Huang et al. (2022) also use the Lex Machina legal database to obtain further information about each individual case. However, this limits their dataset from 2008 to 2016 due to the lack of available information in Lex Machina. This is similar to Bereskin et al. (2022) who only use the Lex Machina database for their study. Again, this limits their dataset from 2000 to 2014 and restricts their ability to identify non-opportunistic and opportunistic litigation events. Notably, Bereskin et al. (2022) only focus on PE litigation events, removing all NPE-related observations.

Following Li et al. (2022), we use the firm-level utility patent and citation dataset constructed by Kogan et al. (2017), and the USPTO patent database supplied by Woeppel (2021). We obtain citation counts and cooperative patent classifications (CPCs) for all patents litigated against in the Stanford NPE Litigation Database, and for all patents held by targeted public firms. As per

Mudambi & Swift (2014), we adjust these citation counts for industry-related truncation bias. Further, we use patent value data from Kogan et al. (2017) to quantify changes in the value of a targeted public firms' patent portfolio. Unfortunately, due to many infringed patents mentioned in the Stanford NPE Litigation Database being held by private NPEs, we are unable to extract patent value characteristics for individual litigation events. Finally, we exclude non-utility patents from our dataset due to the lack of citation and value information available for these patents.

To determine whether a patent is a green innovation, we follow methods used in Li et al. (2022) to match CPC classifications, provided by the Organization for Economic Cooperation and Development (OECD) (Haščič & Migotto, 2015), to individual patent numbers. At a broad level, GCIs are split into four major categories: (1) environmental management, (2) water-related adaption technologies, (3) biodiversity protection and ecosystem health, and (4) climate change mitigation (CCM). Category 4 (CCM technologies) can be split into another six categories: (1) energy, (2) GHG, (3) transportation, (4) infrastructure, (5) waste management, and (6) goods processing related CCM.

Finally, we obtain financial and accounting data from Compustat and CRSP. Given that the Stanford NPE Litigation Database does not contain any universal company linking keys, we adopt a variety of fuzzy matching techniques to combine these datasets. This methodology is recommended in Xu & Kim (2021), and further employed in Li et al. (2022) who match EPA toxic emission data to Compustat and CRSP. We use historical firm name information from CRSP (with additional information from 10K, 10-Q, and 8-K filings using the SEC Analytical Package in WRDS) to assign linking keys to each public alleged infringer within the Stanford NPE Litigation Database. Through four different iterations of fuzzy matching and comprehensive manual checks, we successfully match 9,179 of the 74,904 unique alleged infringer names in the Stanford NPE Litigation Database to a relevant identifier. We consider this match to be successful as we only focus on publicly listed firms in the Stanford NPE Litigation Database. Additionally, we obtain considerably more matches in comparison to Bernard et al. (2022) (1,059 public firm matches), with our results aligning with Huang et al. (2022) (11,529 public firm matches). Using PERMCO identifiers, we link these public firms to Compustat and CRSP, to attain historical firm-year financial information for each litigation observation involving a public alleged infringer. Finally, using the same linking keys we merge a consolidated firm-year version of the Stanford NPE Litigation Database with Compustat and CRSP, to obtain a time-series dataset for all public firms between 2000 and 2020. Further details surrounding the matching process can be found in Appendix A.1.

3.2 Variable Construction

3.2.1 Litigation Identifiers

In our initial patent-level dataset, which outlines each individual litigation event between 2000 and 2020, we construct the dummy variable *NPE* which equals one if the patent asserter category is related to an opportunistic NPE or non-opportunistic NPE following Miller (2018) (shown in Table A.2). This implies that the patent asserter is a PE if *NPE* is equal to zero. Additionally, we generate the dummy variable *Opportunistic*, which is equal to one if the patent asserter category represents an opportunistic NPE as per Miller (2018). When consolidating our patent-level dataset into our firm-year dataset, we create variables for the total litigation events experienced by a firm each year. Thus, we construct *Litigations*, *NPE Litigations,* and *Opportunistic NPE Litigations*. In addition to this, we redevelop our dummy variables *Litigation, NPE,* and *Opportunistic,* if a firm experiences at least one litigation of that kind in a given year *t* (see Table A.1 for variable names and descriptions).

3.2.2 Measuring Future Innovation

To measure future innovation levels, we analyse three metrics of innovation, quantity, and intensity. Following Li et al. (2022), we define *Ln(Total Pat), Ln(Green Pat)* and *Ln(CCM Pat)*, to measure changes in the quantity of total, green, and CCM patents after a litigation event takes place. Additionally, we generate *GCI Pat Intensity,* which represents the total number of filed green innovations divided by the total number of filed innovations for a given year. We further generate *CCM Pat Intensity*, which represents the total number of CCM technologies produced divided by the total number of innovations produced each year. When calculating the cumulative number of patents produced by a firm each year, we follow Kogan et al. (2017) by summing all filed patents, not granted patents. This is important as patent applications can take between 2-3 years before being granted or declined. Thus, we consider all innovation made by a firm at the time of filing to get a better representation of their overall innovation strategy (Li et al., 2022).

Following Li et al. (2022), we also create a set of variables to track the quality and value of patents produced for each firm-year. Firstly, we generate *Ln(Total Adj. Citations)*, which represents the natural logarithm of one plus the cumulative adjusted citation counts of all patents filed each year. Additionally, we generate *Ln(Adj. Green Citations)* and *Ln(Adj. CCM Citations)* which evaluates the natural logarithm of one plus the total adjusted citation counts for all filed GCI and CCM technologies each year. These variables allow us to observe how the quality of patent production changes after an opportunistic NPE litigation event takes place. Finally, we evaluate a set of variables to analyse changes in patent value after a litigation event. *Ln(Total Real Value)* represents the natural logarithm of one plus the cumulative patent value for each firm-year, using data supplied in Kogan et al. (2017). Following Kogan et al. (2017) and Li et al. (2022), we account for patent values being calculated on isolated stock price changes when an innovation is granted not filed. Noting that the unconditional probability of a filed patent being granted is 0.56 (Kogan et al., 2017), we adjust for this bias by multiplying all patent values by 2.27 (1/(1-0.56)). This allows us to estimate the total value of all filed patents, instead of the value of granted patents.

3.2.3 Control Variables

Accessing firm-year financial and accounting data from Compustat and CRSP, we develop a set of control variables. Consistent with innovation-related literature, we include *Cash*, a firm's cash holdings, *Ln(Assets),* the natural logarithm of one plus a firm's total assets, and *Ln(Employees),* the natural logarithm of one plus a firm's employee count. Specifically, we track *Ln(Employees)* to better assess the human capital resources in a firm, and hence their size. This also assists in identifying the presence of start-ups and individual inventors in our dataset. We include *Tobins Q*, the ratio of a firm's market value and replacement cost, *ROA*, the ratio of operating income (after depreciation) to total assets, and *Leverage*, the sum of short and long-term debt divided by total assets. Finally, we include *Stock Return*, the percentage change in a firm's stock value compared to the previous financial year, *R&D Expense*, a firm's R&D expenditure, and *Ln(Total Pat)*, the natural logarithm of one plus a firm's innovation output in a given year. A list of all variables can be found in Table A.1.

4. Summary Statistics

We develop a firm-year dataset, outlining yearly observations of public alleged infringers between 2000 and 2020. In this dataset, we analyse the effect of cumulative yearly litigation events on public firm-level characteristics. We remove all firm-year observations that are missing data for our dependant, independent, and control variables, resulting in a sample of 69,211 public firm-year observations. We summarise the relevant variables and their respective summary statistics in Table 1. Within this, we summarise the number of observations, mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, and maximum.

[Insert Table 1 here]

Table 1 reports the mean patents produced to be 8.12 innovations, which equates to approximately 561,993 patents filed between 2000 and 2020 when multiplied by the number of firm-year observations. We also find firms to, on average, produce 0.29 green innovations (20,071 total green patents filed). This infers that green innovations relate to 3.57% of total innovation in this period. This observation aligns with Kogan et al. (2017) and Li et al. (2022). Table 1 also displays 48% of firms in our sample to be exposed to litigation across the 20-year sample. Further, 30% of firms experience an NPE litigation event, and 24% of firms experience an opportunistic NPE litigation event. Thus, our sample infers there to be approximately 33,221 total litigation events and 16,611 opportunistic NPE litigation events.[2] In our final sample, the average firm has an *Ln(Green Pat)* of 0.10, and an *Ln(CCM Pat)* of 0.08. In addition, firms

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[2] We also use our firm-year dataset, to identify the total number of litigation events that involve public alleged infringers in our sample. In Table 1 of the Internet Appendix, we observe a sample of 52,505 individual litigation events between 2000 and 2020. Of these, 34,955 involve an NPE as the patent asserter (approximately 66.57%). This is significantly higher than the sample results of Miller (2018), whose sample of 10,812 litigation events between 2000 and 2015 finds 41.8% of all litigation events to be driven by NPEs. Our results demonstrate that NPEs are now a more active player in the litigation space. This is consistent with Caviggioli & Ughetto (2015), who notes that since the early 2000s, NPE litigation activity has been growing at a faster rate than PE litigation activity. 30,060 litigation events involve an opportunistic NPE as the patent asserter (approximately 57.25% of total litigation events and 86.00% of total NPE litigation events). This aligns with Miller (2018), who finds 83.25% of all NPEs to be opportunistic.

We illustrate time-series changes in litigation activity in Figure 1. Panel A displays the change in yearly litigation events involving public alleged infringers. We observe a substantial increase in litigation activity in 2005, however we find this drop off in 2007 – 2008 due to the GFC. Interestingly, we observe an increase in litigation events after 2008, with this peaking in 2011 due to the introduction of the American Invents Act (AIA). Since then, we find litigation events to steadily decline. Further, Panel B breaks NPE litigation events into their respective classifications of opportunistic and non-opportunistic (see Table A.2). We observe opportunistic NPEs to be the dominant driver of NPE litigation behaviour and find opportunistic NPE litigation activity and NPE litigation activity to follow similar time-series trends as before. Nevertheless, we find that these trends to be less salient for non-opportunistic NPE litigation activity, signifying that non-opportunistic NPEs do not drive litigation trends. This affirms our view that the litigation market is crowded with harmful opportunistic NPE’s.

have a mean *GCI Pat Intensity* and *CCM Pat Intensity* of 0.01. Our control variables find each firm to have a mean *Cash* of 0.11, and a mean *Ln(Assets)* of 6.61. Firms have an average *Ln(Employees)* of 1.25 and an average *Tobin's Q* of 1.78. Additionally, firms have a mean *ROA* of 0.01, *Leverage* of 0.22, and *Stock Return* of 0.15. Finally, firms have an average *R&D Expense* of 0.03.

5. Main Results: Opportunistic NPE Litigation

5.1 Methodology

In Hypothesis 1, we theorise that firms prioritise the reduction of future green innovation over non-green innovation after an opportunistic NPE litigation event $(Opportunistic_{i,t})$. Alternatively, in Hypothesis 2 we hypothesise that firms preserve their future GCI technologies, by instead reducing their future non-GCI technologies. Our methodology for Hypothesis 1 and 2 follows Huang et al. (2022), who studies how firms adjust their innovation output and quality after a litigation event. Given our focus on GCI technologies, we differ from Huang et al. (2022) by analysing how *Ln(Total Pat), Ln(Green Pat), Ln(Non-Green Pat)* and *GCI Pat Intensity* changes one, two, and three years after the litigation event. Therefore, we set these four variables as the dependent variables in our analysis $(Dependent_{i,t+1,t+2,t+3})$. We define our independent variable as $Opportunistic_{i,t}$, a dummy variable equal to one if a company is targeted by an opportunistic NPE each year. This is similar to Huang et al. (2022)'s use of *Post-NPE.* Thus, we build off the least squares (OLS) regression models used in Huang et al. (2022) to develop the following model.

$$Dependent_{i,t+1,2,3} = \alpha + \beta_1\, Opportunistic_{i,t} + \gamma\, Controls_{i,t} + FEs + \varepsilon_{i,t}$$

We also include control variables $(Controls_{i,t})$ for *Cash, Ln(Assets), Ln(Employees), Tobin's Q, ROA, Leverage, Stock Return, R&D Expense,* and *Ln(Total Pat).* Further, we include firm and year fixed effects *(FEs)* and cluster standard errors $(\varepsilon_{i,t})$ at the firm level.

