

The firm-level anatomy of innovation in climate change mitigation technologies

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ABSTRACT

Achieving net-zero emissions requires widespread climate change mitigation technology (CCMT) adoption. However, there are two main challenges to overcome: CCMT innovation and diffusion. On the innovation front, existing CCMTs are insufficient for the goal of net-zero emissions. On the diffusion front, patent ownership concentration may restrict access to the existing CCMTs. To the best of available knowledge, this study is the first to pinpoint firm-level financial factors that impact the rate of CCMT innovation and to examine patent ownership concentration in CCMT domains. Analyzing balance sheets and patent data from US public firms (1976–2020), the paper documents significant CCMT patent growth, driven by large, established firms with ample debt, and smaller firms increasing equity issuance post-2008. This CCMT surge may be partly resulting from reductions in post-2008 corporate debt yield and equity price hikes, enabling external funding, especially for smaller firms, with potential policy implications concerning the role of monetary policy. While most CCMT domains see dispersed ownership concentration, there has been a noteworthy rise in ownership concentration in several CCMT domains. This development could potentially impede innovation and has substantial implications for industrial policy.

1. Introduction

Human actions in the pursuit of economic prosperity have caused the earth's temperature to increase, resulting in a global warming of 1.07 °C above the temperature range of pre-industrial times, with negative effects and subsequent harm and damage to both the natural world and human populations (IPCC, 2023). Through a worldwide employment of 100% renewable energy systems, it is imperative to achieve a state of net-zero emissions of greenhouse gases to prevent further global warming caused by human activities.

However, there are two key challenges: the innovation and diffusion of climate change mitigation technologies. First, the current technologies are inadequate in achieving the goal of net-zero emissions without compromising energy security and economic prosperity, and significant cost reductions during deployment and operation are necessary for many of the available clean energy technologies today to be widely adopted and utilized (IEA, 2020). As a case in point, 40% of the decrease in CO₂ emissions in IEA (2020)'s Sustainable

Development Scenario depends on technologies that have not yet been widely implemented for commercial use.

After all, the challenge of transitioning to the net-zero economy is essentially a challenge of rapid innovation in climate change mitigation technologies (CCMTs). Although numerous studies have presented evidence of the technical feasibility of 100% renewable-electricity systems based on existing technologies (for an extensive examination of the relevant literature, see Jacobson (2023)), Heard et al. (2017) argue that majority of these studies often rely on mitigation technologies like wave, tidal, or enhanced dry rock geothermal, which have not been implemented on a comparable scale anywhere in the world (p.1126).¹ This first challenge requires a deeper understanding of the firm-level factors that influence the pace of CCMT innovation. To the best of my knowledge, this study is the first to pinpoint firm-level financial factors that impact the rate of CCMT innovation.

Second, CCMTs are highly experimental, capital- and knowledge-intensive, and generally have a shorter life span, and patents related

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¹ My personal estimates, which can be provided upon request, indicate that among the 39 technologies employed by four models validating the viability of 100% renewable energy systems, only five are regarded as fully developed. Meanwhile, 24 are in the initial phases of implementation. Six technologies are currently in the demonstration phase, and the remaining four fall into the categories of either large or small prototypes. One notable implication of these findings is that research on 100% renewable energy systems might tend to overestimate the level of technological readiness of the incorporated technologies in their models.

to CCMTs typically exhibit greater complexity, and originality, and generate more extensive knowledge spillovers, with first-mover capital owners facing considerable risks in investing in these technologies (Rondrik, 2014; Barbieri et al., 2020; Orsatti et al., 2020; IEA, 2023). To innovate top-notch CCMTs, therefore, firms may need to attract high-risk capital, invest heavily in research and development, achieve economies of scale by growing quickly, and navigate the intricacies of the patent system and patent litigation (Acs and Audretsch, 1988; Rothwell, 1989; Avnimelech and Teubal, 2006).

