THREE ESSAYS ON ECONOMIC INNOVATION IN THE ENERGY SECTOR

by

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ABSTRACT

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Under the Supervision of Professor Itziar Lazkano

My dissertation studies the impact of public policy and market forces on technological innovation in the energy sector, with a focus on both the United States and China. The first chapter investigates patent litigation risks in the U.S. energy sector, finding that patents with higher citation counts, those originating from small firms, and those with shorter examination periods are significantly more likely to be involved in legal disputes. These results shed light on how innovation characteristics influence legal vulnerability in a critical sector.

The second chapter evaluates the effect of electric vehicle (EV) adoption policies on energy storage innovation in China. Using a novel firm-level patent database from 2000 to 2021, I find that subsidies for EV purchases alone have limited impact on stimulating innovation. However, when paired with infrastructure-oriented policies-such as investments in charging networks-the probability of energy storage patenting increases significantly.

The third chapter examines the differential impacts of policy and market conditions on renewable and fossil fuel innovation among Chinese listed firms. Analyzing data from 2008 to 2020, I show that China's 2014 new energy demonstration city policy promoted renewable innovation, while rising electricity prices deterred fossil fuel innovation. The results emphasize the importance of well-targeted policies in directing technological change toward sustainability.

Together, these chapters contribute to our understanding of how innovation systems respond to policy signals, legal risks, and market conditions, and offer implications for the design of future climate and energy policies.

To

my parents

my advisors,

and my colleague

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LIST OF ABBREVIATIONS

AIPA American Invents Patent Act

BYD Build Your Dreams (Chinese EV company)

CEIC CEIC Data (Economic/Industry Database)

CO_2 Carbon Dioxide

DID Difference-in-Differences

EV Electric Vehicle

FE Fixed Effects

GDP Gross Domestic Product

IPR Intellectual Property Rights

IPO Initial Public Offering

ML Machine Learning

OECD Organization for Economic Cooperation and Development

OLS Ordinary Least Squares

PME Patent Market Entry

PSM Propensity Score Matching

R&D Research and Development

SME Small and Medium-sized Enterprise

US United States

VC Venture Capital

WIPO World Intellectual Property Organization

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Chapter 1

Introduction

Innovation in the energy sector sits at the heart of efforts to address climate change, enhance energy security, and foster sustainable economic growth. As countries seek to accelerate the shift from fossil fuels to cleaner technologies, it is critical to understand how legal, policy, and market forces interact to shape innovation outcomes at both firm and sectoral levels. This dissertation brings together three independent but closely related studies, each examining a distinct mechanism through which institutions and incentives affect energy innovation in the United States and China.

The first chapter investigates the rising tide of patent litigation in the U.S. energy sector and its implications for innovation. By analyzing large-scale patent and litigation data, I show that highly cited patents and those owned by small firms face disproportionately high litigation risks. The findings highlight both the costs and unintended consequences of current legal frameworks and suggest policy options-such as small-claims adjudication and shared licensing pools-to help reduce unnecessary litigation and support innovation.

The second chapter shifts the focus to China, evaluating how government policies targeting electric vehicle (EV) adoption drive technological change in energy storage. Using a quasi-experimental design with matching and difference-in-differences methods, this chapter quantifies the impact of major EV promotion policies on firm-level patenting in energy storage technologies. The analysis reveals how policy intervention can accelerate clean energy innovation, providing new evidence on the effectiveness of government incentives in a rapidly growing market.

The third chapter provides a broader view of the Chinese energy sector, examining how firms allocate innovation resources between clean and fossil fuel technologies. Leveraging a rich dataset that combines patent records, financial data, and regional indicators, I analyze the determinants and patterns of directed technical change. The results demonstrate the importance of both policy signals and firm-level capabilities in guiding the direction of technological progress, with implications for the design of future innovation and energy policies.

Together, these chapters offer new insights into the interplay of legal risks, government policies, and market incentives in shaping the landscape of energy innovation. By connecting the experiences of two of the world's largest economies, this research contributes to a deeper understanding of how institutions can be designed to foster sustainable technological change in the energy sector.

Chapter 2

Patent Litigation in the Energy Sector

2.1 Introduction

The rising number of patent litigations presents a significant economic challenge, leading to substantial legal costs, resource diversion, and potential negative impacts on innovation. In the energy sector, the potential rewards to innovation are high since new and improved technologies play a crucial role in the global efforts to reduce carbon emissions and transition to cleaner energy sources.

The number of patent litigations have been increasing in the U.S. since 2000 (see figure 1). While all sectors have seen an increase in the number of disputes, in this paper we focus on the energy sector.

For example, between 2003 and 2017, litigation in the energy sector increased from 23.6% to 30.4% of all litigation in the United States (figure 2). In the year 2012 alone, energy patents accounted to 36.4% of all litigation (figure 3). We aim to examine patent litigation in the energy sector to understand the likelihood of a litigation.

We identify patent characteristics that influence litigation risk in the energy sector. To do so, we build a data set that combines patent lawsuit information with patent application data from the United States Patent and Trademark Office (USPTO). We estimate a Poisson pseudo-maximum likelihood model with fixed effects to learn how patent attributes affect litigation risk in the energy sector.

Our data set includes patent lawsuits in the U.S. from 2001 to 2016 as well as patent

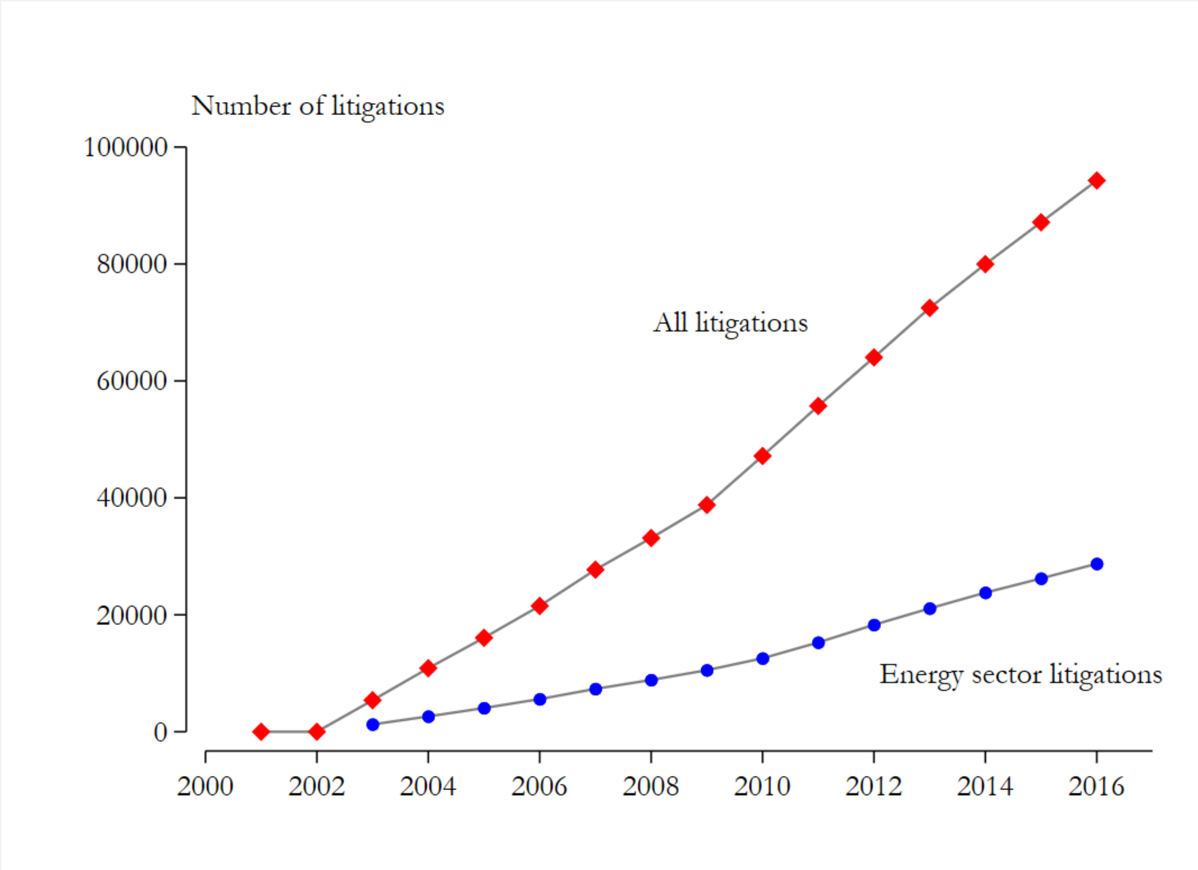

Figure 1: The number of litigation of all patents v.s. Energy sector's patents.
Source: Calculated from USPTO patents data

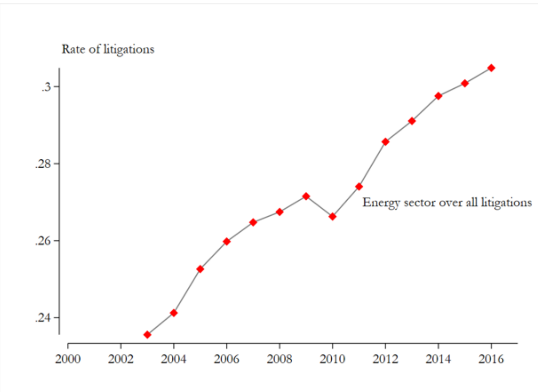

Figure 2: The accumulated proportion of litigated energy patents to all litigated patents.
Source: Calculated from USPTO patents data

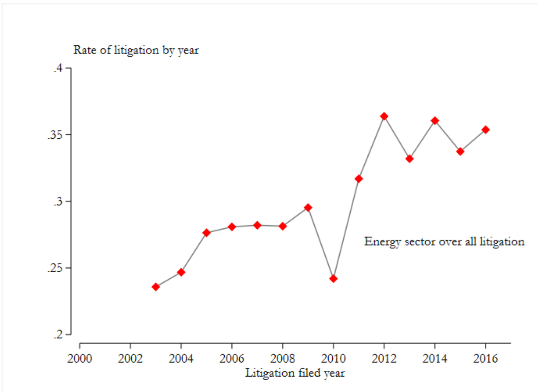

Figure 3: Proportion of litigated energy patents to all litigated patents by year.
Source: Calculated from USPTO patents data

applications dating back to 1931. The extensive patent dataset helps us understand the profiles and prior achievements of inventors. Of the 6,639,403 patents in the dataset, there are 43,687 patents involved in a litigation.[1] A patent litigation refers to any instance in which a patent is drawn into lawsuit either as a plaintiff or as a defendant. In the energy sector, out of 2,336,095 patents, 11,857 have faced legal disputes. In addition to disputes over time, we also analyze geographical differences in litigation and the locations of inventors.

We draw from the past literature to establish testable hypotheses that drive our empirical analysis. Specifically, we estimate the importance of patent recognition, the patent review timeline, firm size, industry type, and the background and expertise of the inventor in the probability of patent litigation. We control for unobserved factors potentially correlated with patent characteristics and the likelihood of litigation and estimate a Poisson pseudo-maximum likelihood model with fixed effects (Cameron and Trivedi, 2013).

Our empirical results show that patents with more citations, inventors from small firms, and patents with shorter review process face an elevated risk of litigation. Specifically, we find that each additional citation increases the litigation risk by 0.25%, and being cited by another patent raises this risk by 0.06%. In addition, patents experiencing longer application-to-grant lags show a reduced propensity for litigation, with each additional month lowering the risk by 0.05%. In the energy sector, the duration of patent review process is even more significant, with each additional month reducing the risk by 0.11%. Moreover, patents from smaller firms in this sector encounter an 11.18% higher litigation risk compared to those from larger firms. Finally, we find that an increase in the number of inventors is linked to a higher litigation risk, with each additional inventor raising the risk by 1.89%. In contrast, an increase in the average team size from the inventors' previous granted patents reduces the litigation risk by 2.99%. These results provide an overview of the characteristics that affect patent litigation.

[1] A patent involved in a lawsuit is categorized in three broad situations: (i) disputes between two firms in the energy sector, (ii) disputes between two firms one in the energy sector and the other outside of the energy sector, and (iii) disputes between inventors on the same team. In our empirical analysis, we consider these three types of disputes.

The economic literature that studies patent litigation is extensive (Cook, 2007; Weatherall and Webster, 2014; Helmers et al., 2018). Theoretically, various methodologies, such as the real option approach (Dixit et al., 1994), fuzzy method (Bessen and Meurer, 2007), and even a combination of both methods (Agliardi and Agliardi, 2011), have been employed to predict the propensity of a patent heading into litigation. In addition, studies such as (Lanjouw and Schankerman, 1997) highlight that patent litigation is more likely to involve valuable, domestic patents, and is particularly frequent in new technology areas, underscoring the complexity of the litigation landscape.

The challenge of protecting intellectual property rights is particularly acute for small firms, as demonstrated in (Lanjouw and Schankerman, 2004), which indicates that small patentees face a significant disadvantage due to higher litigation risk, unaffected by faster resolution of suits. This issue is further exacerbated by the increasing frequency of patent disputes, a phenomenon known as ”The Patent Litigation Explosion” (Bessen and Meurer, 2005), illustrating how public firms, especially smaller ones, face dramatically increased hazards of litigation, primarily driven by legal changes rather than increased patenting rates or R&D. Moreover, the financial implications of these disputes are significant, as revealed in (Bessen and Meurer, 2008), where the average cost of patent litigation for alleged infringers far exceeds mere legal fees. While there has been extensive research in various sectors such as textiles, combustion engines, pharmaceuticals, software, and biotechnology (Lanjouw, 1998; Hall and Ziedonis, 2001; Allison et al., 2003; Hall and Ziedonis, 2007; Bessen and Meurer, 2009), the energy sector has received far less attention.

Innovation in the energy sector is crucial to address global energy challenges and promote clean energy transitions (Gielen et al., 2019). This literature emphasizes the role of intellectual property rights, patent strategies (Alvarez-Herranz et al., 2017), and technological advancements in renewable energy, energy storage, and efficiency (Barlev et al., 2011). Government policies (Peuckert et al., 2015; De Laurentis, 2012) and the diffusion of clean energy technologies, international cooperation, technology transfer, and regional innovation systems (Dechezleprêtre, 2013; Miyamoto and Takeuchi, 2019; Ter Wal and

Boschma, 2011) also play a pivotal role. However, less is known about the patent disputes among inventors. Our paper contributes to the understanding on patent disputes by providing a descriptive analysis of patent litigation in the US for the 2011-2016 period.

The organization of this paper is as follows. Section 2.2 presents the conceptual framework while section 2.3 presents the empirical methodology followed by a detailed description of the data. Section 4 presents the empirical results and finally Section 5 offers conclusions and policy recommendations.

2.2 Conceptual framework

In this section, we describe the conceptual framework that drives out identification strategy in the next section. We follow this approach because our estimation model is empirically motivated rather than purely theoretical. Our study investigates patent litigation within the energy sector by drawing on theoretical models from Cooter and Rubinfeld (1989), which suggest four key determinants of litigation. These determinants guide our selection of data and our empirical analysis.

The first determinant we explore is the significance of the patent. Patent litigation is more likely when the stakes are high, both in terms of direct patent value and indirect strategic benefits (e.g., reputation, bargaining power). We collect data on patent citations as a proxy for value, distinguishing between backward citations (references in the patent application) and forward citations (references made by subsequent patents). These citations reflect the patent's foundational influence and also its perceived value in the field (Albert et al., 1991; Cremers, 2009; Reitzig, 2004; Ruiz and Banet, 2008). With this, we explore whether patents with higher citation counts are more likely to be litigated, given their perceived value in the field.

Next, explore the relationship between past experience and the probability of litigation. Specifically, patents associated with more experienced inventors are more likely to face litigation. We proxy past experience using data on inventors' past patenting activity, as prior research suggests that experienced inventors navigate the patent system differently (Hall et al., 2001; Singh and Fleming, 2010). For example, Hall et al. (2001) shows that inventors with an extensive history of prior work typically demonstrate better skills in navigating the patent application process.

The third consideration is industry affiliation. Legal disputes often arise in industries with high technological or legal uncertainty. For this reason, we examine whether patents in specific technological domains are more likely to be litigated. We are particulary interested in the energy sector which faces frequent regulatory and technological changes, potentially increasing litigation risk. One of the advantages of working with patent data is that there are more than 250,000 patent categories easing the study of different industries and technologies.

Finally, prior research suggests that patents with longer examination periods face higher uncertainty, which may increase litigation risk (Harhoff et al., 2003). We study this by calculating the application-to-grant time per patent. The channel linking examination length to litigation sharpened after the American Inventors Protection Act of 1999 (AIPA), which since 29 Nov 2000 obliges the USPTO to publish most applications 18 months after the earliest priority date (Johnson and Popp, 2001; United States Patent and Trademark Office, 2000; Graham and Hegde, 2013). An application that remains pending beyond this window forfeits the traditional secrecy that once lasted until grant, thereby alerting a larger pool of potential challengers and increasing the probability of infringement allegations before or soon after issuance. We quantify this effect with the variable grant lag,the number of months from filing to grant and expect a positive coefficient, especially in cumulative, R&D intensive technologies where early disclosure accelerates competitor scrutiny. The likelihood of litigation may also be influenced by differences in trial costs, settlement incentives, and firm size. We collect firm size data to explore whether patents from smaller firms and inventor origin are more likely to be litigated. Given that direct cost measurements are unavailable, we examine firm size, patent grant lags, and patent origin (domestic vs. foreign) as proxies.

2.3 Identification Strategy

Next, we describe the econometric approach we follow to estimate the relationship between patent characteristics and litigation risk. We adopt a fixed-effect Poisson Pseudo-Maximum Likelihood model to estimate our baseline specification in equation 1.

$$Litigated_i = \exp(\beta_0 + \boldsymbol{\beta}_1\mathbf{W}_i + \boldsymbol{\beta}_2\mathbf{X}_i + \boldsymbol{\beta}_3\mathbf{Y}_i + \boldsymbol{\beta}_4\mathbf{Z}_i + \alpha_r + \gamma_t) \times \eta_{ij} \tag{1}$$

where $Litigated_{ij}$ is equal to one when patent i is litigated and zero otherwise. The covariates $\mathbf{W}$, $\mathbf{X}$, $\mathbf{Y}$, and $\mathbf{Z}$ represent patent attributes discussed in section 2.2. Specifically, $\mathbf{W}$ measures patent citations, signifying the extent of recognition and influence each patent possesses. $\mathbf{X}$ focuses on inventor related variables, offering insights into the inventors' background, teamwork experience, and past accomplishments. $\mathbf{Y}$ measures the technological classification of the patent, and $\mathbf{Z}$ includes several patent attributes like firm size or origin of the inventor. The model includes fixed effects to control for regional disparities among patents, α_r, and time effects γ_t, where t is a patent's application month and year. η_{ij} represents the error term, capturing the unobserved factors or random disturbances that the model does not explicitly account for.[2] Our estimation employs a Poisson pseudo-maximum likelihood (PPML) regression model, which offers consistent and asymptotically normal estimators.[3]

2.4 Litigation and Patent Data

We draw data from the United States Patent and Trademark Office (USPTO), which contains patent applications from 1931 to 2020. We also incorporate detailed records of patent litigations between the years 2001 and 2016. Our dataset includes 6,639,403

[2] We include regional fixed effects to account for variations across states within the U.S., as well as time fixed effects associated with the dates of patent application. These fixed effects enable us to capture unobserved heterogeneity and control for potential confounding variables.

[3] The PPML approach is particularly suitable for patent data, which are often subject to over-dispersion or under-dispersion.

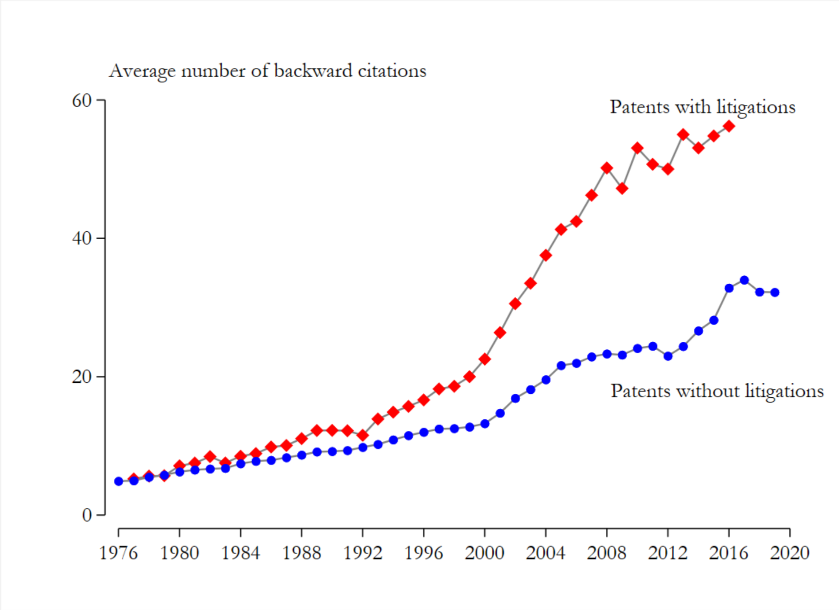

Figure 4: Average Backward citations per year for litigated patents and non-litigated patents
Source: Calculated from USPTO patents data

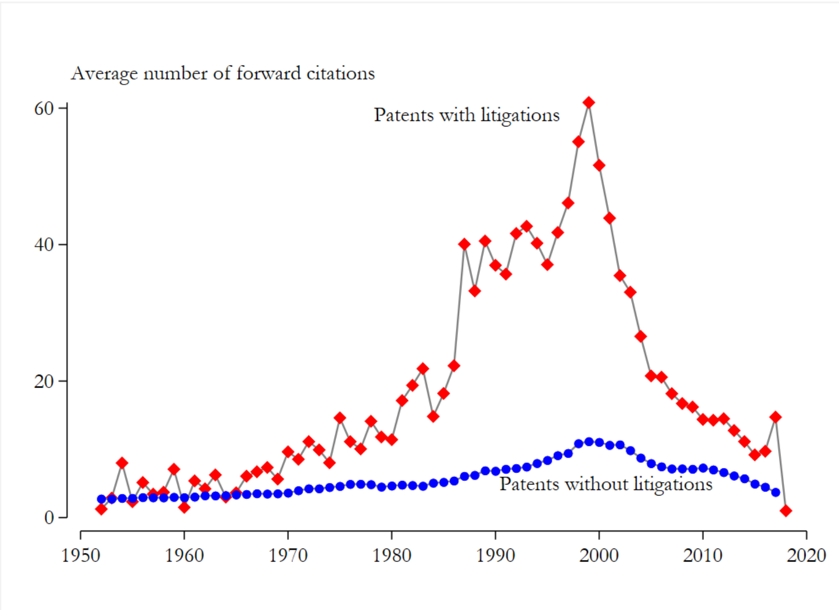

Figure 5: Average Forward citations per year for litigated patents and non-litigated patents
Source: Calculated from USPTO patents data

patents, of which 43,687 have been involved in litigation. We identify patents in the energy sector using the Cooperative Patent Classification (CPC) sub-section and observe 2,336,095 patents, with 11,857 of these facing litigation. In the following, we describe

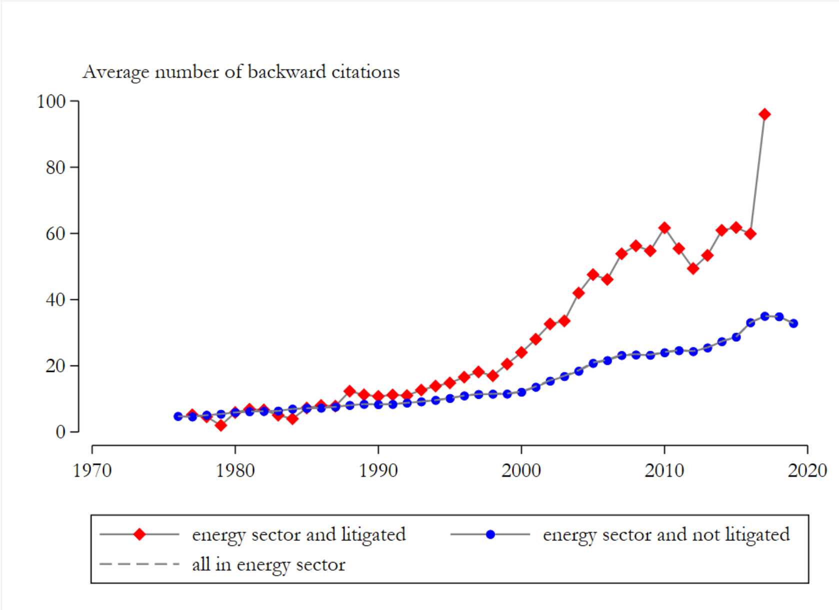

Figure 6: Average Backward citations in the energy sector with litigation
Source: Calculated from USPTO patents data

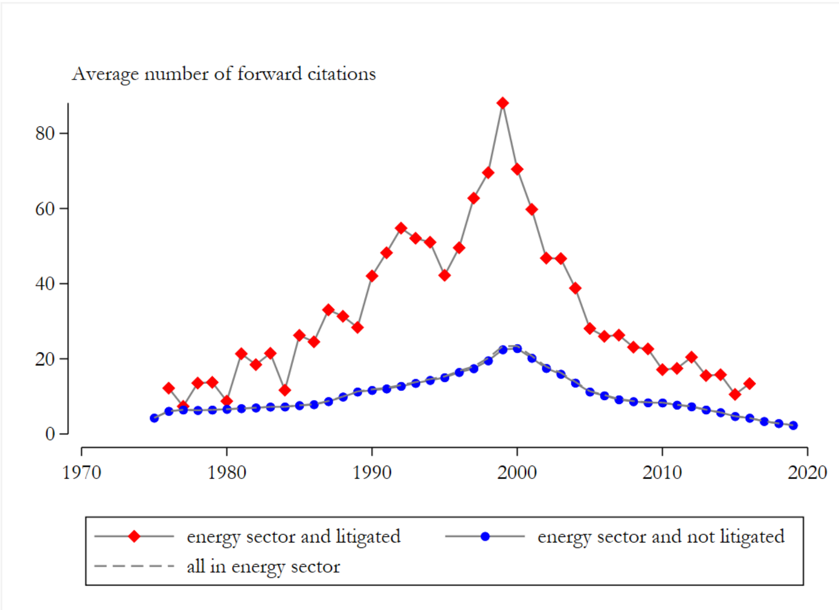

Figure 7: Average Forward citations in the energy sector with litigation
Source: Calculated from USPTO patents data

the calculation of the variables used to estimate equation 1. Appendix 2.7.1 provides additional information of the construction of our dataset.