5.2 Future Firm Innovation Output

In this section, we investigate whether being targeted by an opportunistic NPE *(Opportunistic$_t$)* influences a firms' future innovation output levels. In our least squares (OLS) regression in Table 2, we investigate total innovation levels *(Ln(Total Pat)$_{t+1,2,3}$)* (columns (1) – (3)), green innovation levels *(Ln(Green Pat)$_{t+1,2,3}$)* (columns (4) – (6)), and non-green innovation levels *(Ln(Non-Green Pat)$_{t+1,2,3}$)* (columns (7) – (9)). In column (1) and (2) we find no significant indication to suggest that firms actively alter their total innovation level in the first or second years following an opportunistic NPE litigation event. In line with patent litigation literature, which widely suggests that litigation activity reduces future innovation levels (Bernard et al., 2022; Bessen et al., 2011; Cohen et al., 2019; Huang et al., 2022), we see a significant decrease in total innovation output in the third year. Economically, when compared to the mean, firms targeted by opportunistic NPEs reduce innovation by 5.93% in the third year following a litigation event.

[Insert Table 2 here]

Our findings in relation to the impacts of opportunistic NPE litigation on future GCI production are noteworthy. Specifically, columns (4), (5), and (6) of Table 2 bear profound significance, accentuating that whilst firms only significantly reduce total innovation in the third year, firms significantly reduce GCI output in all three years after being targeted by an opportunistic NPE. Economically, we find that firms targeted by opportunistic NPEs reduce *Ln(Green Pat)* by 26.03%, 21.41%, and 29.11% compared to the mean *Ln(Green Pat)* of 0.10, for years one, two, and three respectively. Finally, in a similar response to total innovation levels, we find firms to reduce their non-GCI output only in the third year after an opportunistic litigation event. In this, we find a change in our explanatory variable *Opportunistic$_t$*, to result in a 5.79% decrease in *Ln(Non-Green Pat)$_{t+3}$*, from the mean level of 0.56.

Wholistically, our findings in Table 2 infer that not only do firms reduce their total innovation following a litigation event, a finding that is well established in literature, however, firms exhibit an observable inclination to immediately reduce their GCI endeavours over their non-GCI production. Hence, our empirical observations substantiate the first hypothesised proposition, in which firms prioritise the reduction of green technologies over non-green technologies following a litigation event. This inherently supports Hypothesis 1 and alludes to the notion that financial constraints, managerial short-termism, climate beliefs, or corporate culture may be the underlying drivers of this behaviour. These results carry substantive implications and are a valuable contribution to understanding the effects of patent litigation in the green technology space. Overall, we find opportunistic NPEs to be more harmful to future GCI production in comparison to non-GCI production, which unveils even greater consequences engendered by opportunistic NPEs.[3]

To further our analysis, Table 3 analyses the change in future green innovation output based on whether these innovations are CCM or non-CCM technologies. Our findings suggest that the reduction in future green innovation is predominantly driven by a reduction in CCM technologies (columns (1) – (3)). That is, we find that when compared to the mean (0.08), firms targeted by opportunistic NPEs significantly reduce *Ln(CCM Pat)* by 30.02%, 25.92%, and 35.62% for years one, two, and three, respectively. Alternatively, we find firms to insignificantly reduce non-CCM technologies in years one (column (4)) and three (column (6))

[3] As a robustness test, we analyse the effects of litigation events brought on by all NPEs (both opportunistic and non-opportunistic NPEs) in Table 2 of the Internet Appendix. Our results substantially differ to those in our main results (Table 2). That is, whilst we find NPEs to have a similar effect on total and non-green innovation in firms, driving a reduction in innovation only in year three (column (3) and (9)), we find different results with respect to green innovation. Particularly, we find NPEs to drive a reduction in green innovation only in years one and three (columns (4) and (6)), with the economic significance of this reduction being approximately half of that of opportunistic litigations. This confirms opportunistic NPEs, not all NPEs, to be the drivers of the large reduction in green innovation in all three years following a litigation event.

following an opportunistic NPE litigation event, and finally, find that firms significantly reduce non-CCM technologies only in year two (column (5)). In this case, firms targeted in litigation events reduce *Ln(Non-CCM Pat)*$_{t+2}$ by 26.11%, when compared to the mean of 0.02. This supports our view that CCM innovation strategies are more dispensable to firms in the short-term. As alluded to in Li et al. (2022), non-CCM technologies are important to a firms' day to day operations. Hence, as supported by our findings, firms prioritise these technologies due to the profit and operational efficiencies, as well as the short-term regulatory benefits that arise from non-CCM related technological production. This further attests to the harmful nature of opportunistic NPEs, with our analysis suggesting that firms are forced to be less committed to long-term climate targets after being involved in a ligation event. These findings also corroborate Hypothesis 1, where climate beliefs are theorised to be a significant factor in a firm's future GCI decision-making in the aftermath of an encounter with an opportunistic NPE.

[Insert Table 3 here]

Finally, in Table 4 we analyse this change with respect to GCI and CCM intensity. Our findings provide further substantiation for Hypothesis 1, demonstrating that firms significantly reduce the intensity of GCI output, or the ratio of green innovations to total innovations, in the first two years following a litigation event (columns (1) and (2)). Specifically, we find the economic significance of *GCI Intensity* in years one and two to imply a 24.70% and 16.46% respective decrease from the mean of 0.01 if targeted by an opportunistic NPE. Further, we find firms to significantly reduce their CCM intensity in the first year following an opportunistic litigation event (column (4)). Notably, compared to the mean (0.01), firms targeted by opportunistic NPEs reduce *CCM Intensity*$_{t+1}$ by 20.84%, in the first year following a litigation event. Overall, this again suggests that firms prioritise the reduction of GCI, specifically CCM technologies, immediately after an opportunistic NPE litigation event, with a similar indifference to innovation reduction in the third year. This leads us to again reject Hypothesis 2, finding additional support for Hypothesis 1.

[Insert Table 4 here]

5.3 Future Firm Innovation Value

In the penultimate section of our baseline empirical analysis, we again adopt a least squares (OLS) regression to analyse how the future value of a firms' innovation strategy changes after an opportunistic NPE litigation event. Table 5: Panel A displays the baseline results for the cumulative real value of patents produced in the three years after a litigation event. In columns (1) and (3), we observe a significant decrease in *Ln(Total Real Value).* Alternatively in column (2), we observe an insignificant decrease in *Ln(Total Real Value).* Specifically, we find that being targeted by an opportunistic NPE results in a 4.30% decrease in year one, a 0.17% insignificant decrease in year two, and a 6.44% decrease in year three from the mean level of *Ln(Total Real Value)* (1.11). With respect to green innovation value, columns (4) to (6) demonstrate that opportunistic NPE litigation leads to a reduction in real value for these technologies in all years (insignificant in year two). In this, we find a significant decrease in *Ln(Green Real Value)* in year one and three, in which, compared to the mean, firms targeted by opportunistic NPEs reduce *Ln(Green Real Value)* by 65.84% and 47.08% respectively, from a mean of 0.02.

[Insert Table 5 here]

Finally, columns (7) to (9) display the effect of opportunistic litigation activity on future non-green real value. In years one and two, firms insignificantly reduce the value of their non-green patent portfolios. Then in year three, firms significantly decrease the value of their non-green patent portfolios, to the extent that an opportunistic NPE litigation event results in a 6.85% decrease in *Ln(Non-Green Real Value)*, from the mean level of 1.10. These results infer that firms prioritise the reduction in green real value immediately (in year one) after an opportunistic NPE litigation event and the value of all innovations in the long term (year 3). This aligns with and further bolsters our findings in Section 5.2, where we observe future green technology production to be a lower priority for targeted firms.

Whilst we consider our findings in Table 5: Panel A to be a robust indication of the influence of patent litigation on patent value, we understand that the results of Section 5.2 may mislead these findings. Section 5.2 demonstrates that firms reduce total, green, and non-green innovation by varying magnitudes in the three years following an opportunistic NPE litigation. Therefore, given our quality metrics are the cumulative citations of patents produced each year, the lower number of issued innovations may be the driver of the lower number of cumulative citations. To verify our results in Table 5: Panel A, we also analyse how average real value changes after a litigation event. As observed in Table 5: Panel B, we find slightly different results to Table 5: Panel A. That is, firms significantly reduce *Ln(Avg. Real Value)* and *Ln(Avg. Non-Green Real Value)* only in year three, and significantly reduce *Ln(Avg. Green Real Value)* in year one. Nonetheless, this still supports Table 5: Panel A and Hypothesis 1, demonstrating that firms prioritise a reduction in green value over non-green value following a litigation event.

5.4 Future Firm Innovation Quality

In the final section of our baseline empirical analysis, we investigate how the future quality of a firms' year-on-year innovation portfolio changes after an opportunistic NPE litigation event. Table 6: Panel A displays the baseline results for our analysis on total adjusted citation counts. Notably, it represents the effect of opportunistic NPE litigation events on year-on-year changes in the cumulative citations for patents produced in the three years after the event takes place. As seen in columns (1) to (3), we find total citation counts for all technology classes to significantly reduce in the years following a litigation event. Economically, we find that when targeted by an opportunistic NPE, firms decrease the quality of their innovations by 21.35%, 20.41%, and 32.70%, in comparison to the mean level of *Ln(Total Adj. Citations)* (0.15) for years one, two, and three respectively. Further, whilst insignificant in year two, columns (4) to (6) all display a firms' total green citations to reduce following an opportunistic NPE litigation event. Specifically, years one and three see firms to reduce their GCI quality by 50.93% and 65.90% from the mean level of *Ln(Adj. Green Citations)* if targeted by an opportunistic NPE. Finally, like *Ln(Total Adj. Citations)* we find a significant reduction in total adjusted non-green citations in all three years after an opportunistic NPE litigation event (columns (7) – (9)). Economically, we find targeted firms to reduce their non-GCI quality by 21.07%, 19.87%, and 32.75% from the mean *Ln(Adj. Non-Green Citations)* of 0.15 for years one, two, and three respectively. Nevertheless, we highlight that the economic significance for *Ln(Adj. Green Citations)* is greater than that of the other variables in all years, suggesting that the quality of GCIs experience a larger reduction. Therefore, our findings substantiate the quality of year-on-year patent portfolios to diminish after an opportunistic litigation event. Economically, we infer that beyond reducing total innovation quality, firms heavily reduce the quality of their GCIs.

[Insert Table 6 here]

As per Section 5.3, we again verify our results by testing *Ln(Avg. Adj. Citations)*, *Ln(Avg. Adj. Green Citations)*, and *Ln(Avg. Adj. Non-Green Citations).* As observed in Table 6: Panel B, we find average adjusted citations for all technology classes to decline in all three years after a litigation event. Further, whilst we find this to be significant for *Ln(Avg. Adj. Citations)* in all years (columns (1) to (3)), we find *Ln(Avg. Adj. Green Citations)* to only be significant in years one and three (column (4) and (6)), and finally, *Ln(Avg. Adj. Non-Green Citations)* in years one and three (columns (7) and (9)). Therefore, whilst we observe this change to be less significant compared to total cumulative citations, we observe similar trends to before (with the exception of column (8)), validating our initial results in Table 6: Panel A.