These market demands can create significant obstacles for firms trying to enter the market, placing those with particular economic characteristics in terms of size, age, profitability, and ability to access debt and equity markets in an advantageous position, especially when financial conditions are favorable, as was the case during the post-2008 period (Brown et al., 2009; Bernstein, 2022; Xiang et al., 2022; Chiapini et al., 2022; Mateut, 2018; Giudici and Paleari, 2000; Hyttinen and Väänänen, 2006; Czarnitzki and Hottenrott, 2011; Alzakri, 2023). This advantageous position can result in a concentration of higher-quality CCMT patents in certain domains in the hands of certain types of corporations, leading to a substantially monopolistic market for the development, deployment, and operation of CCMTs (Watson and Holman, 1970; Tether, 1998; Moir, 2009; Rammer and Schubert, 2018). To my knowledge, there has been no prior investigation that specifically examines the full spectrum of patent ownership concentration in CCMT domains.

This study aims to bridge these two gaps by using data from US firms' financial balance sheets, the US Patent and Trademark Office (USPTO) patent database, and the OECD patent quality indicator database.² First, while earlier studies have reported a decline in CCMT innovation and tend to attribute the decline in CCMT innovation to a downward trend in oil prices or the shale gas boom (Acemoglu et al., 2019; Probst et al., 2021), the findings presented here indicate a continued rise in both the absolute and relative number of patents pertaining to CCMTs in the US since 2009. Between 2013 and 2020, companies that are older, bigger in size, or higher ability to increase leverage and find internal financing are observed to generate a greater quantity of CCMT patents.³ Small firms that experience an increase in access to external equity funding and have more internal funds observe an increase in CCMT patent applications. For example, a percentage point increase in the sales of equity ratio from the previous year leads to an increase of about 64% in quality-adjusted CCMT patents for small firms. However, this effect is only observed during the 2013–2020 period. Even after considering the potential endogeneity of the predictors, this evidence remains valid. In short, small firms producing CCMT tend to be liquidity-constrained and a change in ability to access equity increases patenting performance.

The rise of CCMTs does not guarantee their widespread use and adoption, however, as acquiring the rights to a particular technology

through patent licensing can be costly or infeasible, especially when only a small number of corporations own the patents in a specific technology domain. Indeed, I report a significant rise in patent ownership concentration in several CCMT domains, with some technology domains experiencing an increase of concentration up to about 1150%. Despite the noteworthy increase in patent ownership concentration in some domains, the overall patent ownership in CCMT fields is not heavily concentrated, and the majority of CCMT fields observed a decrease in patent ownership concentration.

These findings have important political implications, with two noteworthy points. First, the growth in CCMTs appears to be linked to both larger corporations with access to debt markets and smaller firms able to obtain funds from equity markets. This suggests that the expansionary monetary policy implemented after 2008, aimed at easing credit availability and boosting equity markets, may have contributed to improved access to external funding. Second, in specific technology sectors such as wind turbines, alternative fuels for internal combustion engines, hydrogen technology in transportation, and various aspects of aeronautics and air transport, where a few companies own and license CCMTs, access to these technologies might be constrained and prohibitively costly. To promote competition and enhance access to these technologies, targeted industrial policies aimed at fostering innovation within these critical CCMT domains may be necessary.

2. Background and conceptual framework

2.1. Firms in bridging innovation gaps for mitigation technologies

IEA (2020) contends that current technologies are insufficient in attaining the net-zero emissions goal without endangering energy security and economic well-being. To be more specific, 40 percent of the decrease in CO₂ emissions in IEA (2020)'s Sustainable Development Scenario from 2020 relies on technologies not commercially utilized. This grim conclusion extends beyond IEA (2020). For example, in their examination of research on 100% renewable energy systems, Heard et al. (2017) evaluated 24 studies using four technological feasibility and reliability criteria essential for meeting electricity demand. Their conclusion is that none of these studies offer proof that these fundamental technological feasibility criteria can be achieved.

100% renewable energy system research shows that it is feasible to fulfill the entire energy requirements of the United States primarily through the utilization of wind, water, and solar (WWS) energy sources or WWS sources coupled with, bioenergy, nuclear power, and carbon capture. A thorough examination of technological assumptions employed by this research brings to light the difficulties associated with realizing the implementation of such comprehensive renewable energy systems and points to the importance of further innovation in CCMTs.