First, we calculate two variables to measure the value of patents (**W** in equation 1). The variable $Backward, Citation_i$ counts the references made by patent i, while

$Forward, Citations_i$ represents the number of times a patent is cited by others. Figures 4-5 illustrate patent citation trends over time across all sectors, while Figures 6 and 7 focus specifically on the energy sector. Figure 4 shows the increasing trend of average backward citations for patents without litigation, which account for 99.57% of all patents. These figures show that litigated patents have a higher average number of backward citations compared to non-litigated ones. Figure 5 demonstrates that the number of forward citations for patents has been increasing over the years. However, more recent patents have fewer forward citations due to the time required for new patents to be cited by other inventors. Notably, litigated patents, which make up only 0.3% of the total, exhibit a higher number of forward citations compared to their non-litigated counterparts. Finally, Figures 6 and 7 depict the average backward and forward citations for litigated and non-litigated patents within the energy sector. These figures reveal similar patterns to those observed in the overall sample: in both cases, litigated energy patents demonstrate a higher number of backward and forward citations compared to their non-litigated counterparts. Within the energy sector, Figure 9 in appendix 2.7.1, shows the trend of patent litigation in electricity-related patents and innovations aimed at reducing greenhouse gas (GHG).

Next, we proxy for past experience by calculating two additional variables related to an inventors' previous experiences. The first variable, $Inventors'\, Previous\, Patents_i$ for $patent_i$, is calculated as follows:

$$\frac{\sum_{\tau=0}^{t} \text{Previous Patents}_{i\tau}}{\text{Number of Inventors}_i}.$$

It computes the sum of previous patents for all inventors of $patent_i$ from October 1978, which is the earliest recorded patent publication date in the data, to the publication date of $patent_i$ and divides it by the total number of inventors for $patent_i$. This variable reflects the prior achievements of inventors before $patent_i$. Their historical accomplishments may impact the patent's susceptibility to litigation, suggesting that past success could influence current patent disputes. The second variable, Inventors' Previous Team Size, is calculated following:

$$\frac{\sum_{k=1}^{N_i} \frac{\sum_{\tau=0}^{t} \text{Previous Team Size}_{k\tau}}{\text{Previous Patents}_{k\tau}}}{\text{Number of Inventors}_i}.$$

In this formula, k represents the index for each inventor in $patent_i$, ranging from 1 to N_i; N_i denotes the total number of inventors for $patent_i$; τ represents the time index, ranging from earliest recorded publication date to the publication date of $patent_i$. It computes the average team size for each inventor's previous patents and divides it by the total number of inventors for $patent_i$. $Previous\,Team\,Size_{k\tau}$ denotes the team size of previous patents for inventor k at time τ; $Previous\,Patents_{k\tau}$ stands for the number of previous patents for inventor k at time τ; and $Number\,of\,Inventors_i$ represents the total number of inventors for $patent_i$. underscores the collaborative experiences of inventors prior to $patent_i$.

The third set of variables includes industry information. We use industry classification data following Cooperative Patent Classification (CPC) system to identify energy related patents. We are particularly interested in two areas, sections H (Electricity) and Y02 (Climate-change-related technologies). Finally, we measure the miscellaneous patent attributes related to an inventor's background. Specifically, $Grant\,Lags_i$ denotes the duration in months between the patent's application and publication, serving as a measure for the length of the patent approval process. $US\,Patents_i$ is a binary variable indicating whether the inventor is from the U.S. and $Small\,Firms_i$ identifies whether the patent is owned by a micro or small firm.

In the following, we present summary statistics of our dataset. Panel 1 in table 1 presents an overview of selected variables in different sub-samples across all sectors. The variables exhibit statistical differences between litigated and non-litigated samples. Litigated patents display more backward and forward citations compared to non-litigated patents. A patent with a high number of forward citations might also face heightened competition. Litigated patents have a similar number of inventors, while their inventors possess fewer published patents and have worked in smaller teams on average. The grant lags do not exhibit statistical differences between litigated and non-litigated patents. For the litigated sub-sample, energy patents have more backward and forward citations compared to non-energy patents, and the energy patents feature slightly more experienced inventors and larger team sizes. Energy patents also have grant lags exceeding four months in this sub-sample, which is statistically significant. The non-litigated sub-sample data reveals minor differences in the number of citations between energy and non-energy patents, highlighting the distinct nature of litigation in the energy sector, which warrants further investigation.

Panel 2 in table 1 focuses on the energy sector. Patents developed by large firms in the energy sector exhibit more citations and greater team sizes. Furthermore, their inventors possess more published inventions and experience working in larger teams. Patents from small firms, on the other hand, have an average grant lag of four months less than those from large firms. In the energy sector, litigated patents show a higher average number of citations, and the differences in citation counts between litigated and non-litigated patents are more pronounced compared to patents across all sectors. Although the grant lags display statistical significance between litigated and non-litigated energy patents, the average difference amounts to only around 20 days.

Table 1: Data Description of Variables

Panel 1: Data Description of Variables in All Sectors

	(1)	(2)	(3)	(4)	(5)	(6)	t-test	t-test	t-test
	All Sectors		Non-Litigated		Litigated		All Sectors	Non-Litigated	Litigated
	Non-Litigated	Litigated	Non-Energy	Energy	Non-Energy	Energy	Non-Litigated vs. Litigated	Non-Energy vs. Energy	Non-Energy vs. Energy
Variable	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE	(1)-(2)	(3)-(4)	(5)-(6)
Backward citations	16.384	28.710	15.971	17.535	26.207	35.428	-12.326***	-1.564***	-9.220***
	[0.109]	[0.168]	[0.125]	[0.218]	[0.184]	[0.366]			
Forward citations	11.054	23.998	10.135	13.612	20.367	33.748	-12.944***	-3.477***	-13.381***
	[0.114]	[0.257]	[0.125]	[0.256]	[0.254]	[0.646]			
Inventors' previous patents	6.527	6.079	6.066	7.810	5.678	7.157	0.448***	-1.744***	-1.479***
	[0.108]	[0.135]	[0.106]	[0.285]	[0.174]	[0.174]			
Inventors' previous team size	2.619	2.446	2.541	2.836	2.364	2.666	0.173***	-0.295***	-0.302***
	[0.008]	[0.008]	[0.009]	[0.014]	[0.009]	[0.015]			
Number of inventors	2.430	2.346	2.370	2.594	2.270	2.552	0.083***	-0.224***	-0.282***
	[0.009]	[0.009]	[0.010]	[0.017]	[0.010]	[0.018]			
Grant lag	30.396	30.551	28.963	34.383	29.367	33.730	-0.155	-5.420***	-4.364***
	[0.081]	[0.094]	[0.091]	[0.170]	[0.108]	[0.188]			
The number of observations	44463	43686	32711	11752	31829	11857			

The value displayed for t-tests are the differences in the means across the groups.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

Panel 2: Data Description of Variables in Energy Sector

	(1)	(2)	(3)	(4)	t-test	t-test
Energy Sector	Large Firms	Small Firms	Non-Litigated	Litigated	Large vs. Small	Non-Litigated vs. Litigated
Variable	Mean/SE	Mean/SE	Mean/SE	Mean/SE	(1)-(2)	(3)-(4)
Backward citations	23.341	16.298	17.535	35.428	7.043***	-17.893***
	[0.181]	[0.198]	[0.218]	[0.366]		
Forward citations	18.805	11.139	13.612	33.748	7.666***	-20.136***
	[0.270]	[0.238]	[0.256]	[0.646]		
Inventors' previous patents	7.595	3.618	7.810	7.157	3.977***	0.654**
	[0.124]	[0.093]	[0.285]	[0.174]		
Inventors' previous team size	2.917	1.816	2.836	2.666	1.101***	0.171***
	[0.010]	[0.010]	[0.014]	[0.015]		
Number of inventors	2.738	1.713	2.594	2.552	1.025***	0.042*
	[0.012]	[0.010]	[0.017]	[0.018]		
Grant lag	31.612	27.180	34.383	33.730	4.432***	0.653***
	[0.104]	[0.139]	[0.170]	[0.188]		
The number of observations	30685	13884	11752	11857		

The value displayed for t-tests are the differences in the means across the groups.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

2.5 Regression Results

Table 2: Poisson fixed effect of litigation risk

	All litigated	Margins litigated	Energy litigated	Margins litigated
Grant lags	-0.00104***	-0.000515***	-0.00215***	-0.00108***
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Backward citations	0.00511***	0.00253***	0.00496***	0.00249***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Forward citations	0.00136***	0.000676***	0.00125***	0.000626***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Inventors' previous patents	-0.0000474	-0.0000235	-0.0000172	-0.00000865
	(0.0002)	(0.0001)	(0.0003)	(0.0001)
Inventors' previous team size	-0.0604***	-0.0299***	-0.0468***	-0.0235***
	(0.0056)	(0.0028)	(0.0093)	(0.0047)
Number of inventors	0.0381***	0.0189***	0.0313***	0.0157***
	(0.0047)	(0.0023)	(0.0077)	(0.0039)
i.US patents	0.181***	0.0860***	0.157***	0.0763***
	(0.0190)	(0.0086)	(0.0339)	(0.0158)
1.Small_firms	0.110***	0.0557***	0.209***	0.112***
	(0.0078)	(0.0040)	(0.0140)	(0.0079)
PERFORMING OPERATIONS	0.0660***	0.0317***		
	(0.0122)	(0.0059)		
CHEMISTRY and METALLURGY	0.139***	0.695***		
	(0.0167)	(0.0087)		
TEXTILES and PAPER	0.0926*	0.0451*		
	(0.0445)	(0.0226)		
FIXED CONSTRUCTIONS	-0.0189	0.00868		
	(0.0204)	(0.0093)		
MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING	0.0749***	0.0361***		
	(0.0162)	(0.0080)		
PHYSICS	0.0807***	0.0390***		
	(0.0105)	(0.0051)		
ELECTRICITY	0.120***	0.0590***		
	(0.0109)	(0.0054)		
GENERAL TAGGING OF OTHERS	0.0639***	0.0306***		
	(0.0143)	(0.0070)		
_cons	-0.973***		-0.849***	
	(0.0199)		(0.0318)	
N	79106	79106	23547	23547

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In this section we present out empirical results followed by a robustness analysis. We present our main results in Table 2.

In line with our first hypothesis, the estimations confirm a relationship between the citation count of a patent and its likelihood of being litigated. Our results show that each additional backward citation increases the litigation risk by 0.249%, underscoring the value of a patent's influence and foundational role in its field. The 0.249% indicates that, on average, adding one extra backward citation raises the probability that a patent will be litigated by 0.249 percentage points. In practical terms, if Portfolio A's 100 patents each carry 100 more backward citations than an otherwise identical Portfolio B, the expected share of litigated patents in Portfolio A is roughly 24.9 pp higher. PPML models are linear approximations of changes in predicted probabilities when baseline is low (Statalist Discussion Forum, 2023; Perraillon, 2021; Piermartini and Yotov, 2016) Forward citations, denoting the patent's impact on subsequent innovations, similarly increase litigation risk by 0.06%. This connection between citations and litigation is particularly evident in sectors marked by rapid innovation and stiff competition, such as chemistry, metallurgy, and electricity, where patents that lay the groundwork for future inventions attract heightened competitive scrutiny and, consequently, legal challenges.

Inventor characteristics are statistically correlated with the probability of litigating a patent. Each additional inventor is associated with a 1.57% rise in litigation risk, reflecting the complexity and potential for disagreement inherent in collaborative invention. However, a contrasting effect is observed when considering the previous collaborative experiences of inventors; an increase in the average team size from prior patents inversely affects the litigation risk, reducing it by 2.35%. This effect suggests that experience in team environments may equip inventors with conflict resolution skills that mitigate the risk of litigation for their current patents.

Next, our estimation results show that patents within the energy sector, particularly those from smaller firms, are at a substantially higher risk of litigation, with an increase of 11.18% compared to larger firms. The analysis underscores the importance of grant lags in this equation, with each additional month of the application process decreasing litigation risk by 0.11%. This sector-specific finding points to the significant influence of regulatory and procedural nuances in the energy sector on litigation risk.

Finally, we find that being a domestic inventors is related with a 7.63% higher probability of being litigated. This finding highlights the geographical and size-related disparities that influence the litigation landscape. Smaller firms, often resource-constrained and more vulnerable to legal challenges, face a steeper risk, illustrating the disproportionate impact of litigation on innovation in different firm sizes.

In the energy sector, our regression results highlight distinct trends in patent litigation risk. We find that each additional citation to a patent increases its litigation risk by 0.249%, while being cited by another patent raises this risk further by 0.06%. Additionally, patents involving a greater number of inventors are linked to a 1.57% higher risk of litigation. Conversely, a larger average team size from inventors' past projects is correlated with a 2.35% reduction in litigation risk. This nuanced interplay of factors in the energy sector is further complicated by the origin of the patent. Specifically, patents with all applicants from the US show a heightened litigation risk increase of 7.63%.

Moreover, our analysis reveals a striking disparity in litigation risks faced by different-sized entities within the energy sector. Patents from small and micro firms encounter a substantially higher litigation risk, showing an 11.18% increase compared to those from larger firms. This finding underscores the vulnerability of smaller entities in navigating the patent landscape. Furthermore, the impact of grant lags is particularly significant in the energy sector. Our model indicates that each additional month in the grant lag period mitigates the litigation risk by 0.11%, a rate of risk reduction that is twice as significant as that observed across all sectors. These insights into the litigation dynamics within the energy sector, underscore the need for tailored approaches to manage legal challenges and reinforce the importance of strategic patent management in fostering innovation and competition.

In summary, our estimation results show the characteristics that are statistically related to patent litigation, emphasizing the distinct challenges within the energy sector. Our findings reveal that patents with extensive citations, those linked to inventors with broad prior experiences, and patents in certain technology areas, particularly the energy sector, show a higher likelihood of litigation. Additionally, the analysis indicates that patents from smaller firms or those with extended grant lags are especially vulnerable to litigation in the energy sector. Consistent with earlier sectoral studies, higher backward and forward citation counts, larger inventor teams, and small entity ownership all significantly elevate litigation risk; Energy sector is different because a longer wait between filing and approval protects them from lawsuits much more than in other fields, while extra citations raise their lawsuit risk, but not as sharply as in most industries. This comprehensive study contributes valuable insights into the dynamics of patent litigation, offering guidance for inventors, firms, and policymakers navigating this complex legal landscape.

2.6 Conclusions

This study methodically gathers and examines data from 43,687 patent litigation from 2001 to 2016 and 6,595,716 non-litigated patents dating back to 1931. Patent litigation trent is increasing, with a notable surge in cases related to the energy sector. Although these litigation represent a small fraction of all patents, they substantially raise the administrative costs associated with innovation, potentially hindering both the development of new technologies and their widespread adoption.

Our analysis shows that most litigated patents involve small groups of 1-4 inventors, commonly from the same country. A significant observation is that while the majority of inventors are involved in only one litigation, a smaller group faces repeated litigations. Interestingly, litigated patents often feature cross-national collaborations, particularly in patents with at least one US inventor. Patents applications by US inventors, those owned by smaller firms, and those with a higher count of citations and inventors generally face a higher litigation risk. In contrast, prolonged periods between patent applications and grants, along with effective teamwork among inventors, are linked to reduced litigation risks. In the energy sector, the litigation risk dynamics exhibit unique patterns. The sector experiences a pronounced increase in litigation risk for patents from small and micro firms, highlighting the disproportionate legal challenges these entities face compared to larger firms. Additionally, the mitigating effect of longer grant lags on litigation risk is more pronounced in the energy sector, emphasizing the sector's specific regulatory and innovative environment.

To ease these pressures, we suggest three practical steps. First, set up a small claims lane inside the Patent Office so that tiny clean energy firms can settle disputes quickly and cheaply instead of spending years and millions in court. Second, give inventors an optional slow-review track that keeps their applications secret for longer than the 18-month publication rule, which would prevent many lawsuits that flare up as soon as new ideas are revealed. Third, support easy-to-join patent pools where any company can pay one fair fee to use a bundle of key green-tech patents, so firms do not have to sue each other every time they want to build on a highly cited invention.

2.7 Appendix

2.7.1 Data Appendix

To construct a database that includes all litigation with their inventors, citation information, and classifications of technology, we obtain 5 datasets collected by the U.S. Patent and Trademark Office (USPTO). The database includes unique 43,687 litigated patents during the period of 2001 - 2016, involving U.S patents and foreign patents. A brief description of the datasets is listed below.

litigation - Each litigated patent has records of its case number, pacer id, court name, date of filing, date of closing, state of the court, etc. The range of filling dates is in the period of 2001 - 2016. One patent can have multiple observations on a different filing date if the patent has been litigated more than once. Because there is no further information about the inventors, citations, and classifications of patents, we need more

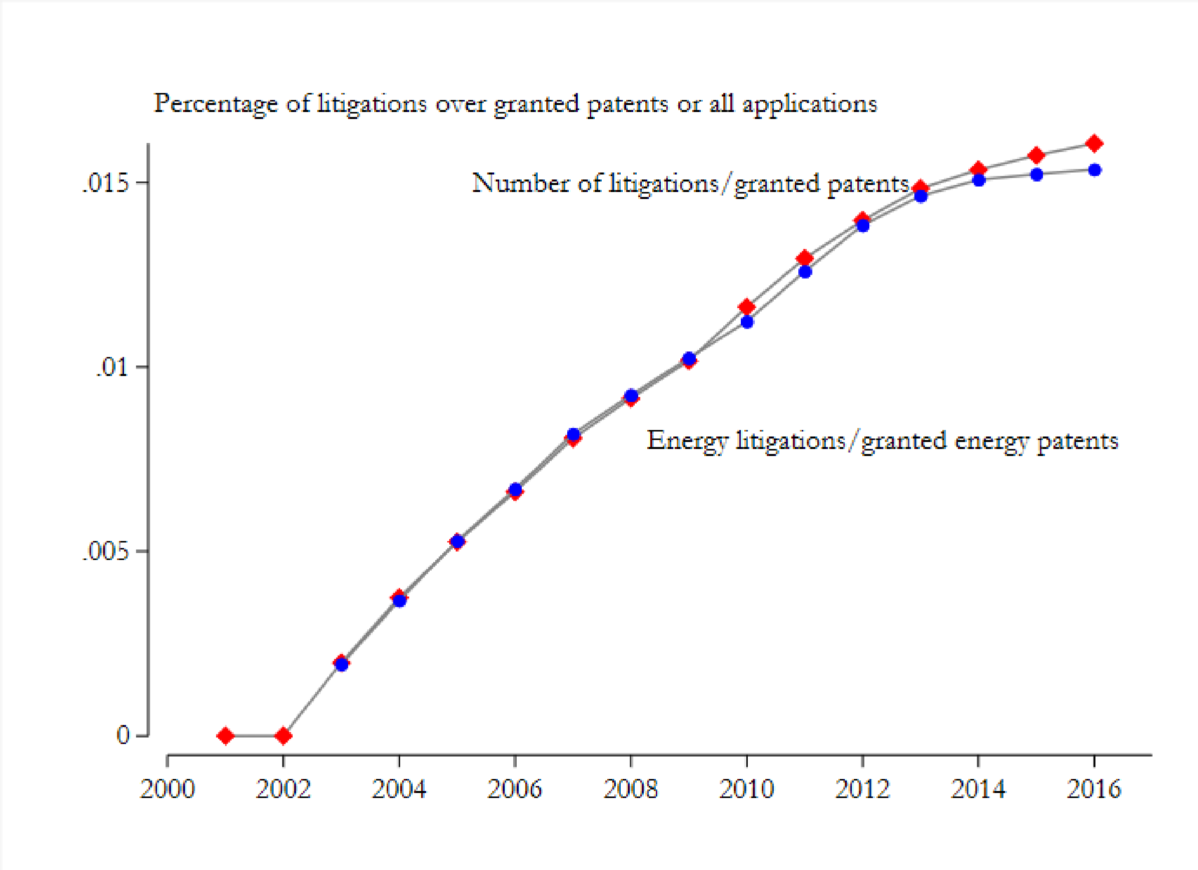

Figure 8: Proportion of litigated patents to applied and granted patents.
Source: Calculated from USPTO patents data

data to identify the litigation.

Cooperative Patent Classification (CPC) - The CPC is the result of a jointly developed system between the European Patent Office (EPO) and the USPTO, it is a common, internationally compatible classification system for patent publications, which has been adopted by many countries throughout the world. The CPC classifies the patents by letters from A to H and Y. For this paper, we are focusing on the energy sector which is a combination of sector H - electricity and sub-sector Y02 - climate change technologies.

Citations - The inventors need to cite all related prior patents as a reference in the application process. The citations help to define the property rights of the patentee in documents. For each patent, the Citations data set includes the number of prior patents cited (backward citation) and their patent numbers, and it also includes the same information on all subsequent patents that had cited a given patent in their applications (forward citation). Prior research concluded that the number of citations can be a measurement of the value of a patent (Hu et al., 2017).

All applications - Each observation of a granted patent has two unique identities to identify, which are the patent number and application number. In the previously described data sets, the patent number is the key variable to connect them. The All applications data sets documented patent applications during 1910 –2019 with the date of acceptance if the patent has been granted. This data set is important because it connects the patent number to its application number, which is the only key variable connecting to inventors.

Inventors - The data set of inventors obtained from US PTO uses application numbers as the key variable of patents. One or more inventors usually contribute to each patent, and the data set ranks the inventors of each patent in order. By connecting the Inventors data set to the All applications data set, inventors can be documented by patent number.

We graphically processed the integrated data in order to show the stylized facts of litigation' trends and distributions in all and in parts.