5.5 Exploitative vs Explorative GCI Strategies

In addition to our baseline empirical analysis, we follow Li et al. (2022) by categorising green technologies as exploitative and explorative. We define an exploitative GCI technology as a green patent with 60% or more of its citations referring to existing knowledge or innovations within the firm. Further, we classify an explorative GCI technology as a green patent with 60% or more of its citations referring to new knowledge not previously known by the firm (see Table A.1). Following the same research design to Section 5.1, we test two new dependent variables, *Ln(Exploitative GCI Pat)*$_{t+1,2,3}$ and *Ln(Explorative GCI Pat)*$_{t+1,2,3}$.

[Insert Table 7 here]

As presented in Table 7, our least squares (OLS) regression reveals noteworthy findings. Firstly, columns (1) and (2) infer that firms do not significantly reduce the number of exploitative GCI technologies in the first two years after an opportunistic NPE litigation activity. However, column (3) finds firms to significantly reduce exploitative GCI technologies in year three. Economically, firms targeted by opportunistic NPEs reduce their exploitative GCI production by 1.44%, 23.92%, and 64.11% from the mean level of *Ln(Exploitative GCI Pat)* (0.03) for years one, two, and three, respectively. Secondly, and more importantly, our findings indicate that firms significantly reduce their explorative GCI production *(Ln(Explorative GCI Pat))* in all three years following an opportunistic litigation event (columns (4) – (6)). That is, we find targeted firms to decrease their explorative GCI production by 77.26%, 55.36%, and 39.91% from the mean level of *Ln(Explorative GCI Pat)* (0.05) for the three respective years following a litigation event. We consider these results to be relatively intuitive. In the immediate years after an opportunistic NPE litigation event, it is conceivable that firms are inclined to mitigate their future litigation risk. To do so, they ensure that the technologies that they produce focus in areas that they know well, and hence, that have a lessened likelihood of infringement. Then concurrently, they reduce the production of innovations in areas that are novel, and thus, violable. This is confirmed by the smaller, insignificant reduction in exploitative GCI technology production in years one and two, but the large significant reduction in explorative GCI technologies in years one, two, and three.

5.6 Environmental Externalities

Further to our analysis of GCI, we also analyse the effects of opportunistic NPE litigation on another proxy for environmental externalities. That is, we investigate how opportunism influences future pollution intensity in firms. Following Hsu et al. (2023), we define *Pollution Intensity*$_t$ as the aggregate amount of total toxic emissions released by a firm (measured in thousands of pounds) scaled by total assets, for a given year, *t*. Toxic releases represent firm-level industrial chemical pollutant emissions, measured using the Toxic Release Inventory (TRI) database and constructed by the United States Environmental Protection Agency (EPA). We consider a firm's pollution intensity to be a strong identifier of environmental performance and commitment, with emission outputs usually being mitigated with novel CCM-related GCIs.

[Insert Table 8 here]

As presented in Table 8, our least square regression, which analyses *Pollution Intensity*$_{t+1,t+2,t+3}$, finds a firm's total toxic releases to significantly increase in all three years following a litigation event. We find these results to be intuitive, but no less significant. Table 2 of our main results highlights that firms prioritise the reduction of GCI production in all three years following a litigation event. Then in Table 8, we demonstrate that not only do firms reduce their green innovation efforts, however, they also increase their toxic emissions output in a similar manner. This implies that in light of opportunistic litigation, firms reduce their investments in CCM-centric technologies which would contribute to toxic emissions mitigation. Hence, a firms' future emission levels increase. At a high-level, our findings infer that opportunistic litigation distracts firms from their existing environmental efforts, not just their future investment efforts. Ultimately, this leads to an increase in their total toxic release levels, suggesting an even more significant environmental externality resulting from opportunistic behaviour.

6. Endogeneity Tests

6.1 IV regression: The America Invents Act, Texas

Whilst our baseline results demonstrate the negative effects that opportunistic NPEs have on GCI strategies, this does not necessarily imply the identification of a causal relationship. It is possible that selection bias or omitted variable bias may drive discrepancies in our results. Following recent patent litigation literature, we therefore establish causality by exploiting an exogenous shock, being the introduction of the America Invents Act (AIA) of 2011, within the state of Texas.

The America Invents Act (AIA), signed into law on the 16th of September 2011, is widely perceived as the *"first comprehensive patent bill to be enacted since the Patent Act of 1952"* (Matal, 2012), to allow firms to *"focus on innovation and job creation rather than costly, and sometimes unnecessary, litigation."* (*Patent Trolls Under the Patent Reform Act*, 2011). The underlying goal of the America Invents Act is to increase the costs associated with litigation for patent asserters, whilst also providing other measures for inventors to better protect their patent rights. As noted in Bryant (2012), the AIA includes a provision in which patent asserters are unable to sue multiple defendants in the same patent-infringement suit. Ultimately, this increases the costs for opportunistic patent asserters who adopt a scatter approach to litigation targeting. Nevertheless, Chien (2014) notes that whilst the AIA may be effective in curbing litigation risk for large, established companies through prior user rights, the benefits of the AIA do not impact small innovators and start-up firms. This is supported by Appel et al. (2019) who states that the AIA does not restrict an NPE's ability to target smaller firms when sending *"abusive demand letters"*, a key strategy for opportunistic NPEs.

Regardless of the overall effectiveness or ineffectiveness of the AIA, Love & Yoon (2017) note that the Eastern District of Texas remained relaxed on the multiple defendant restrictions. This allowed patent asserters, who filed individual patents cases against different entities, to combine multiple cases into a single lawsuit. Hence, Love & Yoon (2017) find there to be an increase in litigation activity in Texas post-2011 compared to all other states. As Huang et al. (2022) explains, this shift in litigation behaviour is likely to result in increased opportunistic NPE litigation risk for firms that are headquartered in Texas. Therefore, we contend that the AIA, with respect to firms headquartered in Texas, is a robust shock to assist in the identification of causality.

We develop a treatment group of firms, being firms that are headquartered in the state of Texas. Hence, we create the dummy variable $Texas_t$, equal to one for firms headquartered in Texas, and zero otherwise. We adopt a propensity score matching (PSM) technique, to match firms in the treatment group with similar financial characteristics, to firms in the control group.[4] We also create the variable $Post\text{-}AIA_t$, which takes the value of one if the firm-year observation is after 2011. Finally, we create the interaction term $Post\text{-}AIA_t$ x $Texas_t$, which is equal to one if the firm is in Texas and if the observation is proceeding 2011. We adopt a two-stage least squares (2SLS) regression model, adjusting our first stage to only analyse how $Post\text{-}AIA_t$ x

[4] We outline the successfulness of our PSM groups Table 3 of the Internet Appendix.

$Texas_t$ influences $Opportunistic_t$. We hypothesise that the introduction of the AIA increases the probability of an opportunistic NPE litigation event for firms that are headquartered in Texas.

In our second stage, we analyse how our predicted independent variable $\widehat{Opportunistic}_t$ influences future total, green, and non-green innovation in the three years following an opportunistic litigation event. We keep all control variables, fixed effects, and standard errors the same as our first stage, that being, we use firm, year, and state fixed effects, however, we cluster standard errors at the state-level. We include the addition of state fixed effects and clustered standard errors as we consider this to be a state-level shock (Abadie et al., 2023; Appel et al., 2019). Additionally, this model centres around our focus on the state of Texas, accounting for time-invariant variations that could influence corporate innovation or litigation activity at the state-level. In this case, we theorise that firms headquartered in Texas adjust their future innovation strategies more after 2011. This is to account for the added litigation risk associated with the relaxed restrictions in the Eastern District of Texas. Hence, our two-stage least squares (2SLS) regression models are as follows.

<u>Stage 1:</u>

$$Opportunistic_{i,t} = \alpha + \beta_1\, Post\text{-}AIA_{i,t} \times Texas_{i,t} + \beta_2\, Post\text{-}AIA_{i,t} + \beta_3\, Texas_{i,t} + \gamma\, Controls_{i,t} + FEs + \varepsilon_{i,t}$$

<u>Stage 2:</u>

$$Dependent_{i,t+1,2,3} = \alpha + \beta_1\, \widehat{Opportunistic}_{i,t} + \gamma\, Controls_{i,t} + FEs + \varepsilon_{i,t}$$

We present our results for the 2-stage least squares regression in Table 9. Consistent with our first stage hypothesis, we find $Post\text{-}AIA_t$ x $Texas_t$ to be positive and significant (column (1)). This substantiates that firms head-quartered in Texas after the introduction of the AIA, face a heightened susceptibility to opportunistic NPE litigations, corroborating the findings of Love

& Yoon (2017). Our second stage regression also finds consistent results with Hypothesis 1. Firstly, columns (2) to (4) and columns (8) to (10) suggests that firms insignificantly reduce their total and non-green innovation in the three years after being targeted by an opportunistic NPE. Further, columns (5) to (7) demonstrates that firms significantly reduce their green innovation in all years following an opportunistic litigation event. This emphasises our baseline results, demonstrating that following an exogenous increase in opportunistic litigation, firms again prioritise the reduction of green innovations over non-green innovations.

[Insert Table 9 here]

This is further supported by the economic significance of all columns. That is, economically, firms heavily reduce their green innovation efforts in all proceeding years, at a greater level than total and non-green innovations. Once more, this aligns with the general consensus of the economic significance of our baseline empirical testing in Table 2. Thus, through our exploitation of this exogenous shock, we confidently establish a causal relationship between $Opportunistic_t$ and future firm-level innovation strategies. Importantly, in the event where firms encounter a heightened level of opportunistic litigation risk, those specifically targeted continue to sacrifice their GCIs over other technologies. This confirms causality in our baseline results, again highlighting the detrimental effects that opportunistic targeting has on a firms' willingness to pursue green technological investments.

7. Further Tests & Mechanisms

7.1 Mechanisms

7.1.1 Managerial Short-termism

Our first underlying mechanism test analyses the role of managerial short-termism on a firm's GCI-related decision-making following an opportunistic litigation event. Managerial short-termism is known to impede a firm's long-term innovation strategy (He & Tian, 2013). Given the long-term nature of GCIs, specifically CCM technologies, we hypothesise that firms with increased levels of managerial short-termism will be more incentivised to sacrifice their future GCI strategies in the face of opportunistic litigation. We theorise that this will be done to focus on short-term operational performance that immediately satisfies key stakeholders. Therefore, we follow He & Tian (2013)'s methodology, by using analyst coverage as a proxy for managerial short-termism, and develop a subset of firms with high and low levels of managerial short-termism, split by the median of our analyst coverage index.

[Insert Table 10 here]

As displayed in Table 10, our findings for the influence of heightened managerial short-termism are consistent with our expectations. In Panel A, we find firms with high analyst coverage, and hence high short-term pressure, to immediately and significantly reduce their GCI output in all three years following a litigation event. Then in Panel B, we find no significant evidence to suggest that firms with low levels of analyst coverage reduce their green innovation output after being targeted by an opportunistic NPE. The findings of both panels are substantial, suggesting that heightened pressure to meet short-term targets significantly undermines a firm's commitments to green technology production. This confirms managerial short-termism to be a key driving mechanism of a firm's GCI-related decision-making following an opportunistic litigation. Therefore, we find strong support for the risks of managerial short-termism.

7.1.2 Climate Beliefs

In our second mechanism test, we analyse the role of climate beliefs on GCI strategies in the years following an opportunistic litigation. Consistent with existing literature, we use political leanings as a proxy for climate beliefs (Baldauf et al., 2020). In recent years, it has been evident that the two major US political parties have held opposing views on climate change. Specifically, politicians within the Democratic party often raise policies in support of climate change mitigation, whereas politicians within the Republican party are often viewed as climate deniers (Fisher et al., 2013). To exploit the political ideologies of these parties as a proxy for climate beliefs, we develop a subset of firms headquartered in Republican dominant states, and a subset of firms headquartered in Democratic dominant states. That is, we hand collect US federal election data from 2000 to 2020, detailing the numbers and percentages of votes for each party in each state. Based on this, we determine states that are blue (Democratic) and states that are red (Republican).[5] We exclude swing states from our sample, being states where the difference in the percentage of votes for the Democratic party versus the Republican party is in the middle tercile.