For example, Jacobson et al. (2015) rely on hydrogen propulsion technologies for transportation and industry sectors, phase change materials, and underground thermal storage for energy storage. Hansen et al. (2019), Ćosić et al. (2012), and Doepfert and Castro (2021) depend on the electrification of the transportation sector, which presumes the availability of several key technologies ranging from fast-charging batteries to battery electric trucks.⁴ Nevertheless, majority of these

² I identify CCMT patents under the Y02 classification scheme developed and maintained by the European Patent Office (EPO). A study of patents granted in the US has multiple advantages. This approach can help avoid inconsistencies in assessment criteria across different patent systems. Additionally, since the US is a prominent technology hub in various fields and is ranked second globally for international intellectual property protection, as well as possessing a significant technology market, top-notch patent holders have compelling reasons to seek patents through the USPTO. I match almost all major CCMT patent assignees to balance sheet data at the firm level and record the financial traits of top-performing CCMT producers as well as CCMT patent ownership concentration.

³ I group publicly listed companies that hold at least one CCMT patent based on their financial fundamentals and analyze the differences between each group over time with respect to the number and quality of CCMT patents they possess. I also estimate a cross-sectional linear regression model and document a significant correlation between total patent count and average leverage, holding other firm traits and industry effects constant.

⁴ Also, despite the significant decline in the cost of electric vehicles and their increasing adoption, electric cars still carry a higher price tag compared to traditional internal combustion engine cars (García-Olivares et al., 2018). The economic benefits of electric vehicles are somewhat restricted due to the cost-related challenges linked to their batteries. Enhancements in the structure of graphite for the anode and the development of gel-like electrolyte materials are required to enable quicker charging rates (Meeus, 2018). To lower expenses, it is necessary to decrease the cobalt content in existing cathode compositions for the cathode (Choubey et al., 2017). Present electric vehicle technologies are inadequate for heavy transportation modes like trucks and

technologies have not attained the requisite level of technological advancement to be effectively employed on the extensive scale proposed by the authors (Clack et al., 2017). There are significant innovation gaps.⁵

To fill those gaps, countries might need industrial strategies directed at incentivizing companies to stimulate additional innovation within critical CCMT domains.⁶ This is because for a company, every CCMT patent is an intangible asset. Building a portfolio of patents is essentially an intangible asset accumulation problem. To accumulate intangible assets, companies have to invest in research and development deliberately, just like they would invest in plant and equipment for tangible asset accumulation. Similar to investing in physical assets like plants and equipment, there are multiple financial factors that companies need to take into account when they decide to build up their intangible assets. These financial considerations include, but are not restricted to, expected return on investment in research and development, the extent to which the output is reliant on patents, access to external financing through debt or equity, and the availability of internal cash flow as the primary source of funds. The financial landscape can significantly impact these financial considerations.

Against this background, it is essential that we seek to address the following question: what are the financial circumstances that foster CCMT innovation, given that CCMTs are characterized by their experimental nature, significant capital and knowledge requirements, and typically shorter lifespans?

Although numerous studies have explored related topics, it is evident that an in-depth examination of this particular question is currently lacking in the existing body of research. Lin et al. (2019) investigate the effect of green innovation strategy on corporate financial performance. Martínez-Ros and Kunapatarawong (2019) investigate the role of firm size in green innovation and document diminishing returns of knowledge breath on green innovation among small firms. Andries and Stephan (2019) show that bigger companies reap financial advantages from environmental advancements that are spurred by regulations or industry standards, whereas smaller companies gain from environmental innovations that emerge as a result of customer needs. To address the question posed above, this study utilizes data from the financial balance sheets of US firms, the patent database of the US Patent and Trademark Office (USPTO), and the OECD's patent quality indicator database.

buses due to the prolonged charging time and limited battery range. Although fuel cell electric vehicles (FCEVs) offer promise as a complementary solution, their high cost and restricted availability remain obstacles (Muthukumar et al., 2021). Substantial reductions in costs related to fuel systems and hydrogen storage tanks are needed, and improvements in the efficiency of FCEV models through the use of low-cost bipolar plate materials are essential (Thompson et al., 2018).