For figure 9, the data set is generated by merging **CPC** dataset to **litigation** dataset using the patent number as a key variable, so that litigation can be identified to different Classifications.

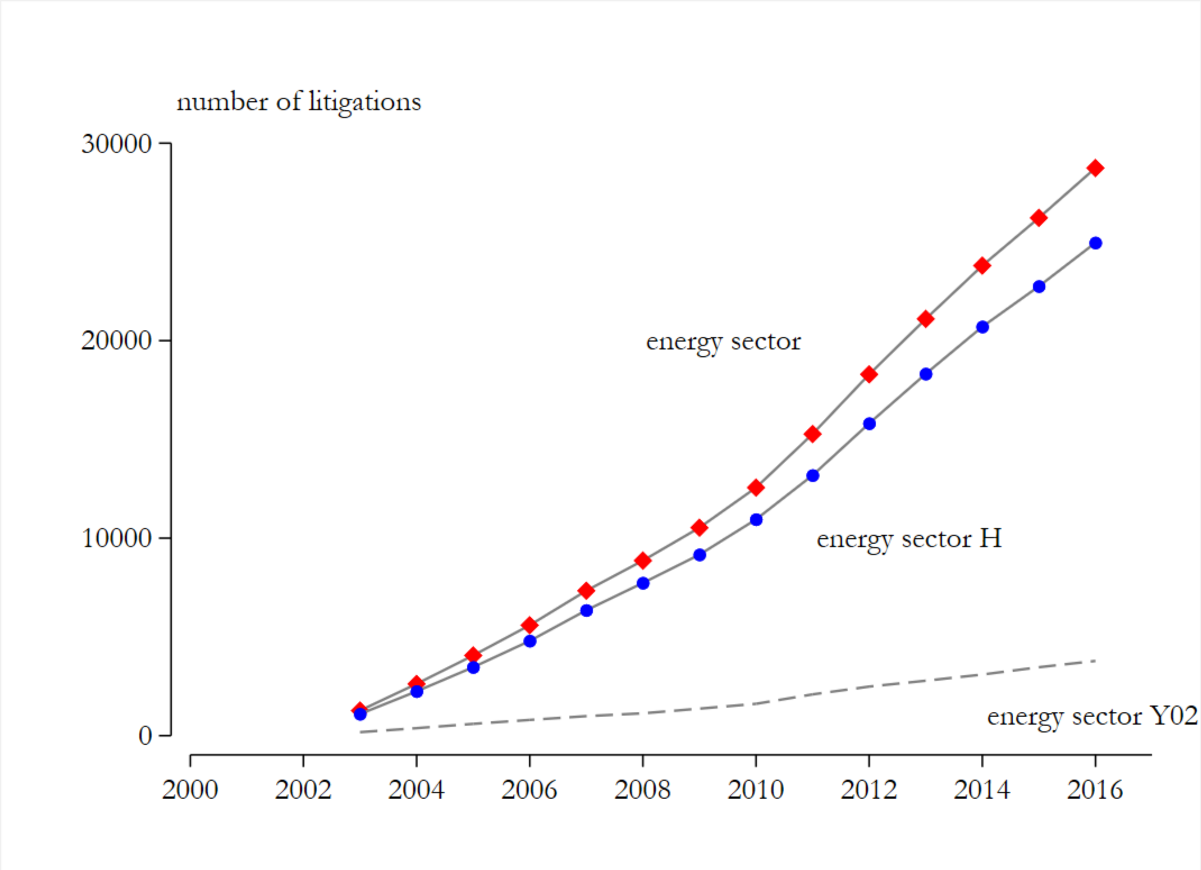

Figure 9: The number of litigation of subsections of the energy sector

Figure 10 is generated by counting the total number of litigation by year and dividing by the total Cumulative sums of granted patents or applications. Granted patents are counted based on their issue dates and applications are counted based on their filling date because only granted patents have issue dates.

In addition to focusing on the absolute number of litigation in the sample period, we also want to show the proportion of litigation in the total number of granted patents or all the applications for patents. Note that the number of granted patents and applications is counted from the year 1991 to 2016. As shown in figure 10, the total number of litigation between 2001 to 2016 is about 1.5% of all patents.

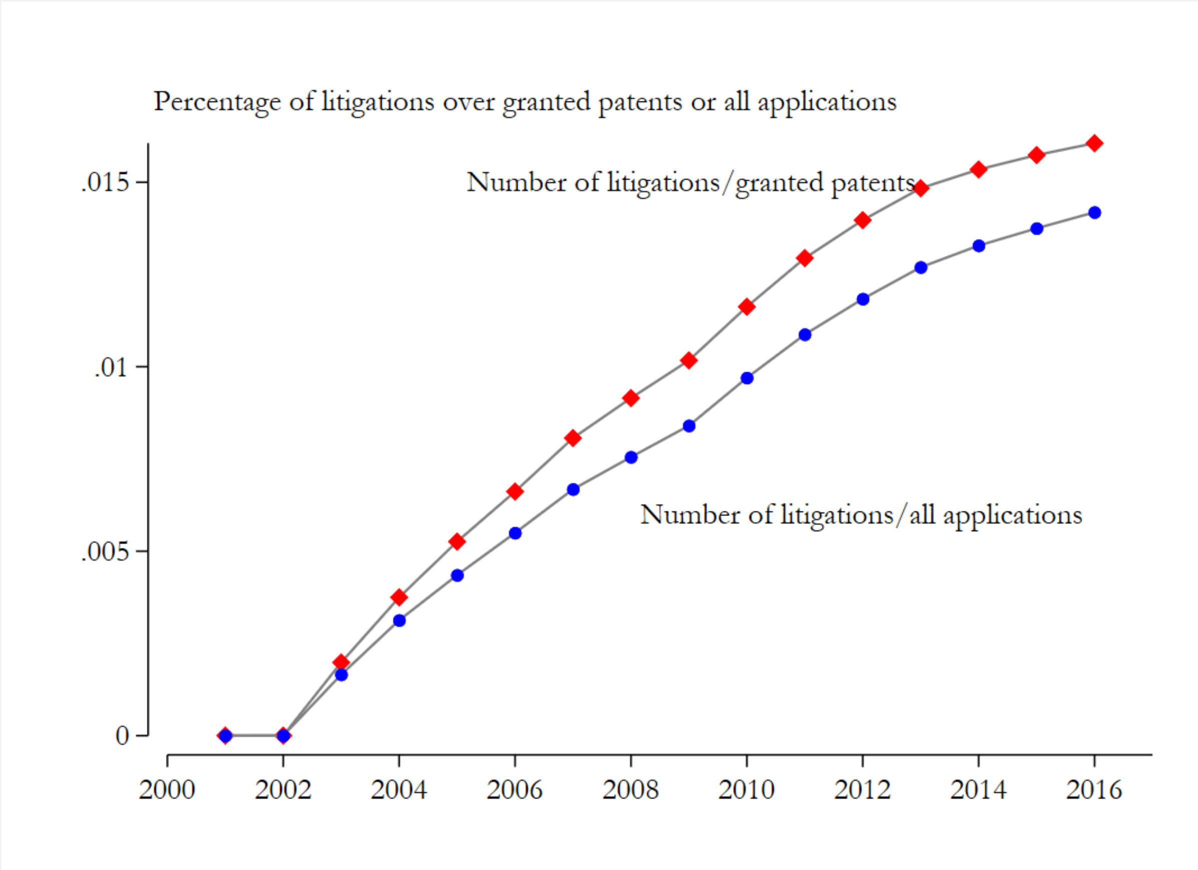

Figure 10: Percentage of litigation over granted patents or all applications

Figures 11, 13, 14, 15, and 3 are generated by the **litigation** dataset, and figure 12 is generated by **All applications** data set

In our litigation data, the distribution of the number of inventors per litigation is shown in figure 4, and the distribution of the number of inventors per application is shown in figure 12. More litigation has 1 to 4 inventors which are similar to more patent applications that have 1 to 4 inventors, although the distribution of litigated patents with 1 inventor is slightly higher than the distribution of all applications with 1 inventor about 0.6%, we can not conclude that patents have fewer inventors will be more likely to be litigated. It needs further empirical analysis.

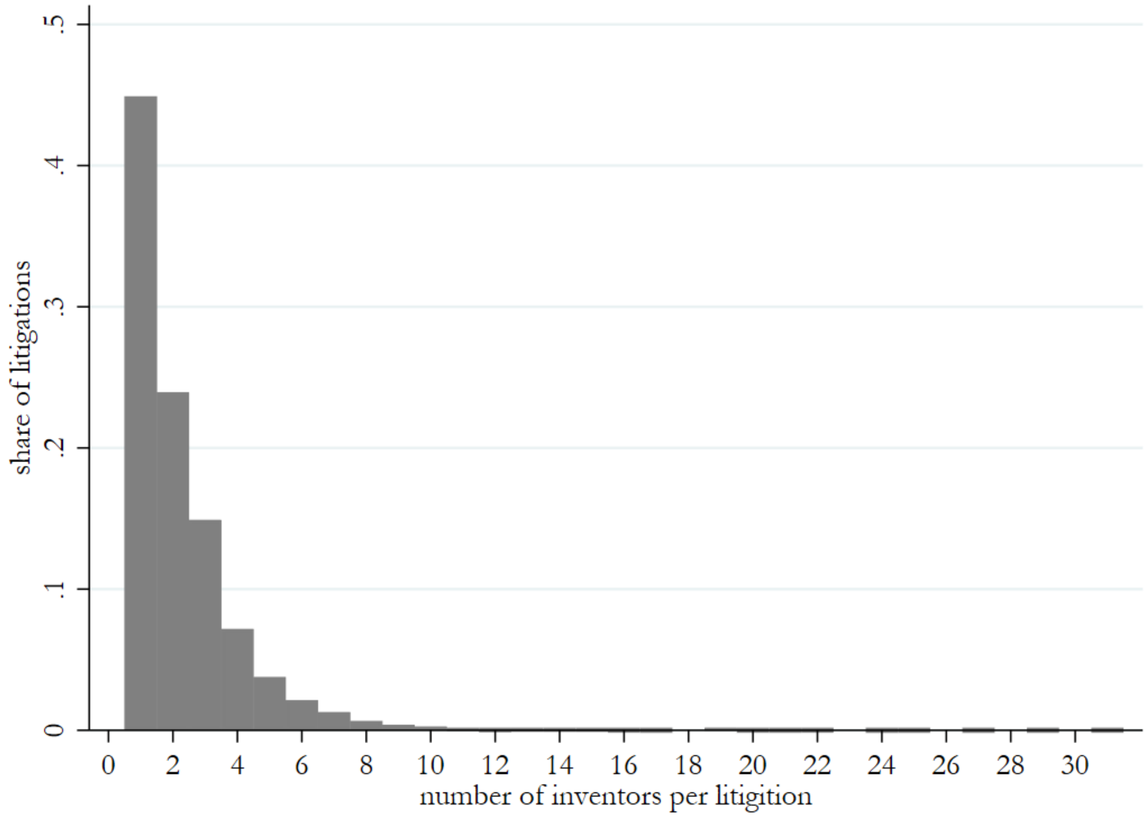

Figure 11: distribution of the number of inventors per litigation

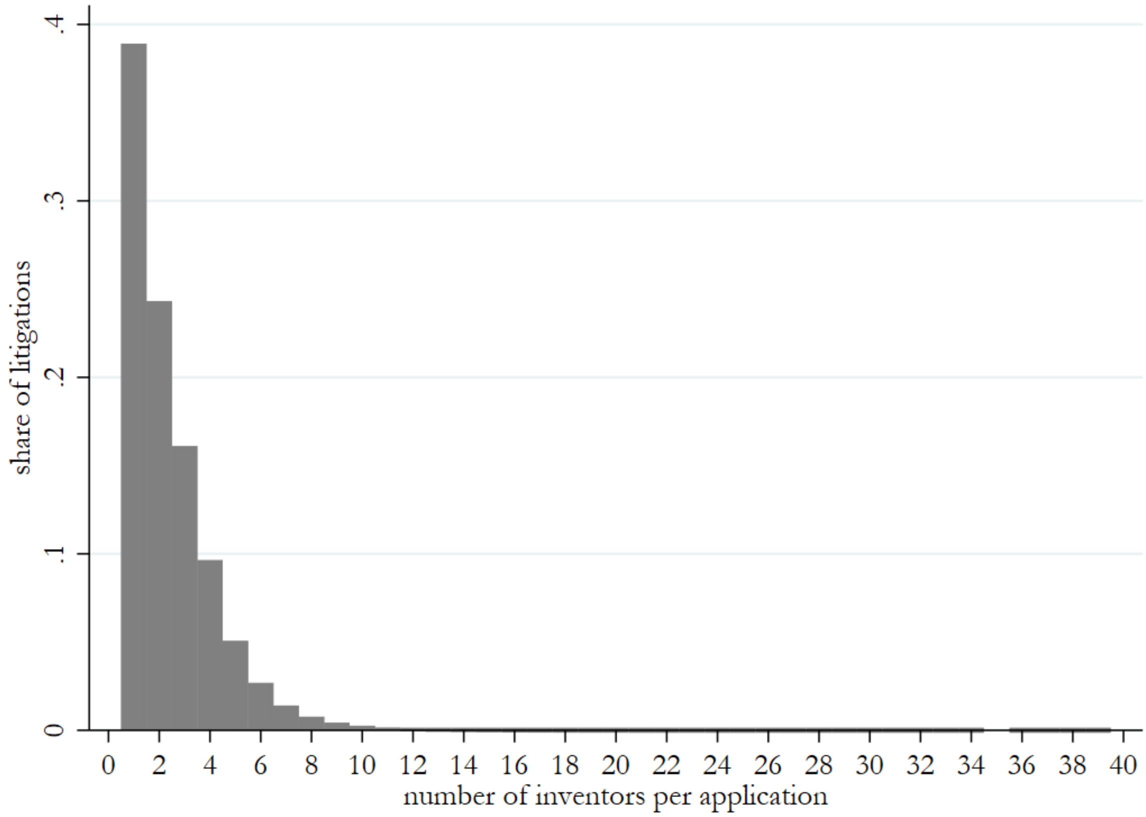

Figure 12: distribution of the number of inventors per application

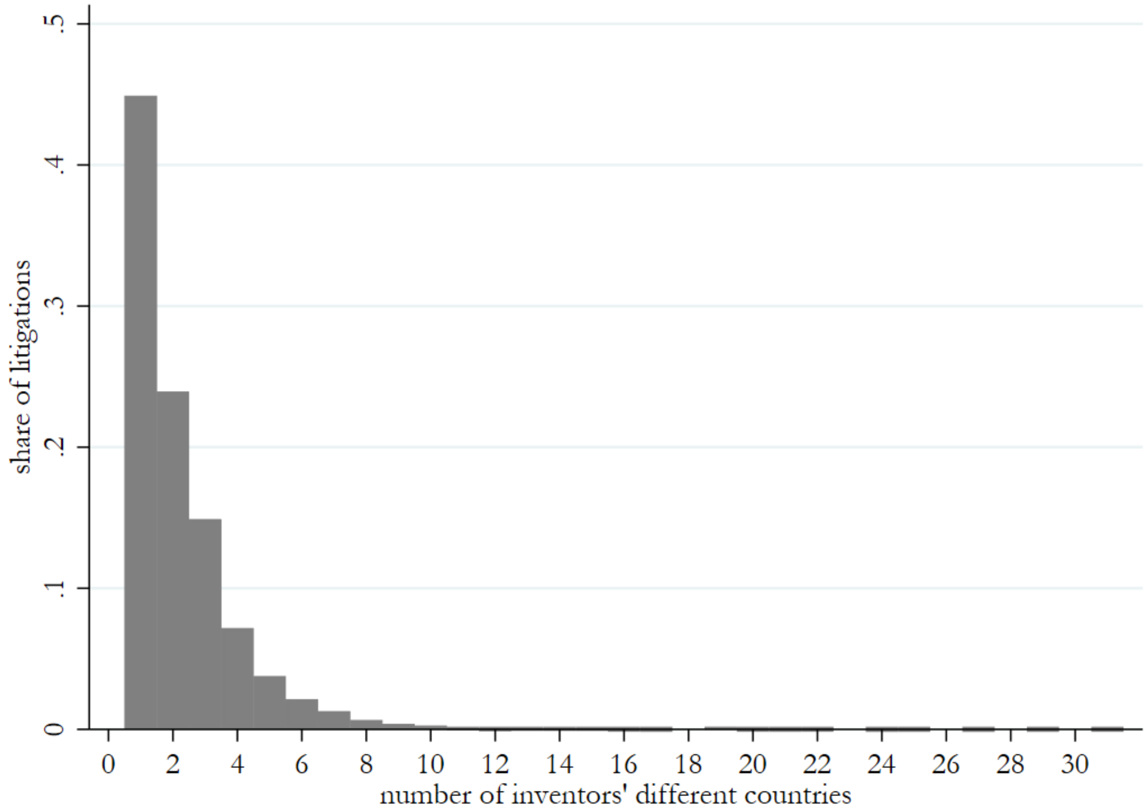

Figure 13: distribution of inventors from different countries

The distribution of the number of countries the inventors from for each patent is shown in figure 13, which is almost the same to figure 11 of the distribution of the number of inventors per litigation and most of the inventors are from the US as shown in figure 14. We can hypothesize that litigated patents' inventors are more likely to be from different countries and most litigated patents with 1 inventor from the US.

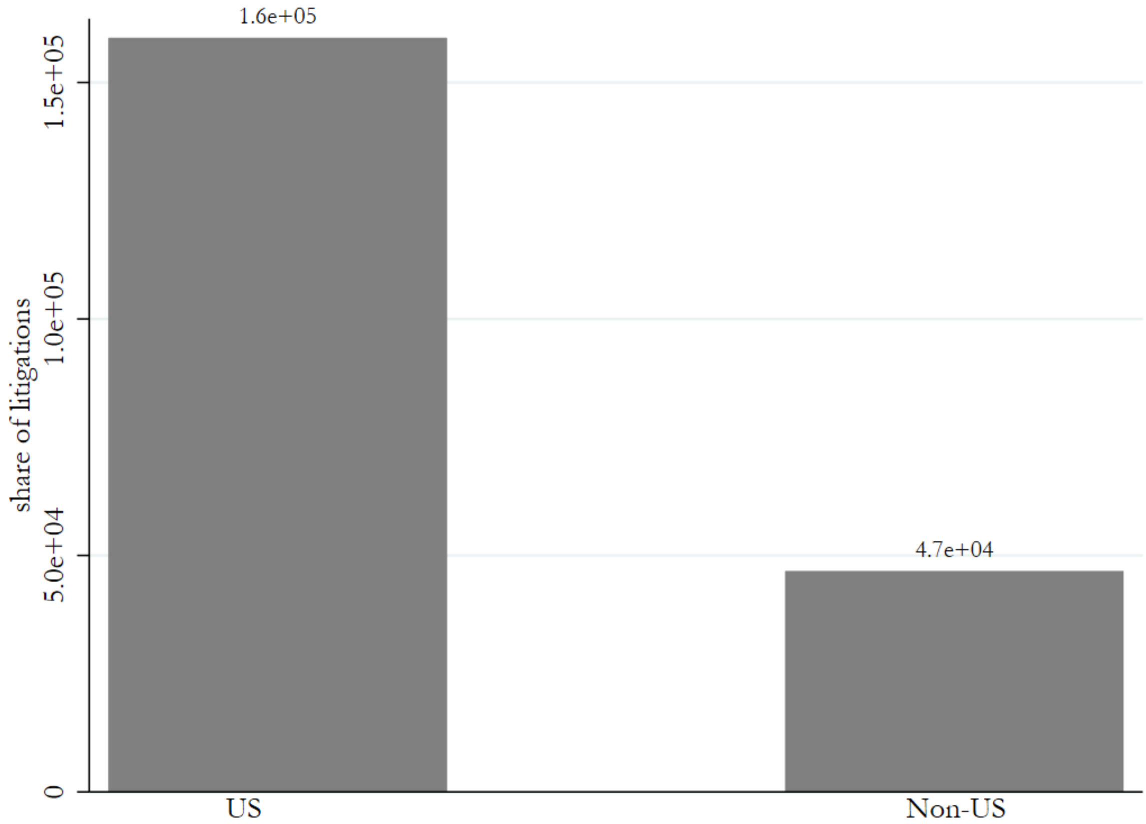

Figure 14: distribution of US and Non-US Inventors

As shown in figure 8, Most inventors only have 1 litigated patent and lots of inventors have multiple litigation. In extreme cases, 4 inventors have more than 400 litigation.

State	Freq.	Percent	Cum.
CA	17,282	19.08	19.08
TX	15,215	16.79	35.87
DE	9,811	10.83	46.70
NY	5,210	5.75	52.45
IL	4,934	5.45	57.90
NJ	4,803	5.30	63.20
FL	3,576	3.95	67.15
MI	2,240	2.47	69.62
VA	2,067	2.28	71.90

Table 3: Distribution of the state of court

In all states of court, inventors prefer the states of California and Taxes as shown in figure 3, which counts for a total of 36% of all litigation.

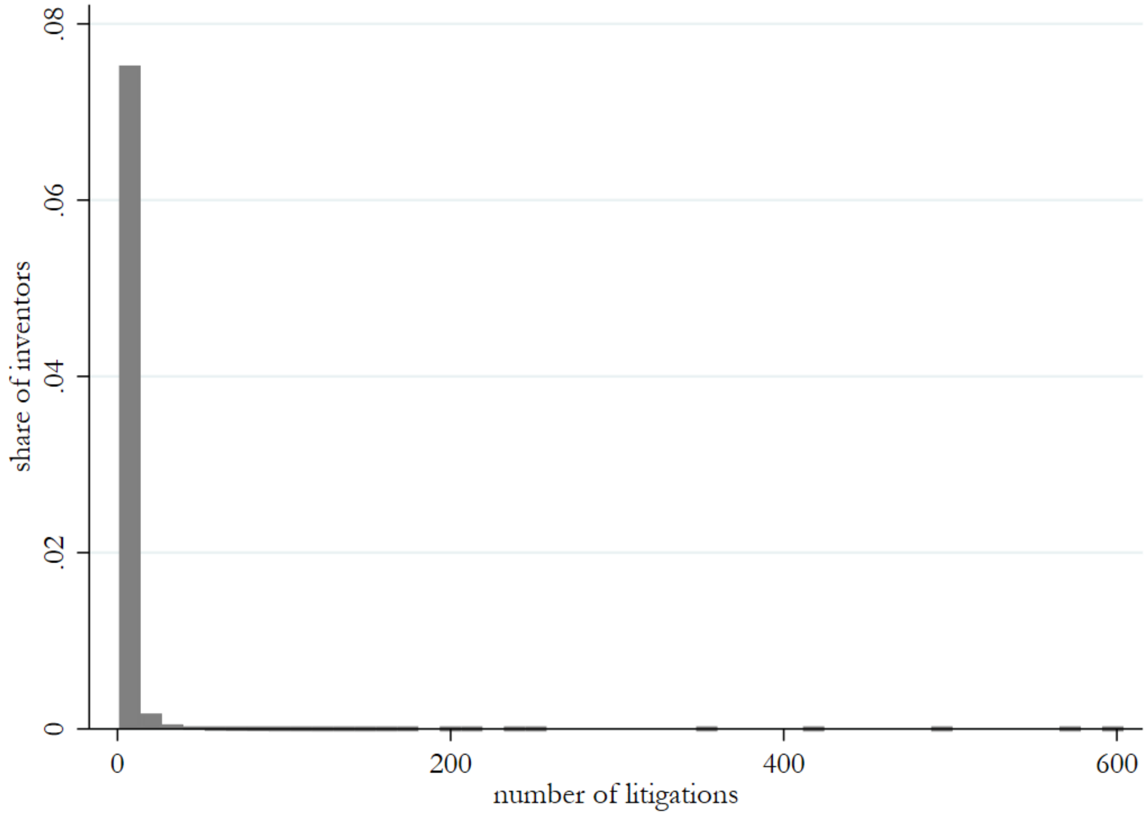

Figure 15: distribution of the number of litigation each inventor has

Figures 4 and 5 are generated by merging the Litigation data set with the Citations data set using the patent number as the key variable. Because Litigation is far less than all cited and citing patents, litigated patents can be marked to distinguish.