[Insert Table 11 here]

Table 11 displays the results of our climate beliefs analysis. Panel A outlines our findings for firms with strong climate beliefs, being those headquartered in Democratic states. Interestingly, we find that following an opportunistic litigation event, firms with strong climate beliefs only significantly reduce their GCI output in the first year, with insignificant results in years two and three. Specifically, we find firms targeted by opportunistic NPEs to reduce their GCI production by 15.13% from the mean level of *Ln(Total Green Pat)* in year one. Additionally, we observe the reduction in GCI output to be lower than that of our main results in Table 2 for

[5] Specifically, a state is identified as a Democratic state if the percentage of votes for the Democratic party is larger the Republican party. A state is identified as a Republican state if the percentage of votes for the Republican party is larger the Democratic party. In addition, after a US federal election, the observations of the following four years (including the election year) are also identified based on that election record. For example, the state-level political leanings in years 2016 through 2019 are measured based on the US federal election in 2016, in which Donald Trump was elected as the 45th president of the United States.

all years. This infers that if a firm has strong climate beliefs, they will attempt to preserve its GCI strategy as best as they can give the circumstances.

Alternatively, Panel B displays our findings for firms with poor climate beliefs, notably being firms headquartered in Republican states. The results in Panel B are even more significant. That is, we find firms with weak climate beliefs to significantly decrease green innovation in all three years following a litigation event. Economically, we find firms to reduce their GCI production by 44.71%, 40.90%, and 44.40% in the three respective years after being targeted, from the mean level of *Ln(Total Green Pat)*. This suggests that the reduction in GCI output in the first year following a litigation event is approximately three-fold for firms with poor climate beliefs when compared to those with strong climate beliefs. This finding is of upmost importance, highlighting the pivotal role that climate beliefs have on a firm's GCI strategy. Additionally, this result confirms climate beliefs to be a significant underlying mechanism in the strategic response of firm's following an opportunistic litigation, and provides additional support to our rationale for Hypothesis 1.

7.1.3 Corporate Culture

In our third test of the underlying mechanisms driving our baseline results, we analyse the role of corporate culture on a firms' GCI-strategy after being targeted by an opportunistic litigator. Corporate culture is found to play a significant role in corporate decisions (Graham et al., 2018, 2022; Zingales, 2015). In the context of GCI strategies, a strong corporate culture incentivises firms to focus on long-term issues, including climate change. Further, strong cultured firms are found to have stronger desire to improve their environmental footprint, driving a focus on climate change and emissions mitigation (Altunbas et al., 2022; Konadu et al., 2022; Liao et al., 2015; Lui, 2018). Therefore, as per Hypothesis 1, we postulate corporate culture to be an underlying mechanism for firms targeted by opportunistic litigation, with firms with strong corporate culture less likely to prioritise a reduction in GCI output after a litigation event, and firms with weak corporate culture more likely to prioritise this reduction.

[Insert Table 12 here]

We utilise novel textual-based corporate culture data developed by Li et al. (2021b), which analyses corporate culture in five categories: innovation, integrity, quality, respect, and teamwork. Split by the median of the total of all scores, we develop subsets of our dataset for strong corporate culture and weak corporate culture. As displayed in Table 12, we draw interesting conclusions. Firstly, in Panel A, which outlines the effects of opportunistic NPE litigation on future GCI output for firms with strong corporate culture, we find the reduction in GCI output to be delayed until year 3. This differs from our original findings in Table 2, where firms immediately prioritise the reduction of GCI output. Specifically, we find firms targeted by opportunistic NPEs to reduce their innovation output by 23.19% from the mean level of *Ln(Green Pat)*.

Additionally, in Panel B, which describes our findings for targeted firms with weak corporate culture, we find firms to immediately reduce their GCI output in the first year, however, find no significant results for the second and third year following a litigation event. Differing from firms with strong corporate culture, this suggests that weak cultured firms prioritise the reduction of GCI output immediately after a litigation event, implying that these firms find such technologies to be non-meaningful and disposable. Economically, we find weak cultured firms targeted by opportunistic NPEs to reduce their innovation output by 19.82% from the mean level of *Ln(Green Pat)*.

Ultimately, the findings of Table 12 suggests that strong cultured and weak cultured firms react differently in the face of an opportunistic litigation. More so, the results infer that firms who are less focused in fostering a culture that is committed to climate change, react as expected, prioritising non-green efforts over long-term GCI strategy. Similar to our analysis on climate beliefs in Section 7.1.2, this finding is significant, uncovering another underlying mechanism in the strategic response of firm's following an opportunistic litigation. In this, we find additional support to our rationale for Hypothesis 1.

7.2 Other Tests

7.2.1 State-level Anti-troll Laws

In an extension to our study, we analyse the effectiveness of various state-level anti-troll laws, passed after the AIA of 2011. "The Patent Litigation Landscape: Recent Research and Developments" (2016) finds the introduction of the AIA to have an insignificant effect in curbing opportunistic NPE behaviour. As explained in Appel et al. (2019), the ineffectiveness of the AIA has led to the introduction of numerous state-level anti-troll legislative changes. Starting with Vermont in 2013, Appel et al. (2019) find that 34 states have introduced revised anti-troll laws between 2013 and 2017. These laws aim to reduce *"the costs that abusive patent claims impose on the state economies"* (Appel et al., 2019). With the intent of these new laws to restrict opportunistic behaviour, we expect firms within these states, after these laws are imposed, to experience lower litigation risk. This infers that green innovating firms will not change their future innovation strategies as drastically as before, once targeted by an opportunistic NPE.

We follow Appel et al. (2019)'s list of 34 state-level anti-troll legislation changes as detailed in Table 4 of the Internet Appendix. We develop the variable $Post\text{-}State\text{-}Law_t$ which equals one if the firms' primary headquarters are in the state of the legislative change and if the year of the observation is after the year that the law is signed. Initially, we test the effect of $Post\text{-}State\text{-}Law_t$ on the likelihood of being targeted by an opportunistic NPE. Then, we adopt least squares (OLS) regression to test the effect that these legislative changes have on future innovation strategies. We include similar control variables to our baseline analysis, and include firm, year, and state fixed effects. Similar to our AIA analysis, we cluster standard errors at the state-level as we infer that these legislative changes represent a state-level shock (Abadie et al., 2023; Appel et al., 2019). For our state-level anti-troll law analysis, we do not conduct our testing with a PSM sample.

[Insert Table 13 here]

Unexpectedly, Table 13: Panel A finds *Post-State-Law*$_t$ to have an insignificant effect on *Opportunistic*$_t$, highlighting that despite the aims of state-level laws to curb opportunistic behaviour, such laws make an unobservable impact. Alternatively in Panel B, we find *Post-State-Law*$_t$ to have a positive effect on future total and non-green innovation levels but no effect on green innovation levels. Thus, firms that are headquartered in states that introduce anti-troll laws increase their innovation efforts, a consistent finding of Appel et al. (2019), who reports IT and Software patents to increase after state-level laws are enacted. Interestingly, Appel et al. (2019) find no change to occur for non-IT patents which may partially explain our insignificant results for green technology production. Notably, Appel et al. (2019), as well as other recent literature including Huang et al. (2022), do not assess whether anti-troll laws have an impact on the likelihood of being targeted by an opportunistic NPE, which makes our findings in Panel A even more important. Our overall interpretation of these findings is that after the introduction of such laws, firms falsely believe that they are less exposed to litigation risk. This incentivises them to innovate more. Nevertheless, whilst firms believe they are less likely to be targeted by an opportunistic litigation, this is not the case, with state-level laws having an insignificant effect on opportunistic NPE activity.

7.2.2 Financial Constraints

In addition to our previous mechanism tests, we also analyse the effects of opportunistic behaviour on financial constraints. Literature suggests that opportunistic NPE litigation poses significant short-term costs to firms, which inherently leads to increased financial constraints (Bessen et al., 2011; Cohen et al., 2019). Further, in the face of financial constraints, firms are found to reduce their environmental efforts (Xu & Kim, 2021). Therefore, in our first hypothesis, we postulate that the financial constraints associated with opportunistic litigation is one of the underlying mechanisms driving a reduction in non-operational innovation investments. We infer that these innovations are likely to be green innovations or more specifically, CCM technologies.

We analyse the influence of opportunism on financial constraints through three measures. As displayed in Table 5 of the Internet Appendix, we initially measure *HM Debt*$_{t+1}$ (column (1)). We follow Hoberg and Maksimovic (2015)'s use of *HM Debt*, who construct this measure from a text-based analysis on mandated disclosures regarding a firm's liquidity within 10-K filings. This methodology is also incorporated in Xu & Kim (2021). Then in column (2), we develop *WW Index*$_{t+1}$, a methodology developed in Whited & Wu (2006), which measures external finance constraints via a generalised method of moments (GMM) estimation model. Finally in column (3), we follow Kaplan & Zingales (1997)'s development of a financial constraints index, which examines a firm's discussions around liquidity and the need for future funds, to develop a variable *KZ Index*$_{t+1}$. As observed in Table 5 of the Internet Appendix, we find that in the first year following an opportunistic NPE led litigation event, there appears to be no significant change in financial constraints. That is, we find *HM Debt*$_{t+1}$, *WW Index*$_{t+1}$, and *KZ Index*$_{t+1}$, to all be insignificant. Ultimately, this suggest that financial constraints are not one of the underlying mechanisms driving our results, in contradiction to our reasoning outlined in

Hypothesis 1. Therefore, we exclude financial constraints as one of our explanations to our baseline findings.

8. Conclusion

This study investigates the effect of opportunistic NPE litigation behaviour on GCI strategies. Our empirical findings further attest to the detrimental consequences of opportunistic NPEs. Firstly, we find firms to prioritise the reduction of green technologies over non-green technologies in the first two years following a litigation event. Then, we find both green and non-green innovation production to reduce in the third year. This implies that firms deem non-green technologies to be indispensable to their immediate operations, whilst regarding environmentally sustainable technologies to be of limited importance. These findings support Hypothesis 1.

We further discern this reduction in green innovations to be dominantly driven by a curtailment in CCM technologies. This suggests an unconcerned willingness to sacrifice the production of technologies that expedite long-term climate change strategies, in a strategic endeavour to safeguard technologies that are primarily oriented towards operational functionality. This highlights a degree of managerial short-termism and climate denial, in which firms prioritise technologies that immediately assist the firm in improving their operational efficiency and financial performance. Nevertheless, it diverts focus from producing technologies that satisfy a firms' long-term ESG commitments. This is supported by our analysis of future exploitative and explorative green patent production. Notably, we find a significant reduction in explorative green patent production after a litigation event, with firms opting to 'stick to what they know' rather than 'thinking outside the box' with their GCI strategies. Hence, opportunistic NPEs disincentivise expansive and risk-taking innovative behaviour, slowing green innovation productivity. This finding bears significant negative implications, particularly in light of the current importance of frictionless GCI.

Finally, our baseline results find firms to significantly and immediately reduce the value of their green innovation in the first year following a litigation event and their green and non-green innovations in the later years following an opportunistic litigation event. Additionally, we find firms to substantially reduce the quality of all innovations immediately after a litigation event occurs. Therefore, not only do opportunistic NPEs reduce a firms' desire to produce essential green technologies, but, across a three-year period, they also force firms to reduce the quality and value of these technologies. We infer and later confirm these results to be driven by three of the four identified mechanisms, being managerial short-termism, climate beliefs, and corporate culture. That is, we find firms that have heightened analyst coverage, more conservative political opinions, and weaker corporate culture to be more likely to sacrifice GCI production following a litigation event. Surprisingly, we do not find financial constraints to have any effects on firms following a litigation.