⁵ These gaps span the industries from heavy transportation to aluminum production. Just to name a few, with existing knowledge, there is no electric replacement for modern jet aircraft. The only feasible and eco-friendly alternatives would entail utilizing jet biofuels, liquid hydrogen, or liquid methane (Daggett et al., 2008). Thus, attaining a state of net-zero emissions within the aviation sector demands a comprehensive overhaul of aircraft design. While adjustments like a clean sheet or tube aircraft designs hold the potential to decrease fuel consumption by 40% (Kharina and Rutherford, 2017), a complete redesign remains necessary. In the realm of iron and steel production, a significant obstacle revolves around the absence of readily accessible smelting methods that do not rely on carbon. The current steel manufacturing process heavily relies on traditional blast furnaces and coke oven technology based on coal use. Although hydrogen can be integrated into blast furnaces, it falls short of completely substituting coal usage (Liu et al., 2021).

⁶ This would be in conjunction with industrial policies focused on fostering publicly funded research, development, and production.

2.2. Patent ownership concentration challenge in mitigation technology diffusion

Up to this point, the discussion has been centered on CCMT innovation. However, increased innovation in CCMTs does not necessarily imply greater diffusion and extensive use of these technologies.

In cases where patents within a domain are complementary and unique, and they are essential for creating a specific final product (e.g., wind turbine), the ownership concentration might not significantly impact licensing fees. This is because, even with a diversified ownership structure involving numerous firms producing distinctive patents required for the production of the final product within that domain, individual firms still possess differentiated patents that grant them some degree of market power.

But acquiring the rights to a specific mitigation technology via patent licensing can be cost-prohibitive or unfeasible due to patent ownership concentration in cases where patents within a given technology domain are imperfect substitutes and serve to create a single CCMT product. As a result, larger number of firms holding distinct yet similar patents within that domain might potentially decrease the licensing expenses linked to the final product's production.

For instance, Gallagher (2014) finds through her field research on clean energy technology diffusion that Toyota, a leading company in hybrid vehicle technology, has refused to license its hybrid vehicle patents to Chinese companies (p.54, 60, 71). As another case in point, Gallagher (2014) notes that Siemens, a prominent corporation in H-class gas turbine technology, is not willing to transfer the technology, and that several companies have been motivated to create their own gasification technologies due to the excessively high licensing fees associated with General Electric's gasification patents. If both Toyota and Siemens, for example, stand as the sole company in their respective technology domains, where patents often serve as substitutes, introducing more companies with patents in that domain might foster increased competition and lowered fees for patent licensing in these domains.

The issue of patent ownership concentration has historical roots, dating back to Watson and Holman (1970), who offered an overview of the literature concerning patent concentration in the 1960s:

Edwards maintains that “patent accumulation ... comes to be a substantial monopolization of the industry itself”. Stocking and Watkins write about the evils of patent accumulation and its tendency to “assure a perpetual monopoly”. Machlup holds that the “accumulation of patents in the hands of large corporations may secure them an almost unlimited monopoly power”. Kaysen and Turner say that patent accumulation can be “something much larger than the sum of its parts”. Patent concentrations can be a barrier to entry; it increases the burden of “inventing around” the technologists of accumulating firms; it puts patent blankets over areas of technology; and it has further oppressive effects, given the risks and costs of patent litigation. That Kaysen and Turner believe patent concentration to be a problem deserving solution is shown by their suggestions for reform, which include the strengthening of the antitrust laws to deal directly with patent accumulation (there is nothing now illegal about large patent holdings) and tentatively a tax per patent varying with the size of a corporation's holdings (p.112).

Notably, this body of work did not endure over time. This research aims to revive this field using the case of CCMTs, in light of the prior discussion concerning the relationship between CCMT diffusion and the concentration of patent ownership.