As shown in figure 4, the backward citations of patents without litigation, which count for 99.57% of all patents, are roughly increasing over years. While, surprisingly, the patents with litigation have more average backward citations. The patents have more backward citations and have advantages in completeness, and they are more likely to be invented by larger firms. Big firms with their well-developed legal departments are easier to get rid of lawsuits. Another reason may be that a small sample size of litigation makes the average backward citation more.

Figures 16, 17, 6 and 7 are generated by merging CPC dataset to previously merged litigation-Citations dataset using the patent number as the key variable. The citing and

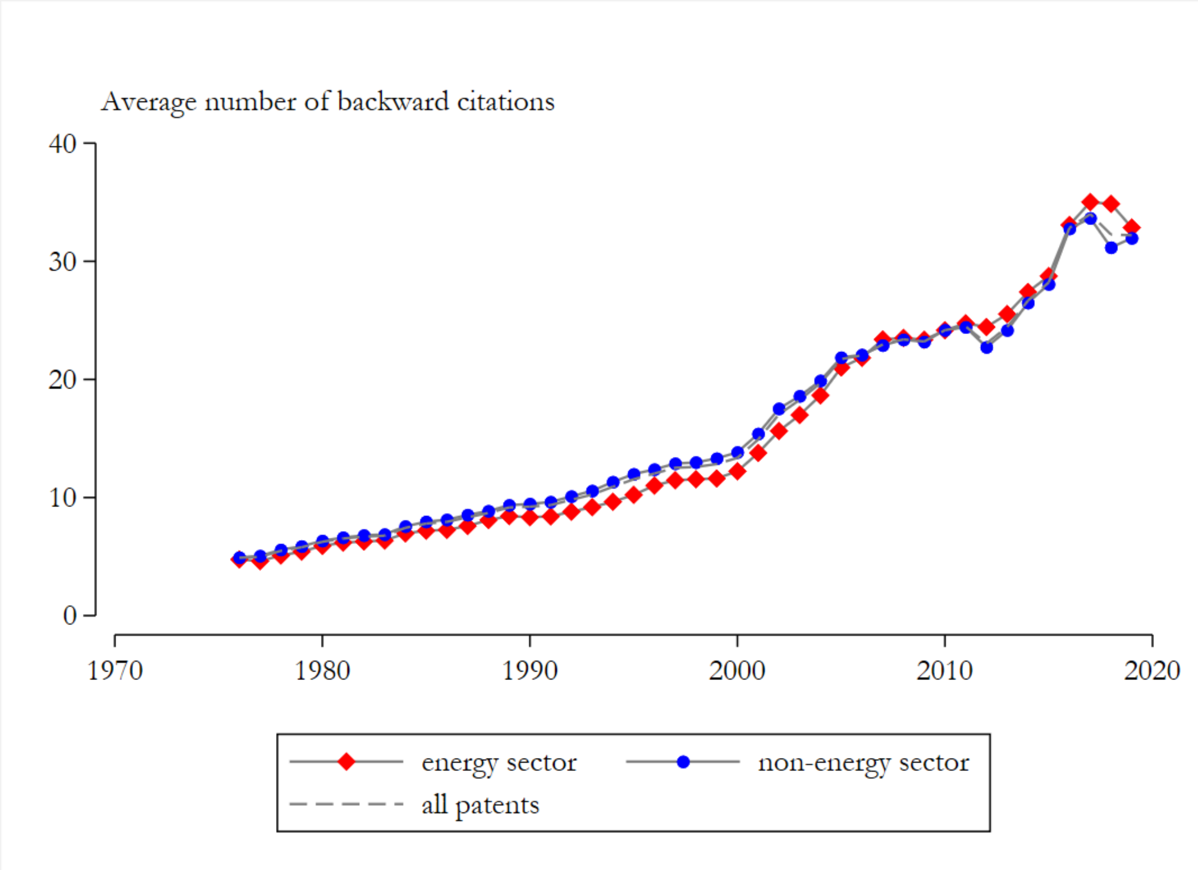

Figure 16: Average backward citations in energy sector

cited patents can be identified whether it is in the energy sector.

The average number of forward citations of litigated and non-litigated patents is shown in figure 5, patents are getting more forward citations by year, and patents in recent years have fewer forward citations because new patents need time to be cited by more inventors. 0.3% of patents are litigated, and they have more forward citations than non-litigated patents. One explanation can be that crowdedness in a research area contributes to litigation. More forward citations increase the number of potential disputes, which could have a direct effect on the level of litigation (Lanjouw and Schankerman, 2001).

From figure 4, we can conclude that there have no significant differences in backward citations for energy and non-energy sectors. For forward citations, the energy sector has more forward citations than the average and the non-energy sector has slightly fewer forward citations than average as shown in figure 17.

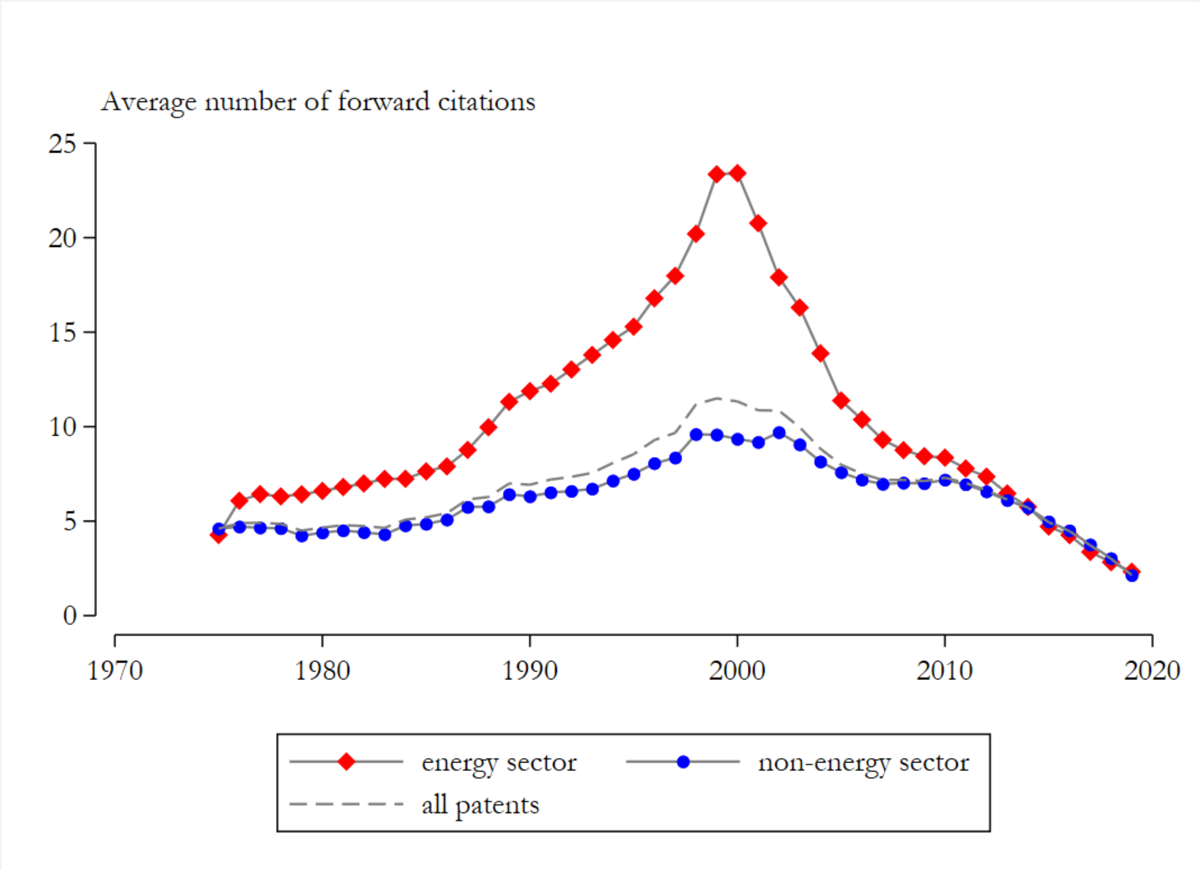

Figure 17: Average forward citations in energy sector

Average backward and forward citations of litigated and non-litigated patents in the energy sector are shown in figure 6 and figure 7, it has similar shape and results as patents in all sectors. Litigated energy patents have more backward and forward citations.

2.7.2 The Heterogenous Impact of Patent Protection Policies in the Energy Sector

Over the past two decades, there has been a noticeable rise in the number of patent lawsuits in the United States (Moore, 2000), as more and more companies and individuals seek to protect their intellectual property rights. Over 40,000 patents have been the subject of court cases in the US since 1976. The increase in the number of patent litigation has led to policy reforms and it brings distinct influences on the patent system. American Inventor Protection Act (AIPA) published in 1999 and enacted on Dec 2000 required patents to be disclosed 18 months after filing an application (Johnson and Popp, 2001). Patent applications in the United States have traditionally been kept secret until the patent is granted. However, as a result of the AIPA, patents that take more than 18 months to be granted lose some secrecy. The time between an initial patent application and its final approval is known as the grant lag and can often be seen as a period of purgatory for the applicant. The longer grant lags make independents and small firms less able to obtain redress if a larger firm infringes and lawsuits may occur (Popp et al., 2003).

We study the impact of AIPA policy change in the time length of patent grant lags and its heterogenous impact on firms of different sizes. To do so, we estimate a difference-in-difference model with fixed effects on patent publication dates and regions. Our results indicate that the AIPA reduced the grant lag among large firms. We do not find evidence that small firms in the energy sector benefited from additional grant lag reductions.

We estimate a the difference-in-difference model to measure the effects of the AIPA 1999 policy on reducing the grant lag in the energy sector. AIPA was published on Nov 29, 1999, and enacted on Dec 2000 (Johnson and Popp, 2001), small firms are selected as the treatment group for the following reasons (Lanjouw and Schankerman, 2004): (1) all applicants' patent filing fees were reduced, the smaller firms' cost reduction is greater compared to larger firms as a ratio of the total cost, (2) the cost of losing secrecy for small firms is higher than larger firms, and (3) large firms are able to reasonably circumvent the 18-month disclosure rule so as not to be affected by AIPA 1999 (Valentine et al., 2019).

$$\begin{aligned} GrantLags_{ijt} = & \beta_0 + \alpha_i + \gamma_t + \beta_1 SmallFirms_i + \beta_2 PostPolicies_t \\ & + \beta_3 SmallFirms_i \times PostPolicies_t + \beta_4 BackwardCitations_i \\ & + \beta_5 ForwardCitations_i + \beta_6 InventorsPreviousPatents_i \\ & + \beta_7 InventorsPreviousTeamSize_i + \beta_8 NumberofInventors_i \\ & + \beta_9 USPatents_i + \beta_{10} SmallFirms_i) + \varepsilon_{ijt} \end{aligned} \tag{2}$$

where α_i is patents' regional fixed effects and γ_t is the patents' application dates time fixed effects. i indexes patents, j indexes detailed classifications, and t indexes months. $SmallFirms_i$ equal 1 if an enterprise has a small or micro indicator, otherwise, it equals 0. The 20 years data sample is selected for patents with application dates between Dec 1990 and Dec 2010. $PostPolicies_t$ equals 1 for all months after Dec 2000 (the policy period), otherwise, it equals 0. $SmallFirms_i \times PostPolicies_t$ is the interaction term between the $SmallFirms_i$ and $PostPolicies_t$, which captures the average differential change relative to the control group during the policy period. If β_3 is significantly negative, then we can infer that the policy was effective at reducing Grant Lags for small firms.

Table 4 shows the improvement of grant lags across all sectors following the adoption of AIPA 1999, the improvement of grant lags across all sectors on small firms, and the effects of grant lags under the energy categories on small firms. With the fixed effect of time and region, AIPA 1999 enacted on Dec 2000 has greatly reduced the time length of grant lags in all sectors. In difference-in-difference results, the AIPA 1999 only has decreased grant lags for small firms less than 1 month more compared to large firms. Although the coefficient of policy effects on small firms is statistically significant, small firms showed little additional improvement in grant lags compared with large firms. The policy effects on the grant lags of small firms in the energy sector are not statistically significant, while the grant lags of patents in the energy sector have improved more than patents across all categories.

In the study, we found that there are significant differences between litigated patents and non-litigated patents in the grant lags, but the elements of the grant lags are many. We hope to learn the effect of policy on the risk of patent litigation by looking at the effects of AIPA 1999 grant lags on patents.

We demonstrate the improvement of patent grant lags by AIPA 1999 through the difference-in-difference model. The results showed that AIPA 1999 significantly reduced the time of grant lags under all categories and had better effects for the energy categories. Although many studies assumed that small firms would be more affected by AIPA 1999,

Table 4: AIPA 1999 effects on Grant Lags

	All Grant Lags	All Grant Lags	Energy Grant Lags
after200012	-28.12*** (-95.97)	-28.70*** (-99.35)	-30.59*** (-60.06)
small_firms		-1.887*** (-12.47)	-0.779* (-2.06)
Policy effects		-0.722** (-3.20)	-0.489 (-0.84)
Backward citations	0.0325*** (12.13)	0.0644*** (24.80)	0.0119* (2.49)
Forward citations	0.00683*** (5.87)	0.0122*** (8.70)	0.00362* (2.27)
Inventors' previous patents	0.00682 (1.06)	-0.00231 (-0.68)	0.0421** (2.92)
Inventors' previous team size	0.523*** (6.43)	0.728*** (9.01)	0.328* (2.32)
Number of inventors	-0.115 (-1.64)	-0.209** (-3.02)	-0.0246 (-0.21)
i.US patents	-0.318 (-1.01)	-0.510 (-1.63)	-0.510 (-0.88)
HUMAN NECESSITIES	0 (.)		
PERFORMING OPERATIONS	-2.376*** (-13.34)		
CHEMISTRY and METALLURGY	2.124*** (7.05)		
TEXTILES and PAPER	-2.186*** (-3.75)		
FIXED CONSTRUCTIONS	-2.876*** (-10.56)		
MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING	-3.244*** (-14.26)		
PHYSICS	2.156*** (12.16)		
ELECTRICITY	2.260*** (12.36)		
GENERAL TAGGING OF OTHERS	-0.0360 (-0.16)		
_cons	45.47*** (144.04)	45.22*** (150.82)	51.03*** (97.24)
N	67043	74460	20154

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

we did not find any additional reduction in the average grant lags of patents for small firms. The possible reasons are that the grant lags are determined mostly by the examination process. In the same period, the number of patent applications by small firms, the number of patent examiners, and the speed of examination of small firms' patents would have a greater influence on the grant lags. More research is needed to confirm this in the future.

Chapter 3

Do EV Adoption Policies Drive Innovation in Energy Storage Technologies? Evidence from the Chinese Market

3.1 Introduction

In the last decade, the global focus on reducing emissions and improving energy efficiency has spurred a global effort to shift road transportation from conventional internal combustion engine vehicles to electric vehicles (EVs).[4] For example, China aims for EVs to make up 40% of all new vehicle registrations, ranging from approximately 9 to 10 million vehicles per year (Ministry of Industry and Information Technology, 2017). Similarly, Germany has set a goal for 40% to 50% of new car registrations to be electric, while the U.S. targets a 50% share of EVs in new auto sales-all by 2030 (Federal Republic of Germany, 2016; U.S. Congress, 2022). To accelerate this transition, many governments have implemented economic policies to encourage EV production and consumption. One of the most ambitious efforts is China's EV adoption policy, implemented between 2009 and 2021, and aimed at transforming the automobile market and reshaping

[4]Over the last decade, China, Germany, and the U.S. have driven most of the growth in EV sales, accounting for 65% of total vehicle sales worldwide and 95% of EV sales in 2023. China leads with 60% of global EV sales, followed by Germany and the U.S., contributing 25% and 10%, respectively (IEA, 2024). In 2023 alone, EVs comprised 38% of total auto sales in China, 21% in Germany, and 10% in the U.S. (IEA, 2024).

the infrastructure supporting EVs. Given China's leading position in global EV sales and production, understanding the outcomes of its policies provides valuable insights into the potential for large-scale policy-driven transitions in other markets.

The efficient and sustainable EV use is based in part on advanced energy storage solutions. Advancements in battery technologies have significantly reduced the cost of lithium-ion batteries, which are critical for EVs and renewable energy storage. By 2023, the price of lithium-ion battery packs fell to a record low of $139 per kWh, with even lower prices in China at $126 per kWh - 11% and 20% less than in the U.S. and Europe, respectively (BloombergNEF, 2023). Global demand for lithium-ion batteries for EVs reached 770 GWh in 2023 (IEA, 2023, 2024). To further reduce costs and expand deployment, ongoing innovation now focuses on reducing reliance on critical minerals, exemplified by the development of sodium-ion batteries. In April 2023, BYD introduced the first sodium-ion battery-powered car, the BYD Seagull. Given that the advancement of energy storage technologies is pivotal for the efficiency and sustainability of electric vehicles, we explore how EV adoption policies influence innovation within the transportation sector.

In this study, we examine whether China's EV adoption policies spurred advancements in energy storage technology. Previous research has focused on the effect of economic policies on EV sales while this paper explores the policy effects on further innovation in storage technologies. Specifically, we ask: do the EV adoption policies boost innovation in energy storage technologies? To answer this question, we focus on China's EV adoption policies, including financial incentives (i.e. subsidies and tax incentives) and infrastructure support, driven by the central government between 2009 and 2021. To empirically assess their impact on innovation, we build a novel firm-level patent dataset for China, covering the period from 2000 onward. Using these patent data, we estimate whether EV adoption policies directed at consumers influence a firms' probability of applying for a new patent in storage technologies.

We summarize China's EV adoption policies before describing our unique patent dataset. In 2009, China implemented a structured and comprehensive plan to promote

EV adoption, initially focusing on incentivizing EV sales in public transportation through tax incentives and subsidies. In 2010, this policy expanded to increase the number of pilot cities eligible for public transportation subsidies and extended the subsidies to include private vehicles as well. In September of 2013, a new policy phase build onto the 2009 and 2010 policies and provided additional subsidies aimed at developing an interconnected EV ecosystem, specifically by supporting the expansion of charging and battery swap stations. This infrastructure was intended to support the seamless integration of EV usage with adequate charging facilities, laying the foundation for sustained EV adoption. Finally, between 2016 and 2020, local governments received further incentives and subsidies to construct charging points (CPs) and charging/swapping power stations (CSPS).

We study innovation by constructing a unique, firm-level patent database for energy storage and green technologies in China, to the best of our knowledge, the first of its kind. Using the ORBIS Intellectual Property dataset, we linked patent applications to firms' headquarters and standardized firm names across regions, which enables a more precise analysis of patent activity by firm. Our dataset spans patent applications from 2000 to 2023 in green and energy storage technologies, identified using the World Intellectual Property Organization's (WIPO) Green Inventory classifications. This comprehensive database includes 3,066,167 patent applications in green technologies, of which 202,011 are specifically related to energy storage technologies. The data reveal a marked growth in innovation within green and storage technologies over the past two decades, particularly from 2010 to 2020, when patent applications in these fields rose from approximately 55,000 to 340,000 per year. Our data also shows a highly fragmented market, characterized by a large number of small, innovative firms. To complement the patent data, we gathered price and economic data from the China Economic Information Center (CEIC) and supplemented these with energy price indices from the China Statistical Yearbook and China Energy Statistical Yearbook. This unique dataset offers a comprehensive view of regional energy prices and economic indicators, facilitating a thorough analysis of the factors influencing innovation in China's green and energy storage sectors.

We estimate a dynamic Poisson fixed-effects innovation model to study whether adoption policies foster patent applications in storage technologies. Our model controls for past innovation, local spillovers, energy prices, as well as time and firm fixed effects. We report our results as incidence rate ratios for more intuitive interpretation; an estimated ratio greater than one for a given variable suggests an increase in the likelihood of patent applications associated with that variable.

Our results highlight the importance of EV adoption policies in encouraging innovation in storage technologies, especially those policies directed at creating and promoting an interconnected ecosystem of EV usage and charging infrastructure. In addition, we find that past innovation by other firms, i.e. local knowledge spillovers, has a positive and persistent influence on patent activity in the subsequent time periods. This result is in line with prior work that shows the importance of knowledge spillovers on a firm's patenting activity (e.g. Jaffe, 1986; Jaffe et al., 1993; Grossman and Helpman, 1991). Finally, we explore the role of energy prices and innovation. We find that neither electricity nor fuel prices consistently show a statistically significant impact on promoting innovation activity in our study. This finding contrasts with prior literature, such as Crabb and Johnson (2010); Aghion et al. (2016) and Knittel (2011), that found a strong positive relationship between energy prices and cost-reducing or clean energy patents. While many related studies use an average energy price index as their instrument, electricity and fuel prices in China are heavily regulated and may not accurately reflect true market conditions. The unique structure of China's fragmented and highly competitive storage technology market may also contribute to our result, suggesting that competitive pressures and market dynamics could play a more substantial role in driving patenting activity.

The paper is organized as follows. First, we describe our data including the EV adoption policies and innovation trends. Section 3 introduces our model and empirical strategy, and Section 4 analyzes the estimation results. Finally, Section 5 concludes the paper.

3.2 The Chinese EV Market

The EV industry in China has experienced rapid growth in the past decade, driven by government policies, technological advancements, and an expanding industrial base. In this section, we begin by reviewing EV sales data, followed by a discussion of China's regulatory environment and how government initiatives, such as subsidies, have promoted the growth of the EV market. Finally, we describe the construction of our patent dataset in energy storage technologies to proxy for innovation.

3.2.1 The EV market share

In 2012, the global stock of EVs was approximately 183,700 vehicles. At that time, the U.S. had the largest share at 38%, followed by Japan at 24% and France at 11%. China accounted for just 6.2% of the global EV stock, reflecting the early stage of its EV market development (IEA, 2013). Since then, through the combined efforts of central and local governments, automobile manufacturers, and supporting industries, China has transformed into the world's largest EV market (Wang et al., 2017; Gnann et al., 2018). Annual global EV sales, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), have grown on average by 60% per year since 2014, reaching 2.1 million units in 2019. By 2023, China's EV sales surpassed 8 million vehicles annually, accounting for more than 38% of all automobile sales in the country.

China's EV market is now larger than the combined markets of Europe and the U.S., driven by a high volume of BEV sales (Hertzke et al., 2018). Figure 18 presents EV sales by powertrain from 2011 to 2023, where EVs refer to the sum of BEVs, which are battery electric vehicles, and PHEVs, which are plug-in hybrid electric vehicles. In 2023, the global EV stock exceeded 40 million vehicles, with China alone holding 21.9 million EVs-nearly double Europe's stock of 11.2 million and more than four times the U.S. stock of 4.8 million (IEA, 2024). That year, China's share of the global EV fleet reached 54%, underscoring its dominance not only in sales numbers but also in market

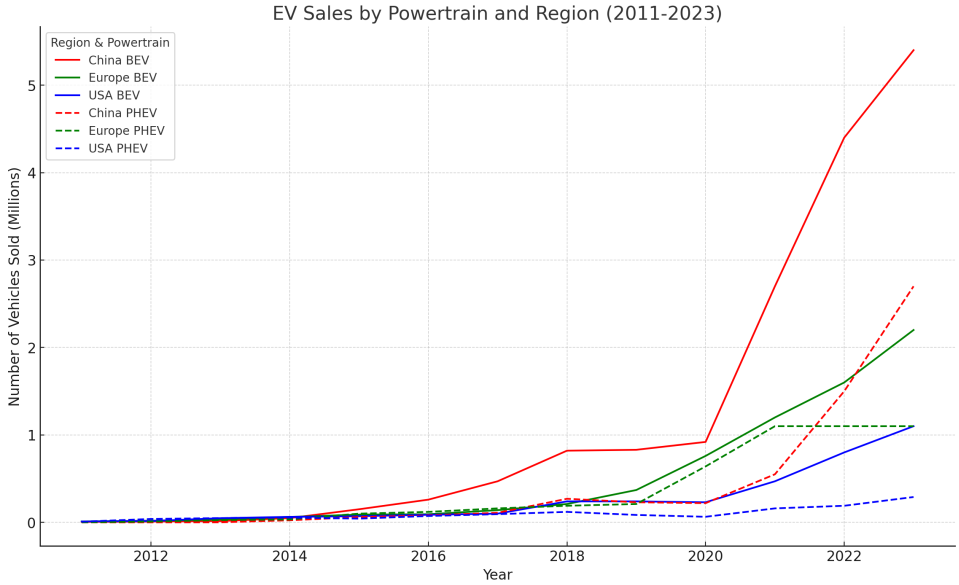

Figure 18: EV sales by powertrain in China, Europe and the US, 2011-2023.

penetration. For example, EVs accounted for 38% of total auto sales in China in 2023, compared to 21% in Europe and just 10% in the U.S. This rapid market expansion has been supported by targeted government policies, such as subsidies for EV purchases, investments in charging infrastructure, and incentives for domestic EV manufacturing. Figure 19 presents the growth rate of EV sales in China, Europe and the US.