Beyond our baseline and mechanistic analysis, we analyse how firms react to an exogenous increase in opportunistic NPE activity. Investigating the introduction of the AIA of 2011 within the state of Texas, we find that when faced with increased litigation risk, firms double down on their green innovation reductions. As per our baseline results, we observe this reduction to be most significant for green technologies in all three years, with a lack of significance for total and non-green innovations. Ultimately, this highlights that green technologies are non-essential for firms when facing an exogenous increase in litigation risk, supporting our baseline empirical results, and establishing causality in our findings.

Finally, in an extension to our original research question, we investigate how the introduction of 34 state-level anti-troll laws influence future GCI. Initially, our findings uncover new insights into the ineffectiveness of state-level laws at curbing opportunistic NPE activity. Further, in relation to future innovation strategies, we find firms to increase their overall and non-green levels of innovation in states where these laws exist, however, observe no significant increase in GCI production. Firstly, this infers that the ineffectiveness of these policies has not yet been signalled to the market, with firms under the belief that their litigation exposure has reduced. Secondly, this highlights that in the face of a false perception of lower litigation risk, firms still do not prioritise green innovations, rather diverting investments to non-green technologies. Fundamentally, we find these legislative changes to be widely ineffective, at the detriment of future GCI production.

To conclude, our investigation into the effects of opportunistic NPE litigation activity on future GCI strategies uncovers another argument for the destructive nature of opportunistic litigation. Not only do opportunistic NPEs disincentivise firms from producing high-quality and high-value green innovations, but they also have an even greater negative impact on explorative green patents and CCM technologies. To coincide with this, we find managerial short-termism, climate beliefs, and corporate culture to play significant roles in this GCI-related strategic response. In addition to our main findings, our extended research suggests that current anti-troll legislation has had an insignificant effect at addressing this growing issue. Frictionless green innovation is pivotal in addressing the growing climate change crisis. Therefore, IP legislation must provide targeted policies at reducing the risks of opportunistic NPEs for green innovators. Ideally, this will provide greater innovation leeway for green innovators, creating an environment that encourages explorative green innovation for effective climate change mitigation.

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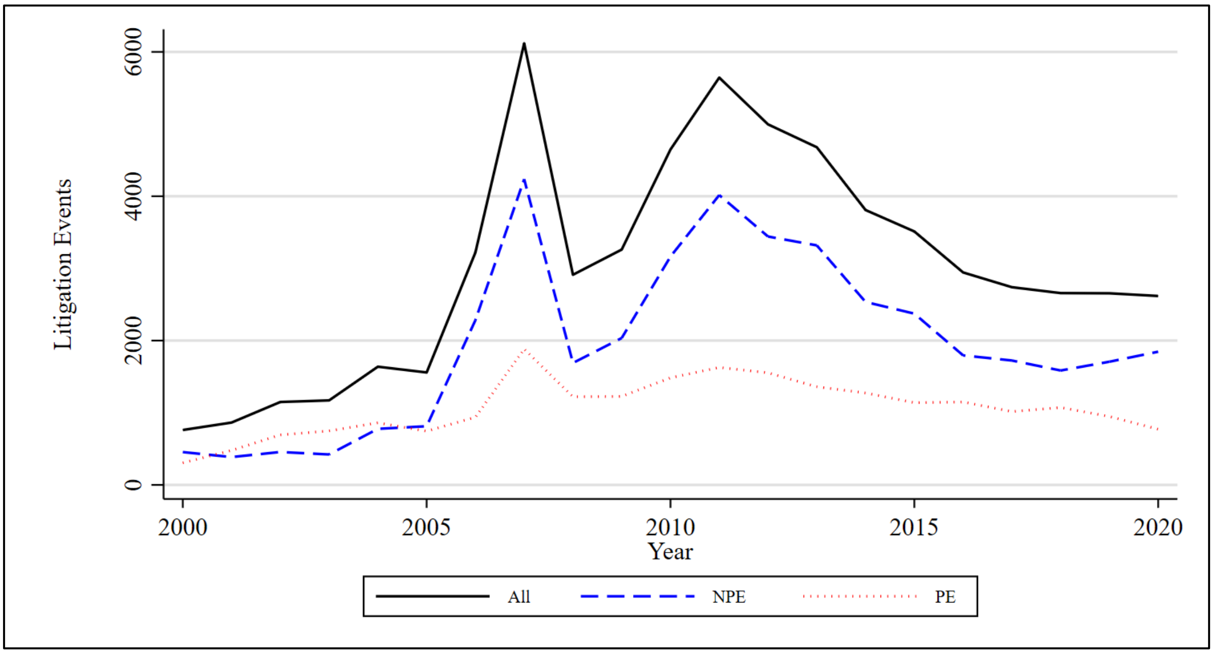
Figure 1: Historical Litigation Activity

This figure displays the time-series of patent-related litigations for public firms in our sample from 2000 to 2020. *Panel A* displays total litigations, which is further separated into NPE-related and PE-related litigations (as shown in Table A.2 in the appendix). *Panel B* displays total NPE-related litigations, separated into opportunistic and non-opportunistic NPE litigations (as shown in Table A.2 in the appendix).

Panel A: All Litigation (2000 – 2020)



Panel B: NPE Litigation (2000 – 2020)

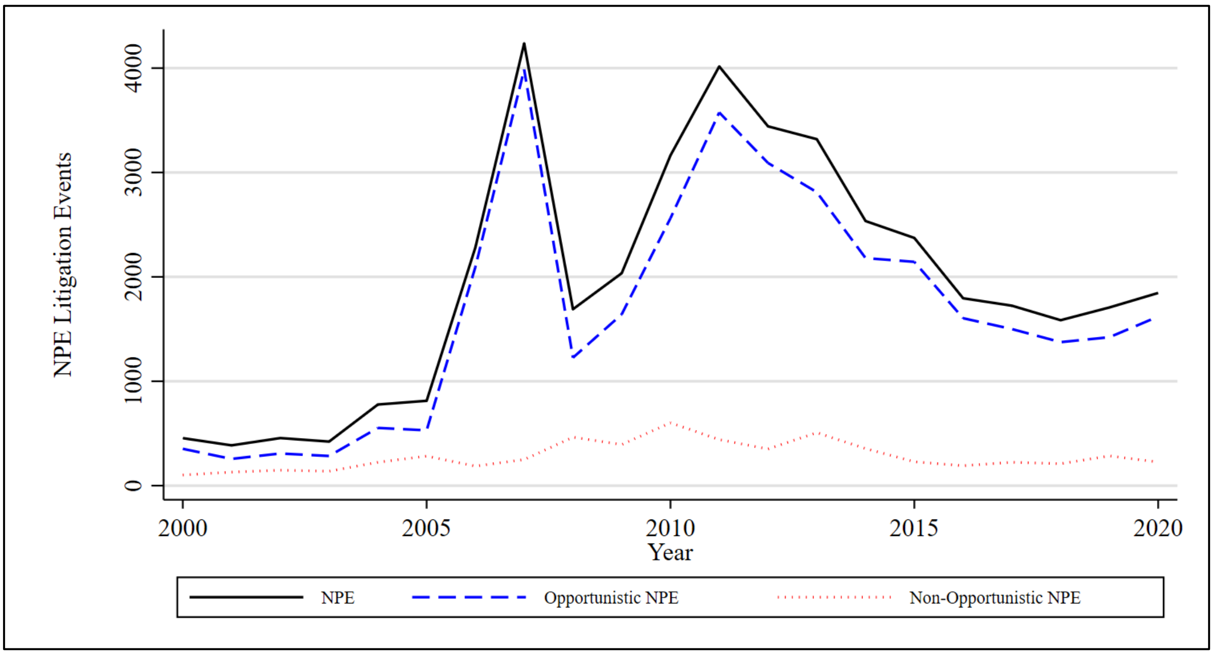


Table 1: Summary Statistics

This table presents the summary statistics of the variables used in our empirical analysis. All variable definitions are provided in Table A.1 in the appendix. The final firm-year sample consists of 69,211 observations of 7,408 unique firms between 2000 and 2020. *Panel A* outlines the summary statistics of litigation-based variables. *Panel B* summarises the firms' innovation characteristics. Finally, *Panel C* presents descriptive statistics on firm-level characteristics. All continuous variables are winsorized at the 1st and 99th percentiles.

N = 69,211	Mean	Median	Std. Dev.	p25	p75
Panel A: Litigation Characteristics					
Total Litigations	0.48	0.00	1.93	0.00	0.00
Litigation (Dummy)	0.11	0.00	0.31	0.00	0.00
Total NPE Litigations	0.30	0.00	1.35	0.00	0.00
NPE (Dummy)	0.08	0.00	0.27	0.00	0.00
Total Opp. NPE Litigations	0.24	0.00	1.11	0.00	0.00
Opportunistic	0.07	0.00	0.26	0.00	0.00
Panel B: Innovation Characteristics					
Total Pat	8.12	0.00	35.19	0.00	1.00
Green Pat	0.29	0.00	1.53	0.00	0.00
CCM Pat	0.22	0.00	1.17	0.00	0.00
Ln(Total Pat)	0.58	0.00	1.23	0.00	0.69
Ln(Green Pat)	0.10	0.00	0.40	0.00	0.00
Ln(Non-Green Pat)	0.56	0.00	1.21	0.00	0.00
Ln(CCM Pat)	0.08	0.00	0.36	0.00	0.00
Ln(Non-CCM Pat)	0.02	0.00	0.14	0.00	0.00
Ln(Exploitative Green Pat)	0.03	0.00	0.20	0.00	0.00
Ln(Explorative Green Pat)	0.05	0.00	0.26	0.00	0.00
GCI Pat Intensity	0.01	0.00	0.05	0.00	0.00
CCM Pat Intensity	0.01	0.00	0.04	0.00	0.00
Ln(Total Real Value)	1.11	0.00	2.29	0.00	0.26
Ln(Green Real Value)	0.02	0.00	0.20	0.00	0.00
Ln(Non-Green Real Value)	1.10	0.00	2.28	0.00	0.00
Ln(Avg. Real Value)	0.62	0.00	1.25	0.00	0.22
Ln(Avg. Green Real Value)	0.02	0.00	0.17	0.00	0.00
Ln(Avg. Non-Green Real Value)	0.62	0.00	1.25	0.00	0.00
Ln(Adj. Total Citations)	0.15	0.00	0.49	0.00	0.00
Ln(Adj. Green Citations)	0.00	0.00	0.04	0.00	0.00
Ln(Adj. Non-Green Citations)	0.15	0.00	0.49	0.00	0.00
Ln(Avg. Adj. Citations)	0.02	0.00	0.07	0.00	0.00
Ln(Avg. Adj. Green Citations)	0.00	0.00	0.02	0.00	0.00
Ln(Avg. Adj. Non-Green Citations)	0.02	0.00	0.07	0.00	0.00
Panel C: Firm-Level Controls					
Cash	0.11	0.06	0.13	0.02	0.15
Ln(Assets)	6.61	6.60	2.04	5.19	7.97
Ln(Employees)	1.25	0.83	1.22	0.25	1.93
Tobin's Q	1.78	1.33	1.26	1.04	1.98
ROA	0.01	0.02	0.12	-0.00	0.07
Leverage	0.22	0.18	0.21	0.04	0.35
Stock Return	0.15	0.04	0.66	-0.21	0.32
R&D Expense	0.03	0.00	0.06	0.00	0.03