3. Empirical approach

3.1. Data sources and samples

As the US is recognized as a major technology hub in most domains and has been ranked as the second-best globally for intellectual property protection, it is an attractive technology market for high-quality patent holders. A US-centered analysis thus allows for capturing the technology trends in the technology frontier. I obtain the US patent data from the PatentsView, a data initiative maintained by the United States Patent and Trademark Office (USPTO).⁷ The raw data contain 8,169,776 patents granted by the USPTO between 1976 and 2022. Only utility, design, and plant patents are selected, resulting in a total of 8,132,354 patents. The dataset includes information on patent assignees, assignee locations, cooperative patent classification (CPC), and application and grant dates.

To identify patents related to climate change mitigation technologies (CCMTs), I use the Y02 patent CPC classification scheme. This tagging scheme was initiated by the collective effort of the European Patent Office (EPO), the United Nations Environmental Program (UNEP), and International Centre on Trade and Sustainable Development (ICTSD) and maintained by the EPO (Veeffkind et al., 2012). It is based on experienced expert examiners' search strategies to tag the patent documents. I include all Y02 subclasses, with the exception of Y02 A, which tags climate change adaptation technologies. Out of 8,132,354 patents, 7,388,798 have CPC information. Of those, 6.3% are classified as CCMT.⁸

The limitations of using the number of patents as a measure of innovation have been well established at least since Griliches (1998). It is a widely known and cited fact that “not all innovations necessarily are patented, and not all patents necessarily are innovative” (Scherer and Harhoff, 2000; Silverberg and Verspagen, 2007). The existence of “patent trolls”, i.e., entities that acquire low-quality patents solely for the purpose of collecting monopoly rents associated with patent protection, is a well-known consequence of strong patent protection (Pagano, 2014; Rikap, 2021). Despite several patent policy reforms aimed at limiting opportunities to extend patent terms, the number of continuing applications – patent applications that seek to expand the scope of an existing patent in order to extend its protection term – has gradually increased (Righi et al., 2023). However, because of the strong inventor incentives to safeguard the monopoly rents linked with obtaining a patent, a significant proportion of widely utilized technologies have been patented (Griliches, 1998). The number of patents that have been adjusted for their respective quality levels can be an informative indicator of where technology is headed.

I employ the OECD Patent Quality Indicators Database to measure the variation in patent quality. Previous research has typically linked patent quality to patent forward citations (Trajtenberg, 1990; Hall et al., 2001; Sampat and Ziedonis, 2005). However, the evidence presented by a wave of research suggests that citation counts alone are prone to substantial measurement errors. As previous studies have demonstrated a correlation between patent value and the number of claims in a patent document (Lanjouw and Schankerman, 2004), the generality of the patent in terms of technologies classes citing the patent (Bresnahan and Trajtenberg, 1995), and the extent of patent protection across various patent offices (Lanjouw, 1998), I use a composite quality index from the quality indicator database that incorporates these measures in addition to forward citation counts.

Using Kogan et al. (2017)'s updated Compustat identifier-patent identifier matching, I merge the patent data with the firm-level data from Compustat spanning from 1976 to 2020. Although Compustat data only includes information on publicly-traded companies, to the best of my knowledge, it remains the sole accessible data source that offers a representative sample of firms over a long time period. The data include an overwhelmingly large proportion of CCMT inventor firms.

Overall, the final sample period is 1976–2020. Variables are described in Table 1. Panel B in Table 2 shows that the patent-level analysis presented below typically is based on 447,362 CCMT patents. There are 1921 firms with at least one CCMT patent between 1976 and 2020, while there are 3549 observations of firm-years, where each observation pertains to a particular company with a specific number of patent applications and distinct financial characteristics during that year.

3.2. Parametric analysis of firm-level CCMT patent count

The empirical analysis below centers primarily on the impact of access to finance on CCMT innovation.