China's leadership in the EV market extends beyond sales figures; it is also the world's largest producer of EVs and the leading supplier of lithium-ion batteries, the technology powering 80% of EVs worldwide. Major domestic manufacturers such as BYD Auto, SAIC Motor, Great Wall Motor, GAC Group, and Geely play pivotal roles in the industry (Zhang et al., 2017). Additionally, China supplies approximately 70% of global lithium-ion battery demand, thanks to its vertically integrated battery supply chain, which includes the production of EV cells, cathodes, and anodes. This level of consolidation far surpasses that of the U.S. and Europe, making China a dominant exporter and a key player in shaping the global EV market's future (IEA, 2024).

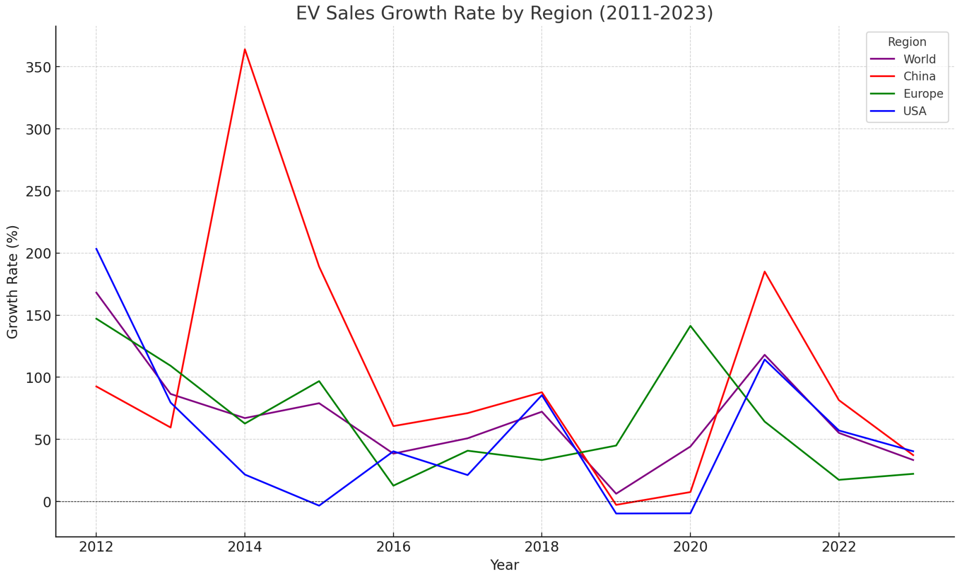

Figure 19: Growth rate of EV sales in China, Europe and the US, 2011-2023.

3.2.2 EV adoption policies

In the last 20 years, China has implemented many policies to support the sale and use of EVs. These policies can be grouped into three categories: financing the purchase of EVs, promotion of infrastructure to support EVs, and the investment in R&D to advance clean and storage technologies.[5] Out of these three types of policies, the literature that studies innovation in the energy sector has established the positive impact of R&D policies on the development of new technologies (see, for example, Aghion et al. (2016)). Thus, we focus on the first two types of policies: finance policies and infrastructure promotion policies.[6] We summarize these policies in Table 9 Appendix . China's earliest EV policy, named *"The long-term special planning for energy efficiency"*, emphasizes the importance of developing hybrid vehicles (HVs) and exploring EV policies (NDRC, 2004). Between 2004 and 2008, this policy presented a roadmap, whereas, since 2009 a more structured

[5]Zhang et al. (2017) provide a comprehensive review of EV policies in China. In addition to providing a review of China's policies, these policies in China relate to EV adoption policies in the US, Japan, and Germany.

[6]"The Energy Conservation and NEVs" and the "Modern Transportation Technology of EV Technology and System Integration" Programs were implemented between 2006 and 2013 to support investments in research and development and advance clean and storage technologies. Additionally, in 2016 the MST initiated a promotion program providing support for R&D efforts on battery technology with the objective of improving the efficiency and safety of batteries for EVs.

and comprehensive plan has been introduced to accelerate the adoption of electric vehicles by increasing financial support and establishing clear, measurable promotion objectives.

In the first category, the EV finance policy consists mainly of fiscal subsidies and tax incentives. Starting in 2009, the policies provided subsidies for the adoption of electric vehicles in the public sector, specifically for buses and taxis, in 13 pilot cities using a tiered approach. These pilot cities included major metropolitan areas such as Beijing, Shanghai, and Chongqing (Finance Construction, 2009). This subsidy was directed towards HEVs (Hybrid EVs), PHEVs (Plug-in Hybrid EVs), BEVs (Battery EVs), and FCEV (Fuel Cell EVs) (Hao et al., 2014). In 2009, approximately half of the subsidies went to HEVs which combine an electric motor/battery assembly with an internal combustion engine. HEVs have a limited electric-only driving range of less than 5 miles because the battery is designed to assist the internal combustion engine rather than to be the primary source of energy. In 2010, an extension policy expanded subsidies in the public sector to 25 pilot cities and also supported EV private sales in 6 cities, including Shanghai and Beijing (MF, 2010). Eligible brands included major auto manufacturers such as BYD, NIO, XPeng Motors, Li Auto, and SAIC Motor (including its joint ventures with GM and VW), as well as battery leasing companies. From 2013 to 2014, the plan expanded subsidies and tax incentives to 40 cities and city groups. These subsidies supported different engines and electric range capabilities. For example, the subsidy for PHEVs was fixed to those with at least 80Km in electric range. In contrast, the amount of the subsidy for BEVs was based on the electric range: 80Km - 150Km, 150Km - 250Km, and $\geq$ 250Km. The highest incentives were directed to EVs with the most range ($\geq$ 250 Km), usually with higher battery energy density or higher battery capacity (Hao et al., 2014).

In the second category of EV adoption policies, the Ministry of Science and Technology (MST) actively promoted infrastructure development to support EVs at a national level. The infrastructure promotion policy started in 2010 and continued through the years with specific goals around the number of charging poles and power stations. Between 2010 and 2015, the MST proposed the construction of 400,000 charging points

(CPs) and 2000 charging/swapping power stations (CSPS) in 20 pilot cities to accelerate transportation electrification (MST, 2012). The first specialized development guideline for EV infrastructure promotion was issued in 2015, which specifically outlined the construction plan for EV charging infrastructure in 2020 based on demand forecasts(NDRC, 2015). From 2016 to 2020, the Ministry of Finance (MF) provided local governments with subsidies for the construction and operation of charging facilities (MF, 2016b). In 2020, the MST determined the business model dominated by pure electric drive (MST, 2012).

Finally, from 2016 to 2020, a subsidy phase-out mechanism was introduced at the end of 2016 which specified the conditions for a gradual reduction of subsidies. It established a priority for EVs with higher driving ranges and larger sizes. The phase-out mandated a reduction of 20% in 2019-2020 for all EV subsidies compared to the standards from 2016, with the exception of those for fuel cell vehicles (MF, 2016a). In 2020, the subsidy reduction was moderated in terms of intensity and pace, with the subsidy standards for 2020-2022 being reduced by 10%, 20%, and 30% respectively (MF, 2020). This phase-out approach aimed to encourage EV battery technology manufacturers to continue to invest in technological advances that would drive battery cost reductions in order to increase EV commercialization and enable the sustainability of the transition to EVs (Hao et al., 2014).

In our empirical analysis, we include these policies with dummy variables. Specifically, we generate five dummy variables to control for the existence of specific policies in various cities. These five policies are: (1) the 2009 subsidies to support the adoption of electric vehicles in the public sector across 13 pilot cities (*Level I*); (2) the 2010 subsidies in the public sector, which is an expansion of the first subsidy to increase the number of pilot cities to 25 (*Level II*); (3) the 2010 subsidies to promote the adoption of EVs in the private sector in 6 cities (*Level III*); (4) the 2013 expansion of subsidies in both the private and public sectors, accompanied by charging infrastructure promotion to create an interconnected ecosystem for EV usage (*Level IV*); and (5) the phase-out mechanism

(*Phaseout*).

3.2.3 Innovation data

Finally, to study innovation, we build a novel patent dataset from the ORBIS Intellectual Property. Specifically, we focus on patent applications filed in China from 2000 to 2023 by domestic and international inventors.[7] The ORBIS Intellectual Property database identifies the current direct owner of each patent application, along with the company's city address and the ultimate parent company. This parent company information allows us to track the ownership of smaller firms, providing a more comprehensive view of innovation activity across both large and small entities. We have firm-level information including location.[8] This harmonization process allows us to standardize entity names across datasets for consistency.

We identify energy storage technologies using International Patent Classification (IPC) codes. Specifically, we follow the World Intellectual Property Organization's (WIPO) IPC Green Inventory, which eases the search of Environmentally Sound Technologies (ESTs).[9] Specifically, we focus on the following storage technologies: fuel cells, hydro energy, hybrid vehicles, charging stations for electric vehicles, storage of electrical energy, and storage of thermal energy. We include the complete list of selected IPC classes in Appendix . In addition to storage technologies, we also identify categories of green patent applications. We present the green patent applications breakdown in the Appendix, Table 12.

From 2000 to 2021, there are over 3 million patent applications in green technologies, and 202,011 (around 6.6%) are related to energy storage technologies (see Table 12 in Appendix). Out of all patent applications in energy storage, 57% are associated with en-

[7]Patent applications in China often include a patent agency. A domestic individual or firm may apply by themselves or seek the help of a patent agency, however, international inventors without an office in China must employ the help of a patent agency to apply for a patent.

[8]For patents where the current direct owner's city address is missing, we use available address information embedded in company names and performed supplementary searches to identify the city location for most of these firms.

[9]The goal of the Green Inventory is to identify ESTs across a wide range of technical fields.

ergy conservation. The breakdown in Table 5 shows that half of these patent applications represent a form of electrical energy storage.

Table 5: Storage Patent Applications Breakdown, 2000-2021.

Storage Patents	Number of Applications
Charging	6,829
Fuel Cells	37,768
Hybrid Vehicles	22,283
Hydro	27,542
Storage Electrical	100,669
Storage Thermal	6,920
Total	202,011

The total number of patent applications in green and energy storage technologies have increased steadily over the 21-year period (see Figure 24 in Appendix). From 2000 to 2021, green technology patent applications have grown at an average rate of 21.4% per year, while storage technology patent applications have shown an average annual growth rate of 18.9%. Next, we illustrate the share of patent applications in storage technologies relative to the total number of green patent applications in Figure 20. This highlights the dynamic nature of innovation within the energy sector. This trend shows a significant increase in the share of storage technology patents from 2000, peaking around 2006, but experiencing fluctuations around 2010 and a steady downward trend from 2013 onward. This is a reflection of the changes in the energy sector and the changes in the public and market incentives toward other green technologies, such as renewable energy generation.

An interesting aspect of these data is that energy intensity is dominated by numerous small firms and so innovation is highly fragmented market in China. Figure 21 shows the distribution of firms by the number of patents per firm. Between 2000 and 2021, up to 95% of patent applications in storage technologies were filed by a large amount of small firms. For example, 68% of total patent applications in storage technologies are owned by firms with fewer than two applications over the 21-year period. We present the distribution of these firms across the country in Figure 22, Appendix . In addition, the research

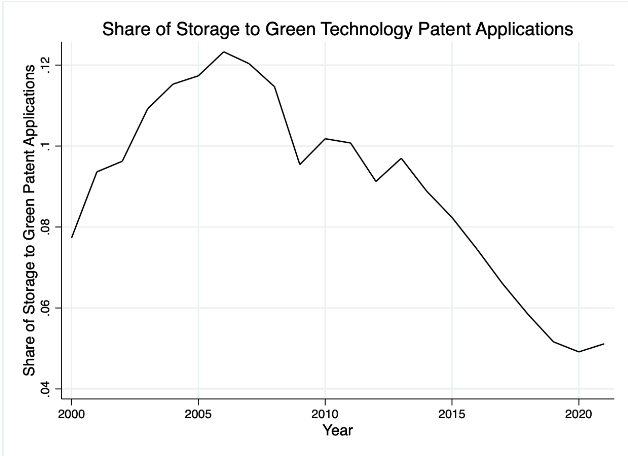

Figure 20: Share of storage patents, 2000 to 2021.

intensity per firm, the number of patent applications per firm, varies considerably. Firms with more than nine applications only accounted for 5% of all firms. Their distribution in Figure 23 in Appendix and its comparison with Figure 22 show regions where a small number of firms are research intensive. Note, however, that the distribution of firms and patent applications is quite dispersed. This is in contrast to patent applications by firm in other top innovating countries, where innovation is often concentrated among the most innovative firms. For example, United States Patent and Trademark Office (USPTO) data from 2000 to 2021 reveal that the top 100 innovators – such as IBM, Samsung, Canon, Microsoft, Intel, Apple, Google, Qualcomm, Sony, LG, and Siemens – each have over 3,500 patent applications, with IBM alone surpassing 100,000 applications during this period.

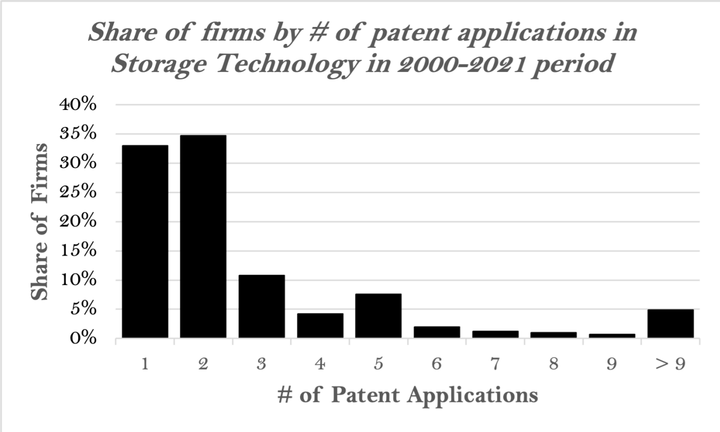

Figure 21: Share of firms by number of patent applications in storage technology, 2000-2021.

3.3 Empirical Strategy

This section describes our econometric approach used to identify the impact of EV adoption policies in firm-level innovation in storage technologies. The innovation literature presents several hypotheses regarding the determinants of innovation in the electricity sector. To empirically evaluate these factors, we employ a dynamic nonlinear model with fixed effects, where current patent applications y_{it} are modeled as a function of market variables, such as prices, the firm's own past patenting activity in year t, and any local knowledge spillovers from other firms. In addition, we incorporate the EV adoption policies detailed in Section 3.2.2.

The baseline specification for firm i's innovation is estimated as follows:

$$ln(y_{iht}) = \alpha_i ln(P_{it-1}) + A_{iht-1} + \gamma_i Citation_{it} + \mathbf{\Gamma} \cdot \mathbf{Z}_{itp} + \delta_i + \delta_t + \varepsilon_{it} \tag{3}$$

where y_{iht} is the number of patent applications that firm i applies for in year t in technology h (storage or green).[10] P_{it-1} indicates a firm's exposure to the previous year' fuel prices. These prices include both electricity and fuel prices, which are common determi-

[10]Previous studies, such as Isaksen and Trippl (2017); Parrilli et al. (2020), show that firm-level incentives to innovate often operate regionally. We also follow this approach and assign region to represent the location. Specifically, we use the eight major economic regions defined by the National Bureau of Statistics of China to represent the regions in our study, which exhibit significant disparities in terms of economic development and structural characteristics Zuo et al. (2006).

nants of innovation in the transportation sector.

We include A_{iht-1} which is a firm's existing knowledge stock in technology h. Following Aghion et al. (2016), we define knowledge stock in terms of internal and external past innovations. Specifically, A_{iht-1} is defined by a firm's own stock of patents in technology h accumulated before time t (K_{iht-1}) and the spillovers from all other firms in firm i's region j before time t ($S_{-ijht-1}$). Thus, past knowledge is defined as:

$$A_{iht-1} = \beta_{1j} K_{iht-1} + \beta_{2j} S_{-ijht-1} \tag{4}$$

In addition to the quantity of patents, we account for the quality of firm's past innovations by including the number of citations received by firm i up to year t, $Citations_{it}$. This variable allows us to assess whether the quality of a firm's previous innovations (as indicated by how frequently their patents have been cited) influences their subsequent innovation activity.

Next, the matrix $\mathbf{Z}_{itp}$ represents the effects of multiple EV adoption policies, each with a varying lag structure. In our baseline specification, we simultaneously consider all EV adoption policies p that were in effect from 2004 to 2020. Specifically, we include five dummy variables to capture policies implemented during this period. As introduced in Section 3.2.2, the variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism. The corresponding vector of coefficients $\mathbf{\Gamma}$ in Equation 5 captures the impact of these policies on innovation over time, with each element in $\mathbf{\Gamma}$ representing the weight of a given policy at a specific lag.

$$\mathbf{\Gamma} \cdot \mathbf{Z}_{itp} = \gamma_1 Z^{(1)}_{i,t-1} + \sum_{k=1}^{3} \gamma_2^k Z^{(2)}_{i,t-k} + \sum_{k=1}^{3} \gamma_3^k Z^{(3)}_{i,t-k} + \sum_{k=1}^{3} \gamma_4^k Z^{(4)}_{i,t-k} + \sum_{k=1}^{2} \gamma_5^k Z^{(5)}_{i,t-k} \tag{5}$$

where the summation represents multiple lagged effects. In our estimation results, we present the weight of a given policy taken all lags into account as well as the weight of a given policy at each specific lag. For instance, the second policy (Level II) was implemented in 2010 and substituted in 2013. Thus, for the second policy, γ_2^1 represents the estimated impact of the policy after one year while γ_2^2 and γ_2^3 represent the estimated impact of the policies in each of the next two years. These coefficients represent the marginal effects of the policy for the specific time period. In addition, we calculate the total cumulative effect of a policy over multiple years by taking into account the immediate and the lagged effects together as shown in Tables 13, 14, and in 15. For instance, Table 13 shows the impact of each policy a year after the implementation while Table 14 shows the cumulative impact of the policy for the first 2 years and Table 15 for the first 3 years after implementation.

Finally, δ_i is the firm-specific fixed effects that controls for unobserved heterogeneity across firms and δ_t is the time fixed effects that captures the influence of year-specific macroeconomic factors. Lastly, ε_{it} is the error term. We use a Poisson fixed effects estimator and report incidence rate ratios (IRRs) for ease of interpretation. IRRs express the change in the rate of an event occurring for a one-unit change in a predictor variable. An incidence rate ratio greater (lower) than one indicates an increase (decrease) in patenting activity. An IRR of one implies no change in storage technology innovation for a one-unit change in the explanatory variable.

3.4 Results and Discussion

In this section, we present our main estimation results followed by alternative specifications to validate the results.[11] Table 6 presents the year-to-year effects of the five EV adoption policies, while Tables 13, 14 and 15 in Appendix present the cumulative effect of the policies. We highlight two main findings: 1) EV adoption policies have effectively promoted innovation in storage technologies; and 2) past inventions play a crucial role in driving further innovation. In the following subsections we describe these results in detail.

3.4.1 EV adoption policies

Table 6 presents the year-by-year estimations of various policies on the likelihood of applying for a new storage technology patent. Among EV adoption policies, the 2013 promotion policy stands out and is particularly impactful in driving innovation in storage technologies. This policy provided subsidies associated with vehicle electric range and additional support to expand the charging station network, fostering an interconnected EV ecosystem. In the first year after implementation, this policy led to a 30% increase in patent applications for energy storage technologies. Although its impact is not significant in the second year, it became positive and significant again in the third year, with a 15% increase in innovation activity. This delayed pattern reflects an initial boost in innovation due to the policy, followed by an adjustment period during which firms may reallocate resources and implement the necessary changes. By the third year, firms can make a more sustained effort in innovation after being adapted to the policy. In contrast, the first three stages of subsidies focused solely on the adoption of public or private EV do not demonstrate significant effects on storage innovation. Although these policies may have facilitated gradual EV adoption, they fall short of driving advancements in EV batteries because achieving this required a deliberate focus on establishing the support

[11] Our patent dataset is available to 2023, however, we exclude the last two years of our dataset in our empirical analysis due to the the truncation effects of the data.

infrastructure necessary to sustain EVs. As noted in Engel et al. (2018), the lack of charging infrastructure could pose a significant barrier to EV adoption as consumers purchase increases. Once policies actively support the development of this infrastructure, battery manufacturers and inventors see the potential to invest in R&D and to foster advancements in more efficient, higher-energy-density batteries tailored to meet the needs of the growing EV market.

Furthermore, the phase-out policy introduced at the end of 2016 also has a statistically significant impact on storage patent applications in its first year, leading to a 56% increase. However, this impact diminishes in the second year and is no longer statistically significant. This pattern may be attributed to stricter regulations and the gradual removal of subsidies, which likely prompts companies to accelerate innovation efforts initially to capitalize on remaining incentives. However, as subsidies are reduced, the recalculated incentives might not be sufficient to sustain firms' investments in R&D for storage technologies over the longer term.

We then analyze the cumulative effects of these policies. Results are shown in Appendix , Tables 13, 14 and 15. These results are consistent with our findings in Table 6, further confirming that the 2013 promotion policy and the phase-out mechanism significantly increase the likelihood of new storage patent applications. Our analysis indicates that policies that promote both infrastructure development and vehicle adoption have a lasting impact on the EV industry by fostering innovation. By creating and supporting an interconnected ecosystem of EV usage and charging infrastructure, these policies encourage firms to innovate in complementary technologies like energy storage, driving advancements in battery performance, charging speed, and energy density. In contrast, policies that focus solely on the adoption of public or private EV appear insufficient to drive comparable levels of innovation in storage. This underscores the critical importance of multifaceted policies that address both the consumer demand for EVs and the infrastructure needed to sustain them in the long term.

Table 6: Storage Patent Applications Regression - Rate Ratios, 2000-2021

	Variable	Lags	Patent applications
EV adoption policies	Level I	L1	1.0275 (.10821)
	Level II	L1	1.0356 (.06916)
		L2	.95982 (.062683)
		L3	.98099 (.056488)
	Level III	L1	1.0109 (.066476)
		L2	.90389 (.061562)
		L3	1.0867 (.066646)
	Level IV	L1	1.3012** (.13298)
		L2	.8582 (.084294)
		L3	1.146** (.059262)
	Phaseout	L1	1.5623*** (.19768)
		L2	.79755 (.092558)
Other variables	Knowledge stocks	L2	.99739* (.0013043)
	Spillover	L2	1.00002*** (4.36e-6)
	Citations	L2	1.00009 (0.000281)
Energy prices	Electricity price	L1	.48757 (.29104)
		L2	3.3091 (3.2632)
		L3	.29654** (.12063)
	Fuel price	L1	.81579 (.32307)
		L2	1.6253 (1.3879)
		L3	.90997 (.68911)
Observations (N)			166,341

[1] Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

[2] Note: Prices are inflation adjusted.

[3] Note: The variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector EV adoption in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism.

3.4.2 Past innovation

Beyond policies, our results highlight the critical role of knowledge spillover between firms, rather than a firm's own past knowledge stock, in shaping continued storage innovation.