Table 2: Future Patent Production of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future corporate innovation. Columns (1) to (3) show the results for the quantity of total patents. Columns (4) to (6) report the results for the quantity of green patents. Columns (7) to (9) present the results for the quantity of non-green patents. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total Pat$_{t+1}$	Total Pat$_{t+2}$	Total Pat$_{t+3}$	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$	Non-Green Pat$_{t+1}$	Non-Green Pat$_{t+2}$	Non-Green Pat$_{t+3}$
Opportunistic$_t$	-0.015	-0.003	-0.034**	-0.026***	-0.022***	-0.032***	-0.015	-0.002	-0.033**
	(-1.459)	(-0.197)	(-2.138)	(-3.582)	(-2.812)	(-3.586)	(-1.386)	(-0.153)	(-2.028)
Cash$_t$	0.007	0.049	-0.029	-0.011	-0.014	-0.028	-0.005	0.038	-0.040
	(0.276)	(1.353)	(-0.689)	(-0.559)	(-0.760)	(-1.438)	(-0.207)	(1.057)	(-0.933)
Ln(Assets)$_t$	0.035***	0.039***	0.044***	0.007*	0.010**	0.014***	0.036***	0.041***	0.046***
	(6.587)	(5.180)	(4.677)	(1.694)	(2.215)	(2.973)	(6.681)	(5.330)	(4.898)
Ln(Employees)$_t$	-0.008	-0.004	0.001	0.025**	0.023*	0.015	0.003	0.004	0.002
	(-0.702)	(-0.233)	(0.029)	(2.085)	(1.856)	(1.187)	(0.253)	(0.212)	(0.119)
Tobin's Q$_t$	0.009***	0.013***	0.013***	-0.001	0.000	0.004	0.009***	0.013***	0.014***
	(2.949)	(3.007)	(2.753)	(-0.310)	(0.130)	(1.327)	(2.721)	(3.034)	(2.882)
ROA$_t$	-0.020	-0.039	-0.029	-0.020*	-0.008	-0.013	-0.014	-0.031	-0.014
	(-0.981)	(-1.490)	(-0.973)	(-1.661)	(-0.622)	(-0.909)	(-0.668)	(-1.161)	(-0.458)
Leverage$_t$	-0.121***	-0.184***	-0.204***	-0.066***	-0.095***	-0.107***	-0.131***	-0.193***	-0.208***
	(-6.252)	(-6.393)	(-5.740)	(-3.742)	(-4.634)	(-4.986)	(-6.383)	(-6.427)	(-5.649)
Stock Return$_t$	0.000	-0.003	0.002	0.001	0.001	0.001	-0.001	-0.004	0.002
	(0.064)	(-1.096)	(0.660)	(0.968)	(0.512)	(0.812)	(-0.278)	(-1.312)	(0.460)
R&D Expense$_t$	0.086	-0.041	-0.053	-0.007	-0.077	-0.033	0.109	0.015	-0.001
	(0.765)	(-0.248)	(-0.267)	(-0.080)	(-0.830)	(-0.343)	(0.945)	(0.090)	(-0.003)
Ln(Total Pat)$_t$	0.630***	0.437***	0.273***	0.127***	0.084***	0.049***	0.623***	0.433***	0.271***
	(52.283)	(28.804)	(16.060)	(12.611)	(8.373)	(5.200)	(49.856)	(28.134)	(15.945)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.896	0.873	0.864	0.754	0.748	0.748	0.898	0.876	0.868
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.0276	-0.0048	-0.0593	-0.2603	-0.2141	-0.2911	-0.0280	-0.0040	-0.0579

Table 3: Future Green Innovation of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future CCM and non-CCM corporate green innovation. Columns (1) to (3) presents the results for the quantity of CCM patents. Columns (4) to (6) report the results for the quantity of non-CCM patents. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) CCM Pat_{t+1}	(2) CCM Pat_{t+2}	(3) CCM Pat_{t+3}	(4) Non-CCM Pat_{t+1}	(5) Non-CCM Pat_{t+2}	(6) Non-CCM Pat_{t+3}
$Opportunistic_t$	-0.026***	-0.024***	-0.034***	-0.004	-0.008*	-0.001
	(-3.507)	(-2.935)	(-3.782)	(-1.011)	(-1.748)	(-0.107)
Observations	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.736	0.731	0.730	0.698	0.695	0.697
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.3002	-0.2592	-0.3562	-0.1280	-0.2611	-0.0167

Table 4: Future GCI & CCM Intensity of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future GCI and CCM innovation intensity. Columns (1) to (3) presents the results for the GCI intensity. Columns (4) to (6) report the results for the CCM intensity. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) GCI Intensity_{t+1}	(2) GCI Intensity_{t+2}	(3) GCI Intensity_{t+3}	(4) CCM Intensity_{t+1}	(5) CCM Intensity_{t+2}	(6) CCM Intensity_{t+3}
Opportunistic_t	-0.003***	-0.002*	-0.001	-0.001**	-0.001	-0.000
	(-3.122)	(-1.883)	(-0.654)	(-2.139)	(-1.339)	(-0.700)
Observations	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.345	0.345	0.348	0.423	0.424	0.424
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.2470	-0.1646	-0.0646	-0.2084	-0.1208	-0.0753

Table 5: Future Innovation Value of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future total real patent value *(Panel A)* and future average real patent value *(Panel B)*. Columns (1) to (3) show the results for the total real patent value *(Panel A)* and average real patent value *(Panel B)* of total patents. Columns (4) to (6) report the results for the total real patent value *(Panel A)* and average real patent value *(Panel B)* of green patents. Columns (7) to (9) present the results for the total real patent value *(Panel A)* and average real patent value *(Panel B)* of non-green patents. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total Real Patent Value

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Real $Value_{t+1}$	Real $Value_{t+2}$	Real $Value_{t+3}$	Green Real $Value_{t+1}$	Green Real $Value_{t+2}$	Green Real $Value_{t+3}$	Non-Green Real $Value_{t+1}$	Non-Green Real $Value_{t+2}$	Non-Green Real $Value_{t+3}$
$Opportunistic_t$	-0.045*	-0.002	-0.072**	-0.033**	-0.013	-0.025*	-0.037	0.005	-0.076**
	(-1.952)	(-0.067)	(-2.418)	(-2.535)	(-0.991)	(-1.883)	(-1.571)	(0.188)	(-2.519)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.880	0.866	0.859	0.218	0.233	0.234	0.880	0.866	0.859
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.0430	-0.0017	-0.0644	-0.6584	-0.2554	-0.4708	-0.0351	0.0048	-0.0685

Panel B: Average Real Patent Value

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Avg. Real $Value_{t+1}$	Avg. Real $Value_{t+2}$	Avg. Real $Value_{t+3}$	Avg. Green Real $Value_{t+1}$	Avg. Green Real $Value_{t+2}$	Avg. Green Real $Value_{t+3}$	Avg. Non-Green Real $Value_{t+1}$	Avg. Non-Green Real $Value_{t+2}$	Avg. Non-Green Real $Value_{t+3}$
$Opportunistic_t$	-0.024	0.009	-0.041**	-0.024***	-0.007	-0.014	-0.018	0.014	-0.045**
	(-1.302)	(0.453)	(-2.000)	(-3.041)	(-0.761)	(-1.550)	(-0.951)	(0.685)	(-2.197)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.767	0.764	0.761	0.170	0.184	0.180	0.769	0.766	0.763
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.0411	0.0150	-0.0647	-0.6810	-0.1849	-0.3709	-0.0302	0.0230	-0.0725

Table 6: Future Innovation Quality of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future total adjusted citations *(Panel A)* and future average adjusted citations *(Panel B)*. Columns (1) to (3) show the results for the total adjusted citations *(Panel A)* and average adjusted citations *(Panel B)* of total patents. Columns (4) to (6) report the results for the total adjusted citations *(Panel A)* and average adjusted citations *(Panel B)* of green patents. Columns (7) to (9) present the results for the total adjusted citations *(Panel A)* and average adjusted citations *(Panel B)* of non-green patents. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total Adjusted Citations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$Citations_{t+1}$	$Citations_{t+2}$	$Citations_{t+3}$	Green $Citations_{t+1}$	Green $Citations_{t+2}$	Green $Citations_{t+3}$	Non-Green $Citations_{t+1}$	Non-Green $Citations_{t+2}$	Non-Green $Citations_{t+3}$
$Opportunistic_t$	-0.032***	-0.031***	-0.051***	-0.016*	-0.013	-0.021**	-0.031***	-0.030***	-0.050***
	(-3.755)	(-3.041)	(-4.334)	(-1.920)	(-1.620)	(-2.516)	(-3.635)	(-2.935)	(-4.318)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.797	0.788	0.785	0.172	0.179	0.181	0.797	0.788	0.786
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.2135	-0.2041	-0.3270	-0.5093	-0.4292	-0.6590	-0.2107	-0.1987	-0.3275

Panel B: Average Adjusted Citation Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Avg. $Citations_{t+1}$	Avg. $Citations_{t+2}$	Avg. $Citations_{t+3}$	Avg. Green $Citations_{t+1}$	Avg. Green $Citations_{t+2}$	Avg. Green $Citations_{t+3}$	Avg. Non-Green $Citations_{t+1}$	Avg. Non-Green $Citations_{t+2}$	Avg. Non-Green $Citations_{t+3}$
$Opportunistic_t$	-0.008***	-0.005*	-0.007**	-0.009**	-0.004	-0.008*	-0.007***	-0.004	-0.007**
	(-2.789)	(-1.722)	(-2.087)	(-2.347)	(-0.991)	(-1.855)	(-2.665)	(-1.613)	(-2.149)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.387	0.377	0.369	0.111	0.110	0.112	0.390	0.382	0.375
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.3571	-0.2192	-0.3475	-0.4898	-0.2394	-0.4302	-0.3424	-0.2080	-0.3581

Table 7: Future Exploitative and Explorative Green Innovation of Targeted Firms

This table presents the OLS regression results for the effect of opportunistic NPE litigations on future exploitative and explorative green innovation. Columns (1) to (3) presents the results for exploitative green innovation. Columns (4) to (6) report the results for explorative green innovation. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Exploitative GCI_{t+1}	(2) Exploitative GCI_{t+2}	(3) Exploitative GCI_{t+3}	(4) Explorative GCI_{t+1}	(5) Explorative GCI_{t+2}	(6) Explorative GCI_{t+3}
$Opportunistic_t$	-0.001	-0.011	-0.030***	-0.043***	-0.031***	-0.023**
	(-0.076)	(-1.248)	(-2.978)	(-5.448)	(-3.001)	(-2.540)
Observations	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.580	0.586	0.597	0.457	0.445	0.439
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.0144	-0.2392	-0.6411	-0.7726	-0.5536	-0.3991

Table 8: Environmental Externalities of Opportunistic NPE Litigation

This table presents the OLS regression results for the effect of opportunistic NPE litigations on firms' pollution intensity. The dependent variable is *Pollution Intensity*, defined as the amount (000's of lbs.) of total toxic releases scaled by total assets. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Pollution Intensity$_{t+1}$	(2) Pollution Intensity$_{t+2}$	(3) Pollution Intensity$_{t+3}$
Opportunistic$_t$	0.065***	0.052***	0.043***
	(4.398)	(3.764)	(3.018)
Observations	11,343	10,314	9,390
Adjusted R-squared	0.797	0.799	0.810
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 9: Future Innovation Output Post-America-Invents-Act (AIA), Texas