3.2.1. Cross-sectional model of total CCMT patent counts

To initiate the econometric analysis, I aggregate the data at the firm level and use the OLS estimator to estimate the parameters of the following naïve cross-sectional linear regression model

$$y_i = \alpha + \lambda \bar{Int}_i + \omega \bar{Ext}_i + \bar{X}_i' \beta + \delta_{s(i)} + \epsilon_i \quad (2)$$

where y_i represents either the log total CCMT patent count or the quality-adjusted log total CCMT patent count granted by the USPTO, $\bar{Int}_i$ is the average cash flow available to the firm i , $\bar{Ext}_i$ is the average available external funds available in the form of net equity or debt, $\bar{X}$ is a vector of covariates including average employment size and maximum firm age in the sample period, finally the full set of four-digit SIC dummies are denoted by $\delta_{s(i)}$. Variable descriptions are presented in Table 1

The model parameters are estimated for various firm sizes and two distinct periods, from 1976 to 2020 and from 2013 to 2020, individually. The group of large firms encompasses the top two quantiles in terms of firm sales, while the group of small firms comprises the bottom two quantiles in terms of firm sales. The baseline sample to estimate this model includes 1921 baseline firms with at least one CCMT patent between 1976 and 2020. But before estimating the model, I exclude firms with a total CCMT patent count of fewer than 20.⁹

3.2.2. Panel model of yearly CCMT patent applications

Fixed effect estimator In order to capture the empirical patterns in CCMT production greater detail and specificity, I leverage the variation that exists between different firms and within firms over time. To establish a useful baseline for comparison, I employ both a pooled regression model and a two-way fixed effect model¹⁰:

$$y_{it} = \alpha + \beta_2 ext_{it-1} + \beta_3 int_{it-1} + \mathbf{X}_{it-1}' \delta + \lambda_i + \theta_t + \epsilon_{it} \quad (3)$$

The effect of current financial conditions on patenting applications tends to be delayed. As a result, I account for this delay by focusing

⁷ The data is available on PatentsView.

⁸ To check the robustness of the analysis to the definition of green technologies, I use an alternative classification scheme, ENVTECH, developed by Haščič and Migotto (2015), which results in 7.7% of patents with CPC information being classified as green technology patents. Throughout the study, I primarily employ the Y02 tagging scheme.

⁹ Given that the number of patents held by the company follows a Poisson distribution, as a robustness check, I also employ a Poisson patent count model.

¹⁰ In a dynamic panel data setting, when the time dimension of the panel is constrained, the OLS estimator is known to exhibit bias and lack consistency. However, in our case, the sample period is extensive enough to mitigate this issue.

Table 1

Variable descriptions.

Variable	Definition
Family size	Refers to the number of elements in the set of patents filed in multiple countries that share one or more common priority filings.
Forward citations	The count of references received by a particular patent.
Generality	$Gx = 1 - \sum_{j=1}^{M_i} (\frac{1}{N} \sum_{i=1}^N \frac{T_{ji}^n}{T_i^n})^2 = 1$ where T_i^n is the total number of IPC n-digit classes in patent y_i citing the patent X , T_{ji}^n is the total number of IPC n-digit classes in the j th IPC 4-digit class in y_i , while $j = 1 \dots M_i$ captures all IPC 4-digit classes in y_i and $i = 1 \dots N$ captures all patents citing the patent X .
Claims	The number of claims per patent.
Patent quality index (4)	A composite quality index based on four components: patent family size, forward citations, generality, and claims. Each component is standardized based on year and technological domain, ensuring they receive equal significance.
Age	The length of time that has passed since the initial public offering (IPO).
Cash flow	Operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt), divided by total assets (at).
Market leverage	Long term debt (dltt) plus debt in current liabilities (dlc), divided by total assets (at) minus book equity (ceq) plus the market value of common equity (csho*prcc f).
Net equity issuance	Net equity issuance is sales of equity (sstk) minus purchases of equity (prstk), divided by assets (at).
Market capitalization	Market value of common equity (csho*prcc f).

Table 2

Summary statistics.