Table 6 shows that a firm's own knowledge stock has a significantly negative impact on the likelihood of applying for a storage technology patent after two years (-0.27%), while the spillovers between firms show a significantly positive effect. This positive impact of spillovers remains consistent in cumulative effects analysis in Tables 13, 14 and 15 with different lag structures, indicating that spillovers will persistently influence patent activity for at least three years. However, a firm's own knowledge stock loses significance over time. The effect of regional knowledge spillovers on innovation is not a surprise and is consistent with prior literature (e.g. Audretsch and Feldman, 2004; Jaffe, 1986; Jaffe et al., 1993). However, the finding that a firm's own knowledge stock in storage technologies does not influence future innovation contrasts with previous literature findings such as Popp (2002). One possible reason, as discussed above and in Section 3.2.3, is the highly fragmented nature of the storage innovation market in China, where 95% of storage technology patent applicants filed two or fewer (≤ 2) patents during our 21-year period. This fragmentation may prevent firms from accumulating the focus and resources needed to develop expertise and generate innovative knowledge in emerging storage technologies. This market structure likely explains the lack of statistical significance in firms' own past innovations, both in terms of quantity (K stock) and quality (Citations), while accounting for the observed significance in knowledge spillovers. It suggests that, in this context, market structure plays an important role, and thus knowledge stock alone is not sufficient to drive innovative activity in storage technologies.

3.5 Robustness analysis

To complete our empirical analysis, we discuss potential caveats associated with our analysis and perform several robustness checks of our results. Specifically, we focus on the international nature of EV markets and innovation in storage technologies and alternative energy prices in Table 8.

We start by considering the international nature of EV markets and innovation in energy storage. In addition to China, many countries have policies and mandates directed at increasing the production and sales of EVs. One could argue that EV policies and mandates in other major markets like Germany or the US could affect innovation in China. To address this, we reduce our sample to domestic inventors. As shown in Figure 21, patent applications in China mainly come from small inventors. This is in contrast with innovation in other markets, where a small number of innovative firms own a large share of total patents. By excluding international inventors from the data, mainly large international companies such as Volkswagen, Samsung, Ford, Tesla, we focus on Chinese inventors.

Next, we focus on the global nature of innovation in energy storage. Feng and Lazkano (2022) study global innovation trends in storage technologies in 93 countries from 1978 to 2019. They show an increasing patenting trend in storage technologies until 2017, mostly coming from seven countries (Japan, U.S., Germany, Korea, France, Switzerland, UK). One may argue China's increasing patenting trend is related to the global market forces rather than domestic adoption policies studied here. To address this, we employ a difference-in-differences (DiD) approach to establish the causal impact of individual EV adoption policies in China on energy storage innovation on Chinese inventors.

We evaluate the causal impact of each individual adoption policy on innovation in energy storage activity by estimating a difference-in-difference (DiD) model with fixed effects. Our baseline specification is:

$$Y_{it} = \beta_0 + \beta_1 \times D_t^{\text{Post}} \times D_i^{\text{Treat}} + \beta_2 \times D_t^{\text{Post}} + \beta_3 \times D_i^{\text{Treat}} + \delta_i + \phi_t + \alpha \times X_{it} + \epsilon_{it}, \quad (6)$$

where Y_{it} is patent applications in storage technologies in firm i in year t. D_i^{Treat} is a treatment dummy equal to one for firms located in cities exposed to the a given EV adoption policy whereas D_t^{Post} is a year dummy equal to one after the implementation year. δ_i is the firm fixed effect that accounts for unobserved and time-invariant firm heterogeneity, while ϕ_t is the time trend that accounts for a common trend. X_{it} is a vector of control variables including knowledge stocks, spillovers, and citations.[12] Finally, ϵ_{it} is the error term. We cluster the standard errors at the firm level. The coefficient of interest is β_3, which captures the causal effect of the EV adoption policy on innovation activity. Since we have five policies, we run each estimation separately.

Table 7: Treatment effects for individuals policies, marginal effects, 2000-2021.

	Firm-level patent applications in storage				
Policy	**Level I**	**Level II**	**Level III**	**Level IV**	**Phaseout**
DiD Coefficient	0.01723	-0.05041	-0.0452	0.1696***	0.1112***
se	(0.06722)	(0.03043)	(0.02924)	(0.05245)	(0.03682)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Firm-level Knowledge stock	Yes	Yes	Yes	Yes	Yes
Firm-level Spillovers	Yes	Yes	Yes	Yes	Yes
Firm-level Citations	Yes	Yes	Yes	Yes	Yes

[1] Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.
[2] Standard errors of the baseline sample are clustered at the firm level.
[3] Note: The variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism.

Our results in Table 7 indicate that neither the 2009 nor the 2010 EV subsidy policies targeted at the public and private sectors (Level I-III) had an immediate statistically

[12] Firm-level knowledge stocks are the cumulative number of storage patents per firm i in year t. Firm-level spillovers are the stock of patents from all other firms in firm i''s region j at time t. And, finally, citations include the number of citations received by firm i up to year t.

significant effect on patent applications in energy storage technologies. This suggests that, at least in the short term, these policies did not drive advancements in storage technologies. The reason could be that HEVs accounted for a large share (close to 50%) of the 2009 subsidies and batteries play a minor role in these vehicles. The subsidies from the 2010 private sector policy were targeted at PHEVs and BEVs but it could be the case that due to the early stage of the EV development market in China and a relatively small EV stock, these subsidies were not sufficient to drive innovation activity in storage technologies. These findings support the idea that additional policy controls promoted the development of the EV market and its commercialization.

In contrast, the 2013 infrastructure development policy and the 2016 phase-out policy both showed immediate and statistically significant effects. Specifically, the 2013 infrastructure policy led to a 16.96% increase in energy storage innovation, underscoring the role of infrastructure investments in advancing technology. Similarly, the 2016 phase-out policy resulted in an 11.12% increase in innovation, suggesting that stricter regulations and a gradual reduction in subsidies can encourage firms to innovate as they look to reduce costs and stay competitive.

Finally, we turn our attention to energy prices. As shown in Table 6, electricity prices do not significantly affect storage innovation in the first two years, but their effect in the third year is negative and statistically significant. Meanwhile, fuel prices do not show a significant effect on innovating activity for storage technologies. One possible explanation is that electricity and fuel prices are heavily regulated in China, which can prevent them from accurately reflecting true market conditions(Shi and Sun, 2017).

Table 8: Alternative prices results, 2000-2021

	L1	L2	L3
Fuel Retail	0.0001779	-0.0011906	0.0008732
Fuel Purchasing	0.0079505***	0.0078566***	0.0039997**
PPI_Power	-0.0038868	-0.0053433	-0.0121352***
PPI_Coal	0.0045002***	0.004667***	0.0021854**
PPI_Petroleum	0.0038578	0.0000588	-0.0035496*

Price effects are measured with control.
Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

To further explore this, we consider three alternative price indices sourced from the China Statistical Yearbook and China Energy Statistical Yearbook: (1) the Fuel Retail Price Index (2) the Fuel Purchasing Price Index, and (3) the Producer Price Indices (PPI) for various industries, specifically the Power, Coal and Coking, and Petroleum industries. The PPI and Purchasing Price Indices are available from 2012 to 2021, while the Retail Price Indices are available from 2000 to 2021. We standardize these indices as alternative price measures in different model specifications.

We present these regression results in Table 8, focusing on the first three lags to capture the short and medium term effects. The Retail Fuel Price Index does not show statistical significance, suggesting that short to medium term fluctuations in retail fuel prices have minimal immediate influence on energy storage patent applications. This result indicates that the firms' innovation effort in energy storage may not be directly responsive to changes in retail fuel prices.

In contrast, the Fuel Purchasing Price Index has a significantly positive effect on storage patenting, with the magnitude of this effect decreasing over successive lags. This positive relationship aligns with innovation theory and previous studies linking energy prices with increased innovation in renewable and efficiency-enhancing technologies (e.g. Newell et al., 1999; Popp, 2002; Verdolini and Galeotti, 2011; Ley et al., 2016; Feng and Lazkano, 2022). These findings suggest that firms are more likely to intensify research in energy storage in response to rising fuel purchasing prices.

The PPI for the Coal and Coking Industry consistently exhibits a highly significant positive influence on storage technology innovation. Given China's position as the world's largest coal producer and its strong dependence on domestic coal, this positive effect probably reflects the impact of coal price fluctuations on industry dynamics (Zhu et al., 2022). As domestic coal prices fluctuate, firms may be incentivized to innovate in energy storage technologies to mitigate reliance on coal. Additionally, the PPI for the Power and Petroleum Industries shows highly significant negative impacts on storage patenting in the third year, in line with our baseline findings for electricity prices.

3.6 Conclusion

The transition to EVs marks a pivotal step in addressing global energy challenges. At the heart of this shift lies the advancement of energy storage technologies, which facilitate the broad adoption of EVs by enhancing battery performance, charging efficiency, and energy density. Public policies are instrumental in accelerating innovation within these areas, especially in high-growth markets like China, where the EV sector has rapidly expanded over the past decade.

Our study examines the impact of China's EV adoption policies from 2009 to 2021 on innovation in energy storage technologies, using firm-level patent data from 2000 to 2023. We find that comprehensive policies integrating infrastructure development with EV adoption, such as the 2013 promotion initiative and the 2016 phase-out mechanism, significantly foster storage-related innovation. These policies act as catalysts to an increase in patent applications for energy storage technologies, underscoring the importance of establishing a supportive ecosystem for transport electrification.

In contrast, the earlier policies that focused solely on incentivizing EV adoption in the public and private sectors show limited direct effects on innovation. This indicates that while adoption incentives are essential, they may not be sufficient to drive technological advancements in energy storage on their own. Infrastructure investments, alongside adoption incentives, appear to be crucial in sustaining meaningful innovation. Our findings also highlight the significant role of knowledge spillovers in China's fragmented innovation landscape, where small firms are highly active in patenting. These spillovers have a more substantial influence on driving new innovations than a firm's own historical research efforts, emphasizing the collective nature of progress in energy storage technology.

In summary, our results indicate that developing an interconnected ecosystem of EV usage and charging infrastructure is essential for promoting innovation in energy storage technologies. These insights provide valuable lessons for other markets and jurisdictions seeking to stimulate technological progress and accelerate the EV transition. As EV adoption expands globally, fostering both adoption incentives and supportive infrastructure will be crucial to overcoming technological barriers.

Future research could explore the long-term impacts of these policies across different sectors within the clean energy landscape to see if similar frameworks could encourage innovation in other green technologies. Additionally, exploring the adaptability of these policies in various economic contexts and their impact on broader energy transitions may offer further insights into optimizing public policy to support and advance global sustainability goals.

3.7 Appendix

3.7.1 Description of EV adoption policies in China

Table 9: Summary of policies from 2009 to 2020

Policy Name	**Cities**	**Policy Summary**	**Original Policy Name**
Level I	Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan, Shenzhen, Hefei, Changsha, Kunming, Nanchang	Launch of a pilot program promoting energy-saving and new energy vehicles (NEVs) in public services such as public transport, taxis, government fleets, sanitation, and postal services through financial subsidies. The policy provided up to 50,000 RMB for hybrid vehicles (including plug-in hybrids) based on fuel-saving rates and maximum electric power ratios, and up to 60,000 RMB for pure electric vehicles.	Notice on Launching the Pilot Program for Demonstrating and Promoting Energy-Saving and New Energy Vehicles (关于开展节能与新能源汽车)

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Table 9 – Continued from previous page

Policy Name	Cities	Policy Summary	Original Policy Name
Level II	Tianjin, Haikou, Zhengzhou, Xiamen, Suzhou, Tangshan, Guangzhou, Shenyang, Chengdu, Hohhot, Nantong, Xiangfan	Expansion of the 2009 NEV pilot program by adding new cities, which ended in late 2012. Most of the 25 pilot cities were home to major automobile manufacturers, representing over 30% of the country's vehicle ownership.	Notice on Expanding the Demonstration and Promotion of Energy-Saving and New Energy Vehicles in Public Service Fields (关于扩大公共服务领域节能与新能源汽车示范推广有关工作的通知)

Continued on next page

Table 9 – Continued from previous page

Policy Name	**Cities**	**Policy Summary**	**Original Policy Name**
Level III	Beijing, Shanghai, Changchun, Shenzhen, Hangzhou, Hefei	Launch of a subsidy pilot program for private purchases of NEVs, focusing on plug-in hybrids and pure electric cars, with financial support for vehicle purchases and battery leasing, from 2010 to 2012. The subsidy was determined based on battery capacity, offering 3,000 RMB per kWh. The maximum subsidy was 50,000 RMB per plug-in hybrid passenger car and 60,000 RMB per pure electric passenger car.	Notice on Launching the Pilot Program for Subsidies for Private Purchases of New Energy Vehicles (关于开展私人购买新能源汽车补贴试点的通知)

Continued on next page

Table 9 – Continued from previous page

Policy Name	Cities	Policy Summary	Original Policy Name
Level IV	Beijing, Tianjin, Taiyuan, Jincheng, Dalian, Shanghai, Ningbo, Hefei, Wuhu, Qingdao, Zhengzhou, Xinxiang, Wuhan, Xiangyang, Changzhutan Area, Guangzhou, Shenzhen, Haikou, Chengdu, Chongqing, Kunming, Xi'an, Lanzhou, Hebei Province Cluster, Zhejiang Province Cluster, Fujian Province Cluster, Jiangxi Province Cluster, Guangdong Province Cluster, Inner Mongolia Cluster, Shenyang, Changchun, Harbin, Jiangsu Province Cluster, Zibo, Linyi, Weifang, Liaocheng, Luzhou, Guizhou Province Cluster, Yunnan Province Cluster	A NEV promotion campaign from 2013 to 2015 targeting both consumers and local governments, aiming to deploy 336,000 NEVs across 39 promotion clusters and 88 cities. The program included subsidies for purchasing NEVs, with financial incentives for developing charging infrastructure. Subsidies for pure electric vehicles were segmented by driving range, with differentiated support levels based on range categories. Demonstration cities had to meet deployment targets, ensure diverse vehicle brands, and maintain NEVs at least 30% of new public service vehicle purchases, with annual evaluations determining continued eligibility.	Notice on Continuing the Promotion and Application of New Energy Vehicles (关于继续开展新能源汽车推广应用工作的通知)

Continued on next page

Table 9 – Continued from previous page

Policy Name	Cities	Policy Summary	Original Policy Name
Phase-out	Cities previously covered by the 2013 NEV promotion policy	Reduction of NEV subsidies from 2016 to 2020, with cities affected by the 2013 NEV promotion policy experiencing greater policy impact. The subsidy reductions aimed to phase out financial incentives by decreasing support by 20% from 2017 to 2018 and by 40% from 2019 to 2020 compared to 2016 levels, encouraging market-driven industry growth and technological advancement.	Guiding Opinions of the State Council on Accelerating the Promotion and Application of New Energy Vehicles (国务院办公厅关于加快新能源汽车推广应用的指导意见)

3.7.2 IPC Codes for Green and Energy Storage Technologies

Table 10: WIPO Green Inventory Storage IPC codes

WIPO GREEN SUB-TOPICS	IPC
FUEL CELLS	H01M 4/86-4/98,8/00-8/24,12/00-12/08
HYDRO ENERGY	E02B 9/00-9/06 F03B F03C B63H 19/02,19/04 F03G 7/05
HYBRID VEHICLES	B60K 6/00,6/20 B60W 20/00 F16H 3/00-3/78,48/00-48/30
CHARGING STATIONSFOR ELECTRIC VEHICLES	H02J 7/00
STORAGE OFELECTRICAL ENERGY	B60K 6/28 B60W 10/26 H01M 10/44-10/46 H01G 11/00 H02J 3/28,7/00,15/00
STORAGE OFTHERMAL ENERGY	C09K 5/00 F24H 7/00 F28D 20/00,20/02

3.7.3 Summary statistics

The heat-maps in figures 22 and 23 present the number of firms by city and the number of patent applications by city.

Table 11: WIPO Green Inventory

Topic	Sub-topics
ALTERNATIVE ENERGY PRODUCTION	BIO-FUELS INTEGRATED GASIFICATION COMBINED CYCLE (IGCC) ***FUEL CELLS*** PYROLYSIS OR GASIFICATION OF BIOMASS HARNESSING ENERGY FROM MANMADE WASTE ***HYDRO ENERGY*** OCEAN THERMAL ENERGY CONVERSION (OTEC) WIND ENERGY SOLAR ENERGY GEOTHERMAL ENERGY OTHER PRODUCTION OR USE OF HEAT, NOT DERIVED FROM COMBUSTION USING WASTE HEAT DEVICES FOR PRODUCING MECHANICAL POWER FROM MUSCLE ENERGY
TRANSPORTATION	▹ VEHICLES IN GENERAL -***HYBRID VEHICLES, E.G. HYBRID ELECTRIC VEHICLES (HEVS)*** -***CHARGING STATIONS FOR ELECTRIC VEHICLES*** VEHICLES OTHER THAN RAIL VEHICLES RAIL VEHICLES
ENERGY CONSERVATION	MARINE VESSEL PROPULSION COSMONAUTIC VEHICLES USING SOLAR ENERGY ***STORAGE OF ELECTRICAL ENERGY*** POWER SUPPLY CIRCUITRY MEASUREMENT OF ELECTRICITY CONSUMPTION ***STORAGE OF THERMAL ENERGY*** LOW ENERGY LIGHTING
NUCLEAR POWER GENERATION	THERMAL BUILDING INSULATION, IN GENERAL RECOVERING MECHANICAL ENERGY
WASTE MANAGEMENT	NUCLEAR ENGINEERING GAS TURBINE POWER PLANTS USING HEAT SOURCE OF NUCLEAR ORIGIN WASTE DISPOSAL TREATMENT OF WASTE CONSUMING WASTE BY COMBUSTION
AGRICULTURE / FORESTRY	REUSE OF WASTE MATERIALS POLLUTION CONTROL FORESTRY TECHNIQUES ALTERNATIVE IRRIGATION TECHNIQUES
ADMINISTRATIVE, REGULATORY OR DESIGEN ASPECT	PESTICIDE ALTERNATIVES SOIL IMPROVEMENT COMMUTING, E.G., HOV, TELEWORKING, ETC. CARBON/EMISSIONS TRADING, E.G. POLLUTION CREDITS STATIC STRUCTURE DESIGN

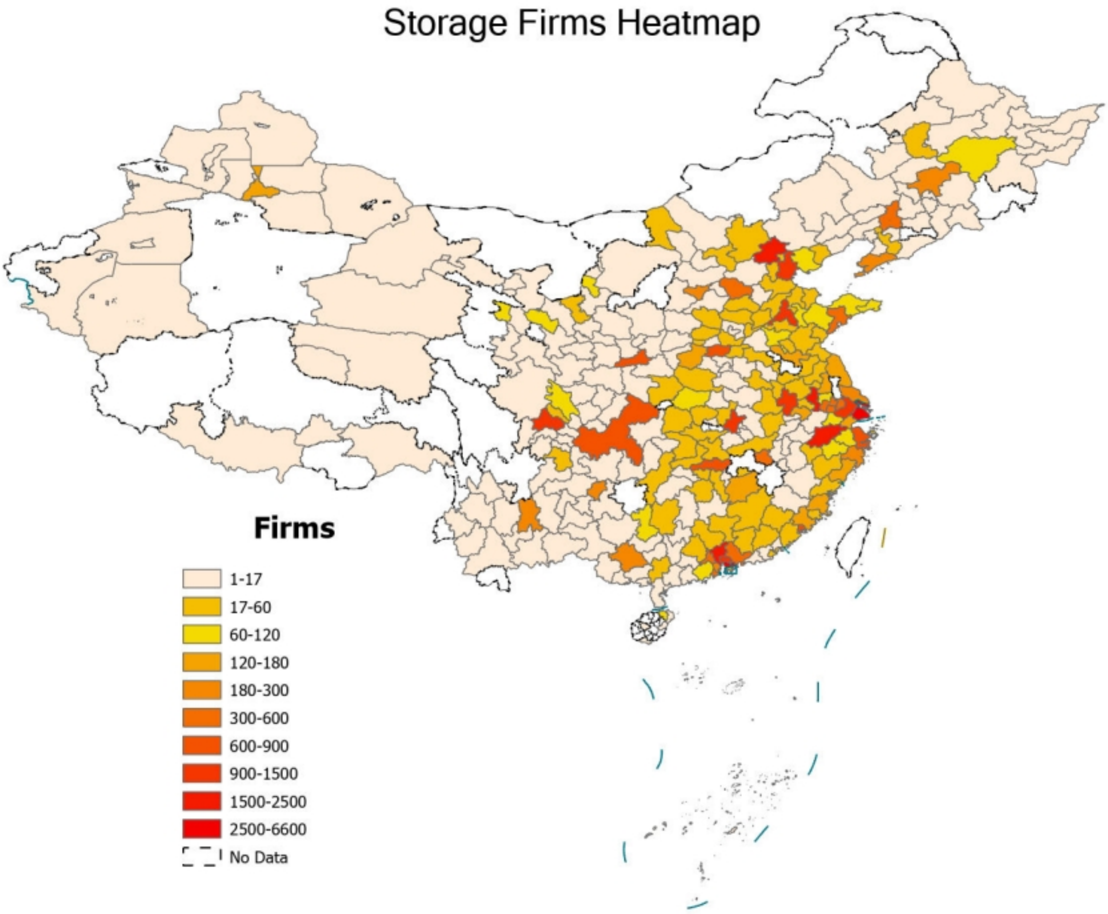


Figure 22: Total number of firms by city, 2000-2021.

Table 12 summarizes the breakdown of green patent applications from 2020 to 2023.

Table 12: Green Patent Applications Breakdown, 2000-2021.

Green Technologies	Applications in Green Tech	Applications in Storage Tech
Administrative	421,613	0
Agriculture Forestry	103,175	0
Alternative energy	497,402	65,170
Energy Conservation	750,625	114,418
Nuclear	22,409	0
Transportation	208,741	22,423
Waste Management	1,062,202	0
Total	3,066,167	202,011

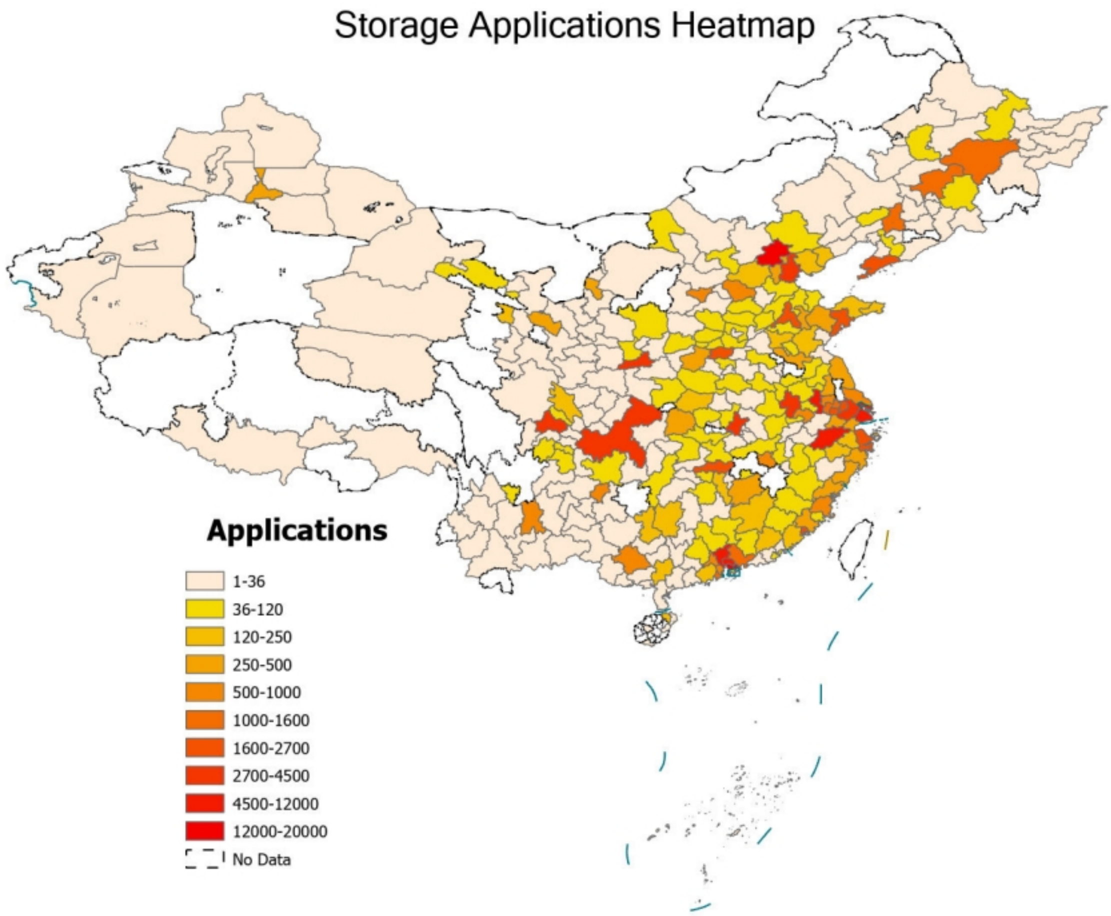


Figure 23: Patent applications by city, 2000-2021.