This table presents the PSM-based two-stage least squares (2SLS) regression results, where the America Invents Act in Texas *(Post-AIA* x *Texas)* is employed as an instrumental variable. Column (1) presents the result for the first-stage regression, while Columns (2) to (10) reports the results for the second-stage regressions. Specifically, Columns (2) to (4) show the results for the quantity of total patents. Columns (5) to (7) report the results for the quantity of green patents. Columns (8) to (10) present the results for the quantity of non-green patents. The dependent variables in Columns (2) to (10) are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. *Post-AIA* × *Texas* equals to one if a firm was headquartered in Texas after 2011, and zero otherwise. $\widehat{Opportunistic}$, is the predicted indicator for opportunistic NPE litigations based on the first-stage regression. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes year, firm, and state fixed effects. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The comparisons between pre-PSM and post-PSM PSM samples are shown in IA Table 3 in the Internet Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	First Stage	Second Stage								
	$Opportunistic_t$	Total Pat_{t+1}	Total Pat_{t+2}	Total Pat_{t+3}	Green Pat_{t+1}	Green Pat_{t+2}	Green Pat_{t+3}	Non-Green Pat_{t+1}	Non-Green Pat_{t+2}	Non-Green Pat_{t+3}
$\widehat{Opportunistic}_t$		0.385	-0.137	-0.402	-0.666***	-0.895***	-1.031***	0.434	-0.114	-0.405
		(0.809)	(-0.253)	(-0.575)	(-3.190)	(-2.978)	(-3.116)	(0.937)	(-0.218)	(-0.574)
$Post\text{-}AIA_t \times Texas_t$	0.043***									
	(3.679)									
$Post\text{-}AIA_t$	-									
	-									
$Texas_t$	-									
	-									
Observations	7,946	7,946	6,763	5,930	7,946	6,763	5,930	7,946	6,763	5,930
Adjusted R-squared	0.287	0.899	0.882	0.873	0.757	0.742	0.743	0.903	0.888	0.878
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	0.645	1.1002	-0.3721	-1.0753	-8.1729	-10.5215	-11.1369	1.2453	-0.3118	-1.0848

Table 10: Mechanism: Managerial Short-termism

This table uses OLS regressions to examine whether managerial short-termism is among the potential mechanisms, where short-term pressure is captured by analyst coverage. The dependent variable is *Ln(Green Pat)*, defined as natural logarithm of one plus the total number of green patents produced by a public firm in a given year. *Ln(Green Pat)* is shown in an abbreviated format - *Green Pat* - for readability. The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. The sample is split based on the median analyst coverage, where analyst coverage is measured as arithmetic mean of the 12 monthly numbers of earnings forecasts for the focal firm extracted from the Institutional Brokers' Estimate System (I/B/E/S) summary file over fiscal year *t*. Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: High Analyst Coverage (High Short-term Pressure)			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.033***	-0.024**	-0.028**
	(-2.922)	(-1.974)	(-2.173)
Observations	22,244	19,697	17,469
Adjusted R-squared	0.777	0.770	0.767
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Panel B: Low Analyst Coverage (Low Short-term Pressure)			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.016	0.005	0.006
	(-1.640)	(0.569)	(0.551)
Observations	21,125	18,101	15,622
Adjusted R-squared	0.531	0.521	0.563
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 11: Mechanism: Climate Beliefs

This table uses OLS regressions to examine whether climate beliefs among the potential mechanisms. The dependent variable is *Ln(Green Pat)*, defined as natural logarithm of one plus the total number of green patents produced by a public firm in a given year. *Ln(Green Pat)* is shown in an abbreviated format - *Green Pat* - for readability. The main variable of interest, *Opportunistic,* is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. The sample is split based on the political leanings of the U.S. states (i.e., Democratic versus Republican), where the public firms are headquartered. A state is identified as a Democratic state if the percentage of votes for the Democratic party is larger the Republican party. A state is identified as a Republican state if the percentage of votes for the Republican party is larger the Democratic party. The swing states are excluded from our sample. Specifically, the swing states are those where the difference in the percentage of votes for the Democratic party versus the Republican party is in the middle tercile. Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Strong Climate Beliefs (Democratic States)			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.019*	-0.008	-0.015
	(-1.762)	(-0.664)	(-1.111)
Observations	19,592	17,107	14,988
Adjusted R-squared	0.762	0.751	0.749
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Econ Significance	-0.1513	-0.0633	-0.1187

Panel B: Weak Climate Beliefs (Republican States)			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.030**	-0.029*	-0.033*
	(-2.219)	(-1.655)	(-1.730)
Observations	19,416	16,998	14,981
Adjusted R-squared	0.720	0.717	0.717
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Econ Significance	-0.4471	-0.4090	-0.4440

Table 12: Mechanism: Weak Corporate Culture

This table uses OLS regressions to examine whether weak corporate culture is among the potential mechanisms. The dependent variable is *Ln(Green Pat)*, defined as natural logarithm of one plus the total number of green patents produced by a public firm in a given year. *Ln(Green Pat)* is shown in an abbreviated format - *Green Pat* - for readability. The main variable of interest, *Opportunistic,* is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. The sample is split based on the median corporate culture, where corporate culture is measured as the sum of a firm's five cultural scores, including innovation, integrity, quality, respect, and teamwork. The cultural scores are based on the novel textual-based corporate culture data constructed by Li et al. (2021b). Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Strong Corporate Culture			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.012	-0.005	-0.033**
	(-1.025)	(-0.421)	(-2.269)
Observations	18,331	16,001	13,897
Adjusted R-squared	0.718	0.715	0.709
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Econ Significance	-0.0907	-0.0372	-0.2319

Panel B: Weak Corporate Culture			
	(1)	(2)	(3)
	Green Pat$_{t+1}$	Green Pat$_{t+2}$	Green Pat$_{t+3}$
Opportunistic$_t$	-0.032***	-0.018	-0.021
	(-2.738)	(-1.423)	(-1.318)
Observations	18,467	16,301	14,369
Adjusted R-squared	0.800	0.792	0.792
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Econ Significance	-0.1982	-0.1091	-0.1209

Table 13: The Impact of State-level Anti-troll Legislation on Firm-level Litigation Risk & Innovation

This table analyses the effects of state-level anti-troll legislations. *Panel A* presents the OLS regression results for the effect of the staggered introductions of the state-level anti-troll legislations *(Post-State-Law)* on the likelihood of being targeted by an opportunistic NPE litigation. *Panel B* reports the regression results for the effect of state-level anti-troll legislations on corporate innovation. In *Panel B*, Columns (1) to (3) show the results for the quantity of total patents; Columns (4) to (6) report the results for the quantity of green patents; Columns (7) to (9) present the results for the quantity of non-green patents. The dependent variables in *Panel B* are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. *Post-State-Law* equals one if a firm is headquartered in a state where anti-troll legislation has been adopted in a previous year to the given year, and zero otherwise. The specification of the state-level anti-troll legislations is shown in IA Table 4 in the Internet Appendix. *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include lagged *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes year, firm, and state fixed effects. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of Post-State-Law on Opportunism

	(1) Opportunistic$_{t+1}$	(2) Opportunistic$_{t+2}$	(3) Opportunistic$_{t+3}$
Post-State-Law$_t$	0.009	0.009	-0.004
	(0.809)	(0.932)	(-0.377)
Observations	57,752	50,669	44,598
Adjusted R-squared	0.345	0.358	0.366
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Panel B: Effect of Post-State-Law on Future Innovation

	(1) Total Pat$_{t+1}$	(2) Total Pat$_{t+2}$	(3) Total Pat$_{t+3}$	(4) Green Pat$_{t+1}$	(5) Green Pat$_{t+2}$	(6) Green Pat$_{t+3}$	(7) Non-Green Pat$_{t+1}$	(8) Non-Green Pat$_{t+2}$	(9) Non-Green Pat$_{t+3}$
Post-State-Law$_t$	0.053**	0.082**	0.095**	0.018	0.024	0.021	0.054**	0.085**	0.102**
	(1.996)	(2.442)	(2.230)	(0.869)	(1.157)	(0.980)	(2.077)	(2.514)	(2.314)
Observations	57,752	50,669	44,598	57,752	50,669	44,598	57,752	50,669	44,598
Adjusted R-squared	0.914	0.901	0.896	0.791	0.792	0.795	0.916	0.904	0.900
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendices

Table A.1: Variable Definitions & Descriptions

Variables	Definition
Panel A: Litigation Characteristics	
Total Litigations	The cumulative total of patent-related litigation events experienced by a public firm in a given year.
Litigation	A dummy variable equal to one if a public firm experiences a patent-related litigation event in a given year, and zero otherwise.
Total NPE Litigations	The cumulative total of NPE-related litigation events experienced by a public firm in a given year.
NPE	A dummy variable equal to one if a public firm experiences an NPE-related litigation event in a given year, and zero otherwise.
Total Opp. NPE Litigations	The cumulative total of opportunistic NPE-related litigation events experienced by a public firm in a given year.
Opportunistic	A dummy variable equal to one if a public firm experiences an opportunistic NPE-related litigation event in a given year, and zero otherwise.
Panel B: Innovation Characteristics	
Total Pat	The total number of patents produced by a public firm in a given year.
Green Pat	The total number of green patents produced by a public firm in a given year.
CCM Pat	The total number of CCM patents produced by a public firm in a given year.
Ln(Total Pat)	Natural logarithm of one plus the total number of patents produced by a public firm in a given year.
Ln(Green Pat)	Natural logarithm of one plus the total number of green patents produced by a public firm in a given year.
Ln(Non-Green Pat)	Natural logarithm of one plus the total number of non-green patents produced by a public firm in a given year.
Ln(CCM Pat)	Natural logarithm of one plus the total number of CCM patents produced by a public firm in a given year.
Ln(Non-CCM Pat)	Natural logarithm of one plus the total number of non-CCM patents produced by a public firm in a given year.
Ln(Exploitative GCI Pat)	Natural logarithm of one plus the total number of exploitative GCI patents produced by a public firm in a given year. A green patent is exploitative if 60% or more of its citations are based on existing knowledge within the firm, being citations of patents produced by the firm or citations of patents that have been cited in the firms' previous innovations for the last 5 years.
Ln(Explorative GCI Pat)	Natural logarithm of one plus the total number of explorative GCI patents produced by a public firm in a given year. A green patent is explorative if 60% or more of its citations are not based on existing knowledge within the firm, being citations of patents not produced by the firm or citations of patents that have not been cited in the firms' previous innovations for the last 5 years.
GCI Pat Intensity	The percentage of green patents to total patents produced by a public firm in a given year.
CCM Pat Intensity	The percentage of CCM patents to total patents produced by a public firm in a given year .

Ln(Total Real Value)	Natural logarithm of one plus the total real value of a public firms' patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Green Real Value)	Natural logarithm of one plus the total real value of a public firms' green patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Non-Green Real Value)	Natural logarithm of one plus the total real value of a public firms' non-green patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Avg. Real Value)	Natural logarithm of one plus the average real value of an individual patent in a public firms' patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Avg. Green Real Value)	Natural logarithm of one plus the average real value of an individual green patent in a public firms' green patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Avg. Non-Green Real Value)	Natural logarithm of one plus the average real value of an individual non-green patent in a public firms' patent portfolio, deflated to 1982 (million) dollars as per the consumer price index (CPI), in a given year.
Ln(Total Adj. Citations)	Natural logarithm of one plus the total forward citations of a public firms' patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Ln(Adj. Green Citations)	Natural logarithm of one plus the total forward citations of a public firms' green patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Ln(Adj. Non-Green Citations)	Natural logarithm of one plus the total forward citations of a public firms' non-green patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Ln(Avg. Adj. Citations)	Natural logarithm of one plus the average forward citations of an individual patent in a public firms' patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Ln(Avg. Adj. Green Citations)	Natural logarithm of one plus the average forward citations of an individual green patent in a public firms' green patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Ln(Avg. Adj. Non-Green Citations)	Natural logarithm of one plus the average forward citations of an individual non-green patent in a public firms' patent portfolio in a given year, adjusted for truncation bias as per Mudambi & Swift (2014).
Panel C: Firm-Level Controls	
Cash	Ratio of cash holdings to total assets.
Ln(Assets)	Natural logarithm of total assets.
Ln(Employees)	Natural logarithm of total number of firm employees.
Stock return	Stock market return to equity.
Tobin's Q	[Total assets + market value of equity – book value of equity] / total assets.
ROA	Ratio of net income to total assets.
Leverage	[Sum of short-term and long-term debt divided] scaled by total assets.
R&D Expense	Maximum (0, Research and development expense)

Table A.2: NPE Classifications

This table outlines the Stanford NPE Litigation Databases classification for opportunistic NPEs, non-opportunistic NPEs and patent asserters as found in Miller (2018).