Statistic	N	Mean	St. Dev.	Min	Max
A. All patents					
Family size	7,092,564	3.954	4.080	1	58
Forward citations	7,092,564	13.542	49.057	0	4650
Generality	5,776,327	0.480	0.275	0	1
Claims	7,092,512	15.693	11.122	1	887
Quality index (4)	7,092,512	0.272	0.126	0.011	0.989
Is CCMT?	7,388,798	0.063	0.244	0	1
Is ENVTECH?	7,388,798	0.077	0.267	0	1
B. Climate change mitigation technology (CCMT) patents					
Family size	447,362	4.291	3.872	1	53
Forward citations	447,362	15.472	60.526	0	2803
Generality	365,640	0.533	0.265	0	0.999
Claims	447,360	15.725	10.881	1	596
Quality index (4)	447,360	0.309	0.135	0.013	0.989
C. All compustat firms					
Patent count	54,644	42.725	213.104	1	9101
Age	378,629	12.482	12.065	0	66
Sale	378,629	1681	10,061	0.001	569,962
Cash flow	358,276	-0.118	5.161	-1467	13.524
Market leverage	296,109	0.202	0.193	-0.263	2.912
Net equity issuance	317,185	0.079	0.574	-41.667	146.500
Market capitalization	299,801	2433	17,922	0	2,324,390
Mean patent quality index (4)	53,357	0.291	0.107	0.014	0.950
D. Matched compustat firms with at least one CCMT patent					
Patent count	30,306	74.109	282.204	1	9101
Age	57,670	19.925	15.496	0	66
Sale	57,670	5652	21,298	0.001	569,962
Cash flow	55,035	0.045	0.598	-58.920	1.711
Market leverage	50,790	0.169	0.149	0	0.913
Net equity issuance	45,396	0.026	0.169	-2.569	5.293
Market capitalization	51,481	8496	37,297	0	2,324,390
Mean patent quality index (4)	29,830	0.291	0.094	0.021	0.933

Note: The table displays summary statistics for patent data and Compustat data separately. In Panel B, only CCMT patents that have a corresponding Compustat identifier are considered, while others are excluded. For Panels C and D, companies that have negative sales, no assets, and no property and equipment are dropped. For detailed variable definitions see Table 1.

on explanatory variables from previous year in the spirit of Acemoglu et al. (2022).¹¹

Linear GMM estimator Of course, the potential presence of endogeneity issues in this model, specifically in the form of reverse causality

and simultaneity, should be addressed. The primary issue is reverse causality, where the relationship between the number of CCMT patents and the utilization of leverage or equity financing or of cash flow could be explained by the impact of patent grants on the accessibility of internal or external financial resources. To put it differently, the availability of debt or equity and cash flow in year $t - 1$, represented by ext_{it-1} and int_{it-1} , could be influenced by the patenting performance observed in year $t - 2$, denoted as y_{it-2} . One potential solution to address this issue is to incorporate omitted variable y_{it-2} as an explanatory variable in the model:

$$y_{it} = \alpha + \beta_1 y_{it-2} + \beta_2 ext_{it-1} + \beta_3 int_{it-1} + X'_{it-1} \delta + \theta_t + (\epsilon_{it} + \lambda_i) \quad (4)$$

¹¹ Wang and Hagedoorn (2014) demonstrate that the first time lag of R&D significantly explains a substantial portion of the variation in the patent count for the current year across all distributed lag specifications in their analysis. Given that the current financial constraints tends to influence the R&D spending for the current period, the lag structure incorporated in the model is deemed appropriate.

Now, the variation in ext_{it-1} and int_{it-1} that can be attributed to y_{it-2} is accounted for. And the left-hand side variable has acquired a dynamic nature as it is now influenced by its own previous values. This introduces a correlation between the lagged dependent variable y_{it-2} and the error term ϵ_{it} . Since y_{it-2} is not strictly exogenous, the standard fixed effects estimator is no longer consistent.¹² Hence, the new model with the lagged dependent variable is estimated using the dynamic panel data model, specifically, the linear generalized method of moments (GMM) developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) for dynamic models that incorporate lagged dependent variables as regressor.

This necessitates making several decisions regarding the type of the linear GMM estimator (i.e., difference vs. system GMM), variable transformation (such as differencing or orthogonal deviations), identifying strictly exogenous variables, length of lags in internal instruments, and determining the method of standard error computation. First, when the dependent variable exhibits persistence in that it is strongly correlated with its lagged values, the difference GMM estimator tends to be biased (Blundell and Bond, 1998). In the regression of y_{it} on y_{it-2} , the observed persistence magnitude is 0.75. I thus employ the system GMM, which estimates simultaneously in differences and levels. Second, given that the second concern involves simultaneity, indicating that variables measuring financial constraints may also reflect expected profitability, I consider all variables on the right-hand side of the equation as potentially endogenous and use lagged variables as internal instruments. Third, assuming that the error is independent and follows an identical distribution, the validity of the instrument set for time period $t - 2$ can be established. However, building on a weaker assumption where the error term follows a MA(1) process, I employ a stronger instrument set consisting of observations from time periods $t - 2$ to $t - 4$, based on the approach outlined in Brown et al. (2009). Finally, to address the downward bias in GMM standard errors, I employ the two-step standard errors proposed by Windmeijer (2005). Ultimately, this is a typical application of the system GMM with Windmeijer correction.

3.3. Non-parametric analysis of patent ownership concentration

The analysis above focuses on the firm-level determinants of CCMT innovation. However, the emergence of CCMTs does not guarantee their universal use and acceptance. Obtaining the rights to a specific mitigation technology through patent licensing can be expensive or impractical, particularly when only a few corporations possess patents in a particular technology field.

To address this issue, I follow a three-step process to compute the concentration of ownership for CCMT patents. First, I calculate the overall count of CCMT patents for each technology domain (also known as CPC group) and year. Second, I compute the “market share” of each patent assignee in the specific technology domain per year. Finally, I use these market shares to create a Herfindahl–Hirschman index (HHI), which involves summing up the squared market shares of each firm.

One concern pertains to the disambiguation of patent assignee names. When a single firm is identified by different names in separate patent applications, it can lead to a downward bias in calculating the patent ownership HHI. The USPTO employs various algorithms

and post-processing techniques to disambiguate the names of patent assignees. I use the unique identifiers provided by the USPTO for assignees to ensure accurate and consistent identification of patent ownership.

4. Results

In what follows, I provide descriptive statistics to analyze the patterns in CCMT innovation using the previously mentioned patent data from the USPTO and I provide estimation results for the empirical models mentioned earlier.

4.1. The increase in the number of CCMT patents

Fig. 1 illustrates the total and proportional count of CCMT patents awarded by the USPTO from 1976 to 2020.¹³ The number of CCMT patents had a gradual growth before 2009, panel (a) shows, and it never exceeded 10,000 annually. Even though the patent output in other technology fields experienced a boost during the late 1990s and early 2000s, the annual number of CCMT patents granted remained low. Panel (a) also demonstrates a notable surge in the yearly count of granted patents since 2009, but the rise was especially remarkable for CCMT patents. The yearly production of CCMT patents increased by more than three times in only ten years. Panels (b) displays the share of CCMT patents among all patents granted by the USPTO, considering the mean OECD patent quality indicator and the estimated value of CCMT patents and of other patents as estimated by Kogan et al. (2017). The proportion of CCMT patents adjusted for value decreased from 2019 to 2020, but the share of CCMT patents adjusted for quality continued to rise after 2009.

4.2. Firms' focus on more established domains of CCMT

Fig. 2 explores which domains have been the main driver of the recent rise in CCMT innovation. It depicts the overall count of patents that were awarded in the domains of CCMT between 1976 and 2008 as well as between 2009 and 2020. As depicted in the figure, firms producing CCMTs as a whole have shifted their focus from applications in nuclear fission reactors, engine management systems, recycling, and internal combustion engine (ICE) efficiency to areas such as energy storage systems, energy-efficient computing, and energy efficiency in communication networks. Technologies related to battery-based energy storage and production processes for final products have remained popular and have been the main drivers of the CCMT rise.

Fig. 2 also points to the swift development of clean energy technologies such as wind power, solar power, and electric vehicles that have demonstrated their capacity to reduce emissions. Nevertheless, it is crucial to emphasize that numerous commonly used climate models' net-zero emission trajectories rely heavily on the widespread implementation of technologies utilizing hydrogen applications and carbon capture (IEA, 2020, 2023). There has been an increase in the number of patents pertaining to hydrogen-related technologies for transportation, production processes, production, storage, and distribution. On the other hand, the increase in the number of patents associated with carbon capture and storage has been relatively modest