3.7.4 Cumulative effects of EV adoption policies

Table 13: Lag 1 Results: Storage Patent Applications Regression - Rate Ratios, 2000-2021

	Variable	Lags	Patent applications
EV adoption policies	Level I	L1	1.029 (.11424)
	Level II	L1	1.0019 (.048778)
	Level III	L1	.97141 (.050441)
	Level IV	L1	1.2666** (.10345)
	Phaseout	L1	1.4063*** (.12871)
Other variables	Knowledge stocks	L1	.99846 (.0010699)
	Spillover	L1	1.000017*** (3.55e-6)
	Citations	L1	1.00002 (.0002674)
Energy prices	Electricity price	L1	.70391 (.14465)
	Fuel price	L1	.82579 (.32038)
	Constant		4.9243 (16.681)
Observations (N)			168,418

[1] Significance levels: *p < 0.10, **p < 0.05, ***p < 0.01.
[2] Note: Past polices are replaced by new policies.
[3] Note: The variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector EV adoption in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism.

Table 14: Lag 2 Results: Storage Patent Applications Regression - Rate Ratios, 2000-2021

	Variable	Lags	Patent applications
EV adoption policies	Level I	L2	1.0125 (.10527)
	Level II	L2	1.0045 (.043814)
	Level III	L2	.94148 (.042039)
	Level IV	L2	1.2108** (.084699)
	Phaseout	L2	1.2162** (.088889)
Other variables	Knowledge stocks	L2	.99839 (.0011938)
	Spillover	L2	1.00002*** (3.38e-6)
	Citations	L2	.99999 (.0002649)
Energy prices	Electricity price	L2	1.0122 (.29031)
	Fuel price	L2	1.1822 (.47757)
	Constant		.27277 (.94564)
Observations (N)			194,868

[1] Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.
[2] Note: Prices are inflation adjusted.
[3] Note: The variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector EV adoption in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism.

Table 15: Lag 3 Results: Storage Patent Applications Regression - Rate Ratios, 2000-2021

	Variable	Lags	Patent applications
EV adoption policies	Level I	L3	.98282 (.10696)
	Level II	L3	1.0385 (.041523)
	Level III	L3	.98149 (.039936)
	Level IV	L3	1.3238*** (.079893)
	Phaseout	L3	1.2604*** (.085086)
Other variables	Knowledge stocks	L3	.99883 (.0012251)
	Spillover	L3	1.000021*** (3.76e-6)
	Citations	L3	.99988 (.0002393)
Energy prices	Electricity price	L3	.5599** (.10377)
	Fuel price	L3	.76825 (.51228)
	Constant		8.7095 (50.807)
Observations (N)			193,669

[1] Significance levels: *p < 0.10, **p < 0.05, ***p < 0.01.
[2] Note: Prices are inflation adjusted.
[3] Note: The variables Level I to Level IV correspond to the policy coverage, expanding over time to include more cities and broader scopes. Specifically, Level I refers to the 2009 subsidies for public-sector EV adoption in 13 pilot cities. Level II represents the 2010 expansion to 25 pilot cities. Level III captures the 2010 introduction of subsidies for private-sector EV adoption in 6 cities. Level IV reflects the 2013 expansion of subsidies in both private and public sectors, along with the promotion of charging infrastructure. The Phaseout variable denotes the subsidy phase-out mechanism.

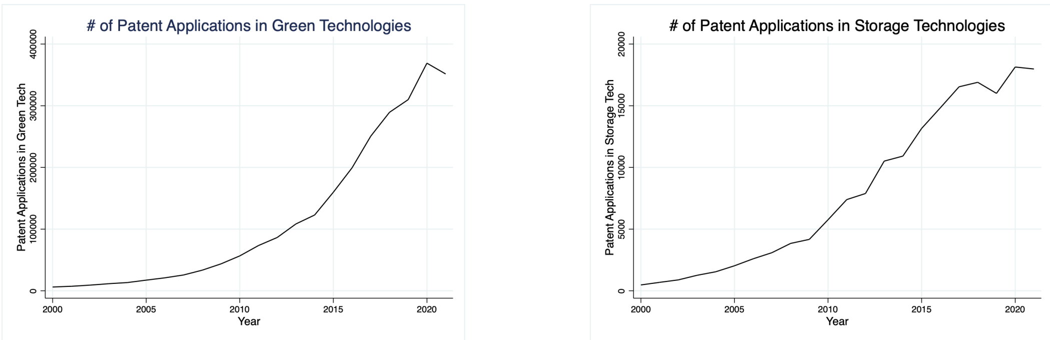


Figure 24: Patent applications in green and storage technologies, 2000 to 2021.

Chapter 4

Induced innovation in the Chinese Energy Sector

4.1 Introduction

The Chinese government has introduced many policies over the past two decades to support clean energy(Ma and Cai, 2018; Liu and Wang, 2017a). For example, the Renewable Energy Law of 2006 gave financial support and subsidies to help build renewable energy projects. Other policies focus on the development of clean technologies. For example the 2014 new energy demonstration cities policy. These government efforts, in addition to market forces have led to innovation in energy and technology in China's energy sector.

According to the National Energy Administration's policy goals, the demonstration cities were expected to raise the share of renewable energy consumption to at least 6% by the end of the 2011–2015 period (National Energy Administration of China, 2014). The cities also had clear targets: install more than 1 million square meters of solar thermal systems or reach 360 square meters per 1,000 people, add at least 20,000 kilowatts of distributed solar PV, and build more than 100,000 kilowatts of distributed wind power. Other goals included using over 100,000 tons of biomass energy (in standard coal equivalent) and installing geothermal systems to heat or cool over 3 million square meters. These plans were designed to reduce fossil fuel use and help cities grow in a greener and more sustainable way.

Previous research on energy innovation and related policies in China mostly used provincial or city-level data to analyze technical change (Li et al., 2023; Yang et al., 2019), or studied listed firms but focused on Green Total Factor Productivity instead of patents (Cui et al., 2023). My paper fills this gap by using firm-level patent data from listed firms, clearly separating Renewable and Fossil Fuel innovations, and showing how the 2014 policy[13] and market conditions steer directed technical change.

In this study, I look at why companies in China decide to innovate in Renewable and Fossil Fuel technologies. From 2008 to 2020, I study thousands of publicly listed firms[14] by combining patent records from the CNIPA and ORBIS Intellectual Property databases with company financial data from the China Stock Market & Accounting Research (CSMAR) database, and macroeconomic data. To analyze the data, I use standard econometric methods, including count-data models, fractional logit models, and PSM-DID (propensity score matching difference-in-differences), to estimate how patent stocks, knowledge spillovers, energy prices, and government R&D spending affect innovation (Griliches, 1979; Popp, 2002; Papke and Wooldridge, 1996; Rosenbaum and Rubin, 1983a). Additionally, I use a machine learning method called extreme gradient boosting (XGBoost) to analyze complicated accounting data and to find the most important features connected to energy innovation.

Understanding what makes companies choose certain energy technologies to innovate in matters for several reasons. First, knowing the differences between what affects Renewable versus Fossil Fuel innovation helps make better policies, making sure resources

[13]The 2014 New Energy Demonstration City policy stands out as one of China's most significant initiatives to promote renewable energy in recent years. It not only set specific quantitative targets for renewable energy adoption at the city level but also served as a comprehensive pilot program to explore the integration of clean energy into urban development. This policy provides a valuable quasi-natural experiment to assess how government-led initiatives can influence firm-level innovation behaviors, particularly in the context of directed technical change towards sustainable energy technologies.

[14]This study focuses on publicly listed firms because they typically possess more resources and stronger innovation capabilities, often leading technological advancements. Their transparency and the availability of detailed financial and operational data make them suitable for rigorous analysis, including propensity score matching. In contrast, data on government-owned firms can be less accessible and less detailed, potentially limiting the scope and accuracy of comparative studies. Moreover, many listed companies in China are subject to significant government oversight or are partially government-owned, allowing the study to still capture the influence of government policies on corporate innovation behaviors.

go to the right place to reach environmental goals. Second, firm-level data helps clearly show how technological change happens, especially how knowledge from earlier inventions and market signals influence new innovations (Jaffe et al., 1993; Scotchmer, 1991). Lastly, besides confirming the importance of traditional factors that drive technical change, using machine learning shows how detailed financial factors at the firm-level, such as cash availability, stock ownership, and company performance, strongly influence innovation decisions. This information can help create better strategies at the company level.

My results show four main findings. First, a company's previous innovation activity strongly boosts future innovation, which matches cumulative innovation theories (Griliches, 1979; Scotchmer, 1991; Jaffe, 1986). Second, listed companies positively respond to government policies. For example, after the 2014 "new energy demonstration city" policy began, firms increased their share of Renewable patent applications by about 2.2%. This fits with other studies that also found the policy increased Renewable innovation but did not significantly affect Fossil Fuel innovation (Zhou and Wang, 2023; Li et al., 2023). Third, higher electricity prices might temporarily slow down Renewable innovation because they increase costs and financial stress. But in the longer term, high electricity prices mainly discourage Fossil Fuel innovation because firms move resources to cheaper renewable technologies. Using machine learning, I also found that specific financial and operational factors are especially important for innovation. For Renewable innovation, spending money on employees and R&D is really important, while for Fossil Fuel innovation, equity structure and market capitalization matter more. These findings show clearly that Renewable and Fossil Fuel innovations react differently to financial and market conditions.

The remainder of this paper is structured as follows. Section 2 describes the sources of the data and how the main variables were constructed. Section 3 describes my empirical approach, including econometric models and analysis of innovation at the firm level implemented using a PSM-DID framework. Section 4 discusses the main empirical findings and their interpretation in relation to the theory of directed technical change.

Section 5 offers the conclusions of the study and discusses the most important results, including suggestions for further research.

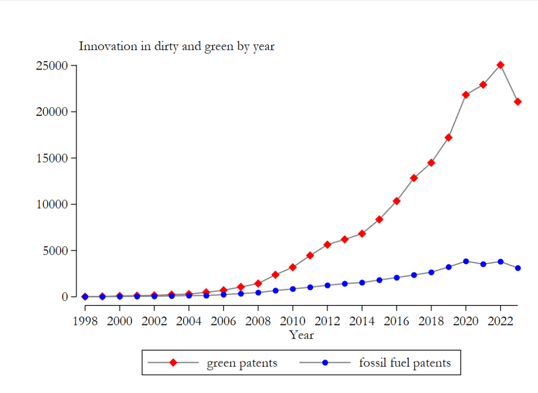
4.2 Data

I build a large dataset that combines patent records, company financial data, and provincial-level indicators related to technology innovation in China. In this section, I describe the data sources, how I create the key variables, and some basic statistics that help show how innovation happens in both renewable energy and fossil fuel technologies.

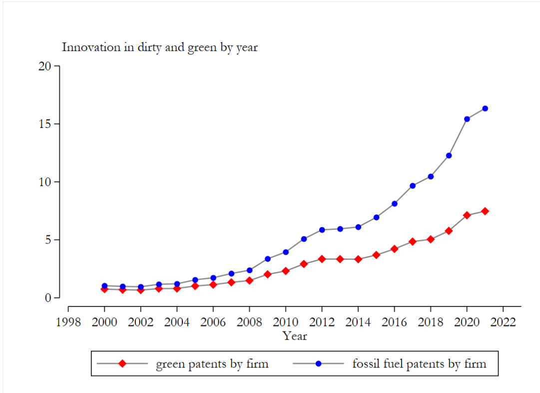
I collected patent applications filed in China from 2008 to 2020. The two main sources are ORBIS Intellectual Property and the China National Intellectual Property Administration (CNIPA). These databases report the current owner of each patent or the parent company if the owner is part of a larger group. This allows me to group the patents from related companies together, so it helps better understand each company's total innovation work. Some patents did not have city address information. In these cases, I used the company name and searched for more details information to find the location of the company's main office. After identifying the company locations, I divided the patents into two categories: renewable energy (clean energy technologies) in Appendix table 20 and fossil fuel energy (coal or oil) in appendix table 21. The classification is based on the International Patent Classification (IPC) codes.

The dataset focuses on companies that are publicly listed in China. Out of these firms, I found that 3,591 have worked on Renewable energy innovation, 1,579 on Fossil Fuel innovation, and 1,484 have done both.

Figures 25a and 25b show how patenting in renewable and fossil fuel technologies has changed over time. Figure 25a reports the total number of patents each year. In the early years, around 2008, the number of patents was low in both groups. After 2010, patenting activity started to increase. Renewable energy patents grew faster, which suggests that companies began to focus more on clean energy. Fossil fuel patents also increased, but at a slower rate compared to renewable patents.



(a) Total Fossil and Renewable patents by year



(b) Fossil and Renewable patents per firm

Figure 25: Patent applications in fossil and Renewable technologies over time.

Figure 25b shows the average number of Renewable and Fossil Fuel patent applications per firm each year for all listed companies. Renewable patents rise starting around 2005 and reach their highest point in the late 2010s. Fossil Fuel patents also go up, and the total number stays higher compared to Renewable. By looking at those two graphs, we can find that even though Renewable technologies have more patents overall, much of this growth comes from the fact that more companies are joining the Renewable innovation space. On the other hand, the average increase in Renewable patents for each company is not as large as it might seem from the total count. The drop in patent numbers during the most recent years is probably because of delays in the patent process. Many new patent applications take up to 18 months to be made public [15]. Because of this, the data for 2020 and 2022 are likely incomplete. To avoid problems from this, I do not include these two years in the later analysis.

To study how a company's financial situation affects its technology choices, I match the patent data with financial records from the China Stock Market & Accounting Research (CSMAR) database. This database gives detailed information on over 1,000 financial indicators, such as total assets, liabilities, R&D spending, income, and cash flow.

[15] In China, invention patent applications are published 18 months after the filing date or the earliest priority date, unless the applicant requests earlier publication. This timeline is stipulated in Article 34 of the Chinese Patent Law. This 18-month disclosure period aligns with international practices and ensures that patent information becomes publicly accessible in a timely manner, facilitating transparency and knowledge dissemination in the field of innovation

These numbers help describe how well a company is doing and how it is managed. By using this data, I can investigate whether firms with greater liquidity or stronger balance sheets are more inclined to invest in Renewable innovation compared to Fossil Fuel technologies.

Along with company data, I also collect marco indicators to show the expenditurs and market conditions. Information about R&D labor, firm internal spending intensity and government support for science and technology comes from sources of China Science and Technology Statistics Yearbook, the Science and Technology Statistical Data Compilation, and the China Major Science and Technology Indicators Database. The electricity energy price data was collected from the China Economic Information Center (CEIC).

In summary, the dataset contains patent records, financial data, and macro-level indicators for publicly listed companies in China. Using these different sources helps build a strong base for studying what factors lead companies to invest in Renewable energy or Fossil Fuel technologies. In the next section, I explain the empirical strategy to explore these questions and to find the main patterns behind firms' choices in technology innovation.

4.3 Identification Strategy

This section explains identification strategy of the relationship between firm-level innovation and different economic factors, including government policy, energy prices, and knowledge spillovers. I use two main outcome variables in my analysis. The first outcome is the number of patents that a company files in either Renewable or Fossil Fuel technologies. The second is the share of the company's total patents that go into each of these two groups. By looking at both the total count and the share, I can learn not only how much innovation is happening, but also how firms decide where to direct their innovation efforts.[16]

[16]This approach allows me to study both the intensity and the direction of R&D activity across technologies.

The approach is based on the idea of directed technical change (Acemoglu, 2002; Acemoglu et al., 2012) and models of innovation developed in earlier studies (Griliches, 1979; Popp, 2002). These theories suggest that firms choose where to focus their R&D to maximize returns, depending on market conditions, policies, and what they have learned from past research.

To study the scale of innovation, I estimate the following Poisson model with firm and year fixed effects:

$$\begin{aligned} Y_{i,t}^{j} \; = \; \exp\Big(& \beta_0 + \beta_1 \, \text{KnowledgeStock}_{i,t-1} + \beta_2 \, \text{Spillover}_{i,t-1} + \beta_3 \, \text{Citations}_{i,t-1} \\ & + \beta_4 \, \text{Policy2014}_{i,t} + \beta_5 \, \text{EnergyPrices}_{i,t-1} + \beta_6 \, \text{Expenditures}_{i,t-1} \\ & + \alpha_i + \lambda_t \Big), \end{aligned} \tag{1}$$

In the model, $Y_{i,t}^{j}$ is the number of patent applications by firm i in year t in technology j, where j is either Renewable (g) or Fossil Fuel (f). The model includes fixed effects for firms (α_i) and years (λ_t) to control for differences across firms and time. All the explanatory variables use a one-year lag to reflect the time needed for R&D decisions to show up in patent data.

To understand how firms split their R&D between the two technologies, I also use a fractional logit model for the share of patents:

$$\text{Share}_{i,t}^{j} \; = \; \frac{Y_{i,t}^{j}}{Y_{i,t}^{all}}. \tag{2}$$

Because $\text{Share}_{i,t}^{j}$ lies in $[0, 1]$, I employ a fractional logit model (Papke and Wooldridge, 1996):

$$
\begin{aligned}
\text{Share}^{j}_{i,t} \;=\; \Lambda\Big(&\delta_0 + \delta_1\,\text{KnowledgeStock}_{i,t-1} + \delta_2\,\text{Spillover}_{i,t-1} + \delta_3\,\text{Citations}_{i,t-1} \\
&+\delta_4\,\text{Policy2014}_{i,t} + \delta_5\,\text{EnergyPrices}_{i,t-1} + \delta_6\,\text{Expenditures}_{i,t-1} \\
&+\mu_i + \nu_t\Big), \qquad (3)
\end{aligned}
$$

In the model, $Share^{j}_{i,t}$ is the share of patent applications by firm i in year t in technology j, where j is either Renewable (g) or Fossil Fuel (f). The model includes fixed effects for firms (μ_i) and years (ν_t) to control for differences across firms and time.

The main explanatory variables in these models reflect different ways that policy, market forces, and knowledge may influence firms' innovation decisions. The variable *KnowledgeStock* measures the total number of patents that the company has already filed up until the previous year, following Aghion et al. (2016), Griliches (1979), and Jaffe (1986). *Spillover* captures the amount of outside knowledge that comes from other firms in the same region, using China's National Bureau of Statistics regional grouping system.[17] The variable *Citations* is the lagged number of citations to the firm's past patents, which shows the quality or importance of its previous innovation work (Jaffe et al., 1993). *Policy2014* is a dummy that identifies whether a company is located in one of the "new energy demonstration cities" chosen by the National Energy Administration in 2014 (National Energy Administration, 2014). The variable *EnergyPrices* represents lagged energy price levels, which may change the relative profits of Renewable versus Fossil Fuel innovation (Acemoglu et al., 2012; Popp, 2002). Finally, *Expenditures*[18] shows the lagged R&D spending from local governments and large firms in the same province, which may provide outside support for companies' innovation activities. This measure also includes the total number of scientific research labor within the province, reflecting

[17] China is divided into four major regions: East, Central, West, and Northeast.

[18] Although the variable *Expenditures* is indexed by firm (i), it actually represents regional-level R&D spending from local governments, large enterprises, and scientific research labor within the province. Therefore, multiple firms located within the same province share the same value for this variable, reflecting regional rather than firm-specific resources.

the broader regional innovation capacity. The 2014 policy was not randomly assigned because the government selected demonstration cities based on specific criteria. This creates a challenge for figuring out if the policy itself caused any real changes in innovation. To help solve this problem, I use a method called propensity score matching combined with difference-in-differences (PSM-DID) (Rosenbaum and Rubin, 1983b; Heckman et al., 1997). First, I predict how likely each company is to be in a demonstration city by using a logit model with firm characteristics from before 2014, such as size, industry, and patenting history. After that, I match each treated company with a control company outside of the demonstration areas that has a similar score. Finally, I compare the changes in innovation outcomes before and after the policy between these two groups. This helps reduce bias and gives a clearer picture of the policy's impact.

By combining the Poisson model, the fractional logit model, and the PSM-DID method, I am able to study both how much firms innovate and where they choose to put their R&D efforts. This approach helps me understand how government policies, energy prices, and knowledge from other firms work together to shape innovation in Renewable and Fossil Fuel technologies.

4.4 Results and Interpretation

This section shows the results from the regression analysis using both count-data and fractional logit models within the PSM-DID framework. I study how different factors, both inside the firm such as patent history and knowledge from other firms and outside the firm such as energy prices, government spending, and policy changes, affect the number of patents and the share of patents going to Renewable and Fossil Fuel technologies.

Table 16 presents the Poisson regression results for the number of patents in each technology. The results show clear differences between Renewable and Fossil Fuel innovations.

Starting with the 2014 policy, it had a strong and negative impact on the number of Renewable patent applications. For example, in the first lag, the policy reduced Renew-

Table 16: PSM-DID Count Regression Results: Determinants of Renewable and Fossil Fuel Patent Applications

		Patent applications		Patent applications		Patent applications	
		Renewable	Fossil Fuel	Renewable	Fossil Fuel	Renewable	Fossil Fuel
Policy	**Policy_2014**	-0.295***	-0.0361	-0.262***	-0.101	-0.252***	-0.180*
		(0.0723)	(0.0896)	(0.0636)	(0.0918)	(0.0614)	(0.0921)
Renewable	**1000 K_stock**	-0.564***	0.302	-1.01***	1.05***	-1.26***	1.45***
		(0.201)	(0.305)	(0.203)	(0.324)	(0.244)	(0.291)
	log(Spillover)	-0.553**	0.0138	-0.543	0.218	0.164	0.0473
		(0.268)	(0.321)	(0.330)	(0.302)	(0.230)	(0.266)
	10k Citations	0.349**	-0.509	0.552***	-1.26***	0.619***	-1.26***
		(0.168)	(0.387)	(0.152)	(0.361)	(0.144)	(0.298)
Fossil Fuel	**1000 K_stock**	1.95**	-1.25	2.93***	-3.98***	3.71***	-6.09***
		(0.808)	(1.16)	(0.804)	(1.17)	(0.914)	(1.05)
	log(Spillover)	0.654**	-0.0924	0.644*	-0.282	-0.233	-0.0938
		(0.303)	(0.344)	(0.390)	(0.316)	(0.263)	(0.276)
	10k Citations	-0.614	3.24*	-0.358	5.33***	-1.36	5.93***
		(0.975)	(1.88)	(0.959)	(1.66)	(0.929)	(1.47)
Expenditures	**Govement**	0.171*	0.401***	0.167**	0.371***	0.233***	0.218*
		(0.0908)	(0.132)	(0.0770)	(0.132)	(0.0762)	(0.121)
	Internal	-0.0573	-0.449*	-0.201	-0.351	-0.0631	0.0764
		(0.139)	(0.252)	(0.151)	(0.259)	(0.153)	(0.225)
Other variables	**Electricity Price**	-0.595*	-0.786	0.0115	-1.972***	-0.319	-2.836***
		(0.356)	(0.606)	(0.450)	(0.654)	(0.453)	(0.684)
	R&D Labor	-0.00825	0.221	0.177	0.0949	0.00147	0.0156
		(0.122)	(0.191)	(0.149)	(0.215)	(0.140)	(0.192)
Constant		3.865***	5.900***	3.431***	6.803***	3.849***	2.749*
		(1.043)	(1.838)	(1.056)	(1.743)	(0.928)	(1.582)
Observations		40104	16366	36803	14951	33484	13453

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

From left to right, the explanatory variables for Renewable and Fossil Fuel patent applications are lagged by 1, 2, and 3 years, respectively.

able patents by about 0.34, and this result is statistically significant at the 1% level. This suggests that firms may have changed their R&D plans in response to the new policy. On the other hand, this policy did not have a significant effect on Fossil Fuel patents, meaning it probably did not change behavior in that area.

Energy prices also had different effects. When energy prices went up, firms filed fewer Fossil Fuel patents. The effect was large and significant in the first two lags. But for Renewable technologies, the effects of energy prices were smaller and less clear, with mixed signs and weaker significance.

The effects of a firm's existing patent stock also varied. A larger stock of Fossil Fuel patents helped lead to more Fossil Fuel patents in the future. But for Renewable technologies, a higher patent stock was linked to fewer new Renewable patents, especially in the third lag, where the effect was significantly negative.

Regional spillovers mattered, too. For Renewable technologies, knowledge spillovers from nearby firms had a positive and statistically significant effect, especially in the early years. This means that companies benefited from being close to other firms working on Renewable energy. In contrast, these spillovers did not have a clear or positive effect on Fossil Fuel patenting.

Next, Table 17 shows the results from the fractional logit models. These models look at the share of a firm's total patents that go into Renewable or Fossil Fuel technologies.

The 2014 policy had a clear and positive effect on the share of Renewable patents. It raised the share by about 0.022, representing an absolute increase of 2.2 percentage points in the share of Renewable patent applications out of all patent applications, and this result is significant at the 1% level. This means the policy helped shift companies' focus more toward clean energy. This finding supports earlier research by (Li et al., 2023; Zhou and Wang, 2023)., which showed that the same policy increased Renewable innovation by giving more support from local governments and tightening environmental rules. In contrast, the policy did not have a meaningful effect on the share of Fossil Fuel patents.

Table 17: PSM-DID Fractional Regression Results: Composition of Green and Fossil Fuel Innovation

		(1) Green	(2) Green	(3) FF	(4) FF
Policy	Policy_2014	0.0223***	0.0214***	0.0013	0.0027
		(0.003)	(0.005)	(0.001)	(0.002)
Green	1m Citations	-3.149**	2.853	-0.918	-1.85**
		(1.28)	(2.39)	(0.587)	(0.804)
	1m K_stock	0.7235***	-4.62	5.972	0.295**
		(0.128)	(0.242)	(8.66)	(0.138)
	log(Spillover)	-0.0005	0.0127	0.0045	0.0133
		(0.007)	(0.022)	(0.004)	(0.010)
Fossil Fuel	1m Citations	0.228**	7.377	0.229**	0.133
		(0.114)	(0.256)	(0.108)	(0.247)
	1m K_stock	-300***	-3.176	-0.678	-100
		(0.236)	(0.970)	(0.490)	(0.905)
	log(Spillover)	-0.0020	-0.0200	-0.0020	-0.0201*
		(0.007)	(0.025)	(0.004)	(0.012)
Expenditures	Govement	–	0.0125*	–	-0.0098***
			(0.007)		(0.004)
	Internal	–	0.0281*	–	0.0241***
			(0.016)		(0.009)
Other variables	Electricity Price	0.0117	0.0112	-0.0100	-0.0101
		(0.016)	(0.011)	(0.007)	(0.006)
	R&D Labor	–	-0.0184	–	-0.0110*
			(0.013)		(0.006)
Constant		0.0677***	-0.1194	0.0049	-0.1155**
		(0.026)	(0.099)	(0.014)	(0.059)
Observations		43018	16800	42838	16800

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Other variables also shaped innovation shares. For example, past Renewable patent citations actually reduced the share of future Renewable patents, while past Fossil Fuel patent citations increased the share of future Fossil Fuel patents. Both of these results were statistically significant and suggest different patterns for how patent quality affects future innovation in the two technology types.

Financial support from within the firm also mattered. Internal R&D spending increased the share of patents in both Renewable and Fossil Fuel technologies. For Renewable, the effect was positive and significant at the 10% level, and for Fossil Fuel, it was also positive and significant at the 1% level.

The count model results support a pattern where innovation increases within the treated cities but does not spill over and may even decline in neighboring areas pattern described by Li et al. (2023), which may be due to the local operational focus of most listed firms in China. The 2.2 percentage point increase in the share of Renewable patents found in the fractional logit model is also consistent with Cui et al. (2023), who argue that while the 2014 policy improved green innovation among listed firms, the overall effect size was modest.

These findings together suggest that internal resources, market signals such as energy prices, and government policies do not affect all innovation the same way. These factors influence Renewable and Fossil Fuel technologies differently, which means that moving toward clean energy in China will require targeted strategies (Jaffe et al., 1993; Scotchmer, 1991; Griliches, 1979).

4.5 Conclusion

This paper studies how government policy, market signals, and firm-level characteristics influence energy innovation in China. I use patent data from publicly listed firms and focus on the effects of the 2014 new energy demonstration city policy. The results show that past innovation activity helps boost future innovation, and firms do respond to government policies, especially in Renewable technologies. The policy led to a 2.2

percentage point increase in the share of Renewable patent applications, while its impact on Fossil Fuel innovation was limited. Electricity prices and financial variables also played different roles: high energy prices pushed firms away from Fossil Fuel technologies, and internal resources like R&D spending and labor costs strongly affected Renewable innovation. These findings support the theory of directed technical change and show that policy and market incentives work differently for clean and traditional energy.

Based on these results, I suggest several policy recommendations. First, the government should increase long-term funding for science and technology, especially in clean energy innovation. More targeted subsidies and support for R&D, rather than just rewarding equipment installation or pollution control, can help generate real innovation outcomes. Second, firms should be encouraged to invest in their own research and technical development, not just rely on government projects. Policymakers could also focus on improving the way local governments implement innovation policies to ensure better results. Finally, programs like the new energy demonstration cities should add more evaluation standards that measure how many new technologies are created and used, instead of only checking how many solar panels are installed. This would help create a stronger connection between policy and long-term green growth.

4.6 Appendix

4.6.1 Machine Learning Approach

Traditional research on how technology changes over time usually uses directed technical change (DTC) models and looks at global innovation by using large-scale economic data (Acemoglu, 2002; Acemoglu et al., 2012; Friedman, 2001). But in China, the economy is more centralized. The central government plays a big role in creating policies and shaping how local economies grow (Chen and Qian, 2019; Zhang, 2017). Also, many macro-level factors like energy prices are controlled or influenced by the government, which can make them less useful for studying how innovation works (Liu and Wang, 2017b). Because of this, my paper focuses on more detailed firm-level data from China's publicly listed companies to better understand what drives innovation in both Renewable and Fossil Fuel technologies.

These listed companies publish a lot of financial and business information every year, sometimes more than 1,000 variables per firm. This gives me a good way to look at things like how much cash a firm has, how it spends on R&D, or how its assets are structured. These details matter a lot in China, where the government can affect how the market works. By using these firm-level numbers together with my data on patents and innovation, I build on the DTC model in a new way. Instead of only using big national-level controls like earlier studies (Acemoglu, 2002; Acemoglu et al., 2012; Griliches, 1979), I bring in detailed company data to learn more about how policy and firm resources affect energy innovation.

To handle this big and complicated dataset, I use Extreme Gradient Boosting (XGBoost), a machine learning method that works really well for prediction and can deal with missing values (Chen and Guestrin, 2016; Friedman, 2001; Hastie et al., 2009; Zou and Hastie, 2005). XGBoost builds many decision trees, and each new tree helps fix the mistakes made by the trees before it. It also uses a special function that helps the model stay accurate without overfitting the data. One thing about XGBoost is that it doesn't use all variables at once. It adds a small group of variables step by step when building the trees.

Because it's important to control for firm-level and year-to-year differences, I add dummy variables for both firms and years. This works like fixed effects (Imbens and Wooldridge, 2009), helping the model ignore things that don't change over time. And since XGBoost only picks some variables for each tree, I make sure that these firm and year dummies are always included every time a new tree is built. This helps the model stay balanced and allows it to focus on how internal financial variable, such as liquidity or R&D spending, are really connected to energy innovation. This setup makes my model different from the usual DTC framework, which mostly relies on national-level data.

Table 18 and Table 19 show which company features are most helpful in predicting how much innovation goes into Renewable and Fossil Fuel technologies. These results help support my earlier regression findings by showing that internal resources, past innovation, and firm structure all matter for energy innovation.

For the Renewable ratio, the most important features include how much companies pay their employees, how many Renewable patents they apply for, and how much they spend on R&D. These factors show that firms with more active innovation history, stronger internal spending, and high labor costs are more likely to focus on clean energy technologies. Being near other innovative firms also seems to help, since regional spillovers show up as useful in predicting Renewable innovation.

Ownership structure matters too, but less than financial or innovation-related inputs. Some features, like number of shareholders or paid-in capital, play a smaller role. Operational data such as selling expenses, cash received from business, and inventory levels also show up as useful predictors, meaning firms that are financially stable and active in daily business may have more capacity to innovate.

For the Fossil Fuel ratio, the most useful features are how many Fossil Fuel patents the firm applied for, how often those patents were cited, and the amount of external knowledge from Fossil Fuel innovation in the same industry. Ownership plays a bigger role here than in Renewable, which may be because Fossil Fuel industries often need large capital investment. Things like total assets, market value, and profits also rank high, which means stronger financial performance gives firms more room to invest in traditional energy technologies. Even some Renewable-related features show up, which suggests firms may adjust their strategy by watching what happens in the green energy space.

Overall, these machine learning results confirm that innovation in Renewable and Fossil Fuel technologies is affected by a mix of factors-past patenting, firm structure, spending decisions, and market signals. But the key drivers for each type of technology are not the same.

Table 18: Renewable ratio Feature Importance

Feature	Importance
Cash paid to employees and on behalf of employees	0.054597
Renewable application by year	0.032456
Selling expenses	0.021739
Number of employees	0.018175
R&D expenditure	0.016522
Top 10 shareholders' ownership ratio (%)	0.015926
Cash received from sales of goods and provision of services	0.015005
Net inventory	0.013802
renewable_citations	0.013130
Spillover effect of national Fossil Fuel patents	0.010563
Paid-in capital (or share capital)	0.010021
Ratio of Fossil Fuel patents to total patent applications	0.009741
Total operating costs	0.008947
Dummy variable for companies in the central region	0.008785
Number of R&D personnel	0.008152
Spillover effect of Renewable patents	0.008021
Intangible assets ratio	0.007937
Total number of shareholders	0.007517
Herfindahl index (D)	0.007505
Total current liabilities	0.007384
Derivative financial liabilities	0.006514
Depreciation and amortization	0.006455
Total shareholders' equity	0.006351
first year of energy application	0.006309
Other current assets	0.006134
Total number of directors holding company shares	0.006130
Advance receipts	0.005999
Taxes and surcharges	0.005921
Net intangible assets	0.005911
Total operating revenue	0.005898
Fossil Fuel application by year	0.005782
Net gain (loss) on disposal of non-current assets	0.005634
Inventory turnover ratio	0.005471

Table 19: Fossil Fuel ratio Feature Importance

Feature	Importance
Annual Renewable patent applications	0.050176
Total shares outstanding	0.022075
Number of Fossil Fuel patent applications (by 4 major economic sectors)	0.019294
Number of citations for past Renewable patents	0.012964
Subtotal of operating cash outflows	0.012927
Fossil Fuel patent spillover effect (by 4 major economic sectors)	0.012887
Total non-current assets	0.012794
Renewable patent application share	0.012635
Total operating costs	0.012224
Number of citations for past Fossil Fuel patents	0.011312
Circulating shares	0.010877
Annual market capitalization	0.010812
Number of personnel with financial institution background	0.010462
Sum of shareholding ratios of top 3 circulating shareholders	0.010441
Ownership proportion of the ultimate controller	0.010133
Cash paid to employees and on behalf of employees	0.009815
R&D personnel	0.009482
Annual Fossil Fuel patent applications by firm	0.008975
Earnings Before Interest and Taxes (EBIT)	0.008959
Selling expenses	0.008918
Development expenditure	0.008830
Cash paid for goods and services	0.008776
Total current assets	0.008557
Total assets	0.008391
Net inventory	0.008005
Registered capital	0.007862
Annual Renewable patent applications by firm	0.007736

4.6.2 Green and Fossil Fuel IPC Codes

Table 20: IPC Green Inventory - Topics and Corresponding IPC Codes

Topic	**IPC Codes**
Bio-fuels	A01H, C02F 3/28, C02F 11/04, C07C 67/00, C07C 69/00, C10B 53/02, C10G, C10L 1/00, C10L 1/02, C10L 1/14, C10L 1/182, C10L 1/19, C10L 3/00, C10L 5/00, C10L 5/40, C10L 5/40-5/48, C10L 9/00, C11C 3/10, C12M 1/107, C12N 1/13, C12N 1/15, C12N 1/21, C12N 5/10, C12N 15/00, C12N 9/24, C12P 5/02, C12P 7/06-7/14, C12P 7/64
IGCC (integrated gasification-combined-cycle)	C10L 3/00, F02C 3/28
Fuel cells	H01M 2/00-2/04, H01M 4/86-4/98, H01M 8/00-8/24, H01M 12/00-12/08
Biomass pyrolysis / gasification	C10B 53/00, C10J
Waste-to-energy	A62D 3/02, B01D 53/02, B01D 53/04, B01D 53/047, B01D 53/14, B01D 53/22, B01D 53/24, B09B, B09B 3/00, C02F 11/04, C02F 11/14, C10J 3/02, C10J 3/46, C10L 5/00, C10L 5/42, C10L 5/44, C10L 5/46, C10L 5/48, C21B 5/06, D21C 11/00, F23B 90/00, F23G 5/00, F23G 5/027, F23G 7/00, F23G 7/10
Hydro energy	E02B 9/00-9/06, E02B 9/08, F03B, F03B 13/12-13/26, F03B 15/00-15/22, F03C, B63H 19/02, B63H 19/04
Ocean-thermal (OTEC)	F03G 7/05
Wind energy	F03D, F03D 11/04, H02K 7/18, B63B 35/00, E04H 12/00, B60K 16/00, B60L 8/00, B63H 13/00

(Table continued)

Topic	IPC Codes
Solar energy	H01L 27/142, H01L 31/00-31/078, H01G 9/20, H02N 6/00, H01L 27/30, H01L 51/42-51/48, H01L 25/00, H01L 25/03, H01L 25/16, H01L 25/18, H01L 31/042, C01B 33/02, C23C 14/14, C23C 16/24, C30B 29/06, G05F 1/67, F21L 4/00, F21S 9/03, H02J 7/35, H01M 14/00, F24J 2/00-2/54, F24D 17/00, F24D 3/00, F24D 5/00, F24D 11/00, F24D 19/00, F24J 2/42, F03D 1/04, F03D 9/00, F03D 11/04, F03G 6/00, F03G 6/00-6/06, C02F 1/14, F02C 1/05, H01L 31/058, B60K 16/00, B60L 8/00, E04D 13/00, E04D 13/18, F22B 1/00, F24J 1/00, F25B 27/00, F26B 3/00, F26B 3/28, F24J 2/06, G02B 7/183, F24J 2/04
Geothermal energy	F01K, F24F 5/00, F24J 3/08, H02N 10/00, F25B 30/06, F03G 4/00-4/06, F03G 7/04
Non-combustion heat	F24J 1/00, F24J 3/00, F24J 3/06
Heat pumps	F24D 11/02, F24D 15/04, F24D 17/02, F24H 4/00, F25B 30/00
Using waste heat	F01K 27/00, F01K 23/06-23/10, F01N 5/00, F02G 5/00-5/04, F25B 27/02, F01K 17/00, F01K 23/04, F02C 6/18, C02F 1/16, D21F 5/20, F22B 1/02, F23G 5/46, F24F 12/00, F27D 17/00
Regenerative heat exchange	F28D 17/00-20/00
Gasification waste-heat recovery	C10J 3/86

(Table continued)

Topic	IPC Codes
Muscle-energy mechanical power	F03G 5/00-5/08
Vehicles - general	B60K 6/00, B60K 6/20, B60W 20/00, F16H 3/00-3/78, F16H 48/00-48/30, H02K 29/08, H02K 49/10, B60L 7/10-7/22, B60L 8/00, B60L 9/00, B60L 11/18, F02B 43/00, F02M 21/02, F02M 27/02, B60K 16/00, H02J 7/00
Vehicles - other than rail	B62D 35/00, B62D 35/02, B63B 1/34-1/40, B62K, B62M 1/00, B62M 3/00, B62M 5/00, B62M 6/00
Rail vehicles	B61, B61D 17/02
Marine vessel propulsion	B63H 9/00, B63H 13/00, B63H 19/02, B63H 19/04, B63H 16/00, B63H 21/18
Cosmonautic solar vehicles	B64G 1/44
Electrical energy storage	B60K 6/28, B60W 10/26, H01M 10/44-10/46, H01G 9/155, H02J 3/28, H02J 7/00, H02J 15/00
Power supply circuitry	H02J, H02J 9/00
Electricity consumption measurement	B60L 3/00, G01R
Thermal energy storage	C09K 5/00, F24H 7/00, F28D 20/00, F28D 20/02
Low-energy lighting	F21K 99/00, F21L 4/02, H01L 33/00-33/64, H01L 51/50, H05B 33/00

(Table continued)

Topic	IPC Codes
Building insulation	E04B 1/62, E04B 1/74-1/80, E04B 1/88, E04B 1/90, E04C 1/40, E04C 1/41, E04C 2/284-2/296, E06B 3/263, E04B 2/00, E04F 13/08, E04B 5/00, E04F 15/18, E04B 7/00, E04D 1/28, E04D 3/35, E04D 13/16, E04B 9/00
Mechanical energy recovery	F03G 7/08, B60K 6/10, B60K 6/30, B60L 11/16
Waste disposal	B09B, B65F
Waste treatment	A61L 11/00, A62D 3/00, A62D 101/00, G21F 9/00, B03B 9/06, B09C, D21B 1/08, D21B 1/32
Waste combustion	F23G
Waste reuse	A43B 1/12, A43B 21/14, B22F 8/00, C04B 7/24-7/30, C04B 18/04-18/10, C05F, C08J 11/00-11/28, C09K 11/01, C11B 11/00, C11B 13/00-13/04, C14C 3/32, C21B 3/04, C25C 1/00, D01F 13/00-13/04, B29B 17/00, B62D 67/00, C08J 11/04-11/28, C10G 1/10, C10L 5/46, C10L 5/48, C22B 7/00-7/04, C22B 19/30, C22B 25/06, D01G 11/00, D21C 5/02, H01J 9/50, H01J 9/52, H01M 6/52, H01M 10/54
CCS (carbon capture & storage)	B01D 53/14, B01D 53/22, B01D 53/62, B65G 5/00, C01B 31/20, E21B 41/00, E21B 43/16, E21F 17/16, F25J 3/02

(Table continued)

Topic	IPC Codes
Air quality management	B01D 53/00-53/96, F01N 3/00-3/38, B01D 53/92, F02B 75/10, C21C 5/38, C10B 21/18, F23B 80/02, F23C 9/00, F23G 7/06, F01N 9/00, B01D 45/00-51/00, B03C 3/00, C21B 7/22, F27B 1/18, F27B 15/12, C10L 10/02, C10L 10/06, F23J 7/00, F23J 15/00, C09K 3/22, G08B 21/12
Water pollution control	B63J 4/00, C02F, C05F 7/00, C09K 3/32, B63B 35/32, E02B 15/04, E03C 1/12, C02F 1/00, C02F 3/00, C02F 9/00, E03F
Radioactive leak prevention	G21C 13/10
Forestry techniques	A01G 23/00
Alternative irrigation	A01G 25/00
Pesticide alternatives	A01N 25/00-65/00
Soil improvement	C09K 17/00, E02D 3/00
Organic fertilisers (waste)	C05F
Commuting / teleworking	G06Q, G08G
Carbon trading	G06Q
Static structure design	E04H 1/00
Nuclear engineering	G21
Fusion reactors	G21B
Fission reactors	G21C
Nuclear power plant	G21D
Gas-turbine plants (nuclear heat)	F02C 1/05

Table 21: IPC codes for efficiency-improving fossil-fuel technologies for electricity generation

Technology category	**IPC codes / descriptions**
Coal gasification	C10J 3 - Production of combustible gases containing CO from solid carbonaceous fuels
Improved burners (excluding combinations with B60, B68, F24, F27)	
	F23C 1 - Combustion apparatus for two or more kinds of fluent fuel
	F23C 5/24 - Arrangement/mounting of burners (loop flame)
	F23C 6 - Combustion apparatus with two or more combustion chambers
	F23B 10 - Combustion apparatus with two or more chambers
	F23B 30 - Apparatus with driven means for agitating/advancing burning fuel
	F23B 70 - Apparatus returning solid residues to the chamber
	F23B 80 - Apparatus creating distinct flue-/gas-flow paths
	F23D 1 - Burners for pulverulent fuel
	F23D 7 - Burners where liquid-fuel drops impinge on a surface
	F23D 17 - Burners for simultaneous/alternative gaseous, liquid or pulverulent fuel
Fluidised-bed combustion	

Continued on next page

(Table 21 continued)

Technology category	IPC codes / descriptions
	B01J 8/20-8/22 - Processes with liquid as fluidising medium B01J 8/24-8/30 - Processes according to ”fluidised-bed” technique F27B 15 - Fluidised-bed furnaces / furnaces for finely divided materials F23C 10 - Combustion in a fluidised bed of fuel/particles
Improved boilers for steam generation	F22B 31 - Boiler/tube-system modifications depending on combustion apparatus F22B 33/14-33/16 - Steam-generation plants combining low- and high-pressure boilers
Improved steam engines	F01K 3 - Plants with steam/heat accumulators or intermediate heaters F01K 5 - Plants using steam storage in alkali (Honigmann/Koenemann) F01K 23 - Plants with >1 engine driven by different fluids
Super-heaters	F22G - Steam superheating characterised by heating method
Improved gas turbines	F02C 7/08-7/10.5 - Air pre-heating before combustion (exhaust-gas heat) F02C 7/12-7/14.3 - Plant cooling

Continued on next page

(Table 21 continued)

Technology category	IPC codes / descriptions
	F02C 7/30 - Preventing corrosion in gas-swept spaces
Combined cycles	F01K 23/02-23/10 - Thermally-coupled multi-fluid engine cycles
	F02C 3/20-3/36 - Gas-turbine plants using special fuel/oxidant/diluent
	F02C 6/10-6/12 - Plural gas-turbine plants with external working-fluid user
Improved compression-ignition (diesel) engines (excluding B60, B68, F24, F27)	
	F02B 1/12-1/14 - Fuel-air mixture compression engines (CI)
	F02B 3/06-3/10 - Air compression then fuel addition (CI)
	F02B 7 - Fuel-air charge ignited by CI of an additional fuel
	F02B 11 - Engines with both mixture and air compression / positive + CI
	F02B 13/02-13/04 - CI engines using air/gas to blow fuel into compressed air
	F02B 49 - Methods for introducing fine-mist fuel into intake air of CI engines
Co-generation / CHP	
	F01K 17/06 - Returning exhaust-steam energy to industrial process

Continued on next page

(Table 21 continued)

Technology category	IPC codes / descriptions
	F01K 27 - Plants converting heat/fluid energy to mechanical energy
	F02C 6/18 - Gas-turbine power-heat plants (waste-heat use outside plant)
	F02G 5 - Profiting from combustion-engine waste heat
	F25B 27/02 - Refrigeration/heat-pump systems using waste heat
Fossil-fuel technologies in general (reference list)	
	C10J - Fuel-gas production by carburetting air/other gases
	F01K - Steam-engine plants; steam accumulators; special-cycle engines
	F02C - Gas-turbine plants; air intakes; fuel-supply control
	F02G - Hot-gas / combustion-product positive-displacement engines; waste-heat use
	F22 - Steam generation
	F23 - Combustion apparatus / processes
	F27 - Furnaces; kilns; ovens; retorts
(Plus all IPC subclasses listed above.)	

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