Category	Description	Classification
1	Acquired patents	Opportunistic NPE
2	University heritage or tie	Non-opportunistic NPE
3	Failed startup	Non-opportunistic NPE
4	Corporate heritage	Opportunistic NPE
5	Individual-inventor-started-company	Opportunistic NPE
6	University/Government/Non-profit	Non-opportunistic NPE
7	Startup, pre-product	Non-opportunistic NPE
8	Product company	Practicing Entity (PE)
9	Individual	Non-opportunistic NPE
10	Undetermined	Non-opportunistic NPE
11	Industry consortium	Non-opportunistic NPE
12	IP subsidiary of product company	Non-opportunistic NPE
13	Corporate-inventor-started company	Non-opportunistic NPE

Appendix A.1: Public Firm Matching Techniques

The Stanford NPE Litigation Database does not contain company-level identifiers such as GVKEY or PERMCO, rather identifying patent asserters and alleged infringers by their historical public and private names, and by the names of their relevant subsidiaries. Following Li et al. (2022), we adopt a similar string-matching technique to match the historical names of alleged infringers to their appropriate PERMCO identifiers. Like Li et al. (2022), the use of historical parent company names is important for this process, with firm names used in Compustat and other resources often identifying companies by their current name, not their historical name in the year of question. We follow Xu & Kim (2021), obtaining historical company names from CRSP, with supplemented name data from 10K, 10-Q, and 8-K filings using the SEC Analytical Package of Wharton Research Data Service (WRDS). Furthermore, we use the WRDS supplied CRSP/Compustat Linking Table to match historical firm names to the related PERMCO identifier.

Individual cases in the Stanford NPE Litigation Database often contain multiple alleged infringers. Whilst these entities often refer to the parent company and their relevant IP subsidiaries, it is sometimes the case that a litigation event targets multiple companies in the same lawsuit. Hence, we separate each case by its alleged infringers, creating an expanded version of the Stanford NPE Litigation Database in which each observation relates to an individual targeted alleged infringer. Using Stata's -reclink- package, which approximates and ranks similarity scores of matched firm names in the Stanford NPE Litigation Database to their corresponding estimates in the Compustat database, we conduct four separate matching iterations. In each iteration we remove confirmed / confident matches, and then continue the next iteration with firm names that were unsuccessfully matched in the previous stage. In our first iteration, we follow Li et al. (2022) and (Woods & Tan, 2018), by making all firm names uppercase and by removing punctuation marks in each string. This leaves us with a list of alphanumeric uppercase firm names. We manually check all firm names with a match score above 98% (approximately 9,900 observations), correcting confirmed matches to 100% successful, and incorrect matches to 0% successful. This yields approximately 5,500 correct matches. Setting these matches aside, we conduct our second iteration, which converts common company name suffixes to their abbreviated form (i.e., "COMPANY" to "CO" or "HOLDINGS" to "HOLD"). Again, we manually check firms with a match score above 98% (approximately 3,000 observations), finding 1,500 additional successful matches.

Our third iteration converts common company descriptions into their abbreviated form (i.e. “CHEMICAL” to “CHEM” or “GENERAL” to “GEN”). Again, we manually check approximately 2000 observations, this time with a match score above 97%, and find only circa 300 new matches. Finally, in our fourth and final iteration, we convert any final common descriptors into their abbreviate forms, and remove any common company suffixes (i.e. “INC”, “CO”, “LTD”). In this iteration we check all observations above 96% (approximately 6,500 observations), finding 1,900 new matches. We conclude our matching process here, combining all successful matches from each iteration, and having a final manual check to ensure that there are no anomalies. Ultimately, we match approximately 9,200 firm names, finding approximately 12.5% of the Stanford NPE Litigation Database to relate to matched publicly listed alleged infringers.

Internet Appendix

for "Does Green Die in Opportunism? Opportunistic NPE Litigation and Green Corporate Innovation"

IA Table 1: Litigation Activity Summary (2000 – 2020)

This table describes overall litigation levels for Compustat public firms based on the Stanford NPE Litigation Database. The public firm matching process is presented in Appendix A.1. GCI and CCM litigation events are defined as litigation events where the referenced patent (held by the patent asserter) is GCI and CCM technology, respectively (Haščič & Migotto, 2015). Litigations represents the total number of patent-related litigations between 2000 to 2020. NPE Litigations represents the total number of patent-related litigations where the patent asserter is an NPE (as per classifications outlined in Table A.2, where NPEs represent both opportunistic and non-opportunistic NPEs). Finally, Opportunistic NPE Litigations represents the total number of patent-related litigation where the patent asserter is an opportunistic NPE (as per Table A.2).

	Total	Non-GCI	GCI	CCM	Non-CCM
Litigations	52,505	50,860	1,645	1,426	219
NPE Litigations	34,955	34,018	937	820	117
Opportunistic NPE Litigations	30,060	29,384	676	596	80

IA Table 2: Overall NPE Litigations and Future Corporate Innovation

This table presents the OLS regression results for the effect of overall NPE litigations on future corporate innovation. Columns (1) to (3) show the results for the quantity of total patents. Columns (4) to (6) report the results for the quantity of green patents. Columns (7) to (9) present the results for the quantity of non-green patents. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(Var.)* are presented as dependent variables in this table. The main variable of interest, *NPE*, is a dummy variable equal to one if a public firm experiences an NPE litigation event in a given year, and zero otherwise. Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The sample spans from 2000 to 2020. The dependent variable is calculated in years *t+1*, *t+2*, and *t+3*, and the independent variables are measured in year *t*. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Total Pat_{t+1}	(2) Total Pat_{t+2}	(3) Total Pat_{t+3}	(4) Green Pat_{t+1}	(5) Green Pat_{t+2}	(6) Green Pat_{t+3}	(7) Non-Green Pat_{t+1}	(8) Non-Green Pat_{t+2}	(9) Non-Green Pat_{t+3}
NPE_t	-0.009	0.005	-0.028*	-0.013*	-0.009	-0.023***	-0.008	0.006	-0.025*
	(-0.969)	(0.368)	(-1.954)	(-1.915)	(-1.222)	(-2.748)	(-0.837)	(0.470)	(-1.770)
Observations	69,211	60,916	53,921	69,211	60,916	53,921	69,211	60,916	53,921
Adjusted R-squared	0.896	0.873	0.863	0.754	0.748	0.748	0.898	0.876	0.868
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Econ Significance	-0.0164	0.0083	-0.0489	-0.1320	-0.0855	-0.2115	-0.0148	0.0110	-0.0450

IA Table 3: Pre-Match vs Post-Match PSM Sample (Post-AIA, Texas)

This table compares the mean values of the treated and non-treated control variables used in our analysis of firms headquartered in the state of Texas after the introduction of the AIA. In this, our treated firms are those that are headquartered in Texas. *Panel A* displays the difference-in-means test for our treated and non-treated groups for our non-PSM sample, before the introduction of the AIA (pre-2011). Alternatively, *Panel B* displays the difference-in-means test for our treated and non-treated groups for our PSM sample, again pre-AIA. Column (4) displays the p-value of the difference-in-means test, where the null hypothesis of the mean values being equal is tested.

Panel A: Means for Treated and Non-Treated Firms Pre-AIA (Pre-Match)

	Treated	Non-Treated	Difference	Mean Test P-Value
$Cash_t$	0.088	0.113	-0.025	0.000***
$Ln(Assets)_t$	6.439	6.180	0.259	0.000***
$Ln(Employees)_t$	1.190	1.116	0.254	0.000***
Tobin's Q_t	1.651	1.736	-0.085	0.000***
ROA_t	0.022	0.001	0.021	0.000***
$Leverage_t$	0.258	0.210	0.048	0.000***
Stock $Return_t$	0.204	0.144	0.060	0.001***
R&D $Expense_t$	0.015	0.033	-0.018	0.000***
Ln(Total $Pat)_t$	0.369	0.544	-0.175	0.000***

Panel B: Means for Treated and Non-Treated Firms Pre-AIA (Post-Match)

	Treated	Non-Treated	Difference	Mean Test P-Value
$Cash_t$	0.088	0.087	0.001	0.833
$Ln(Assets)_t$	6.482	6.442	0.040	0.421
$Ln(Employees)_t$	1.236	1.208	0.028	0.368
Tobin's Q_t	1.660	1.686	-0.026	0.380
ROA_t	0.027	0.023	0.004	0.124
$Leverage_t$	0.250	0.260	-0.010	0.076*
Stock $Return_t$	0.195	0.177	0.018	0.336
R&D $Expense_t$	0.015	0.017	-0.002	0.117
Ln(Total $Pat)_t$	0.404	0.382	0.022	0.402

IA Table 4: State-level Anti-troll Laws

This table outlines the state and signing date of various state-level anti-troll laws across the US, introduced after the America Invents Act of 2011. All information on state-level anti-troll laws has been sourced from Appel et al. (2019). We note that state names have been abbreviated to their commonly adopted two-letter codes for matching purposes to the Compustat database. Using this table, we construct the variable *Post-State-Law*, which equals one if a firm is headquartered in a state where anti-troll legislation has been adopted in a previous year to the given year, and zero otherwise.

State	Law Signed
AL	2/4/2014
AZ	24/3/2016
CO	5/6/2015
CT	1/1/2017
FL	2/6/2015
GA	15/4/2014
ID	26/3/2014
IL	26/8/2014
IN	5/5/2015
KS	20/5/2015
LA	28/5/2014
ME	14/4/2014
MD	5/5/2014
MI	1/1/2017
MN	29/4/2016
MS	28/3/2015
MO	8/7/2014
MT	2/4/2015
NH	11/7/2014
NC	6/8/2014
ND	26/3/2015
OK	16/5/2014
OR	3/3/2014
RI	4/6/2016
SC	9/6/2016
SD	26/3/2014
TN	1/5/2014
TX	17/6/2015
UT	1/4/2014
VT	22/5/2013
VA	23/5/2014
WA	25/4/2015
WI	24/4/2014
WY	11/3/2016

IA Table 5: Opportunistic NPE Litigations and Financial Constraints

This table presents the OLS regression results for the effects of opportunistic NPE litigations on financial constraints. The dependent variables include three measures of financial constraints, namely *HM Debt* (Column (1)), *WW Index* (Column (2)), and *KZ Index* (Column (3)). *HM Debt* is the text-based debt-market constraint measure developed by Hoberg & Maksimovic (2015) for the years 1997 through 2015. *WW Index* is constructed following Whited & Wu (2006), and *KZ Index* is calculated following Kaplan & Zingales (1997). The main variable of interest, *Opportunistic*, is a dummy variable equal to one if a public firm experiences an opportunistic NPE litigation event in a given year, and zero otherwise. Firm-level controls include *Cash*, *Ln(Assets)*, *Ln(Employees)*, *Tobin's Q*, *ROA*, *Leverage*, *Stock Return*, *R&D Expense*, and *Ln(Total Pat)*. All variable definitions are provided in Table A.1 in the appendix. The dependent variable is calculated in years $t+1$, and the independent variables are measured in year t. Continuous variables are winsorized at the 1st and 99th percentiles. This regression includes both year and firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) HM Debt $_{t+1}$	(2) WW Index $_{t+1}$	(3) KZ Index $_{t+1}$
Opportunistic$_t$	-0.001	0.001	-0.172
	(-0.844)	(0.969)	(-0.962)
Observations	31,631	66,285	59,212
Adjusted R-squared	0.466	0.947	0.733
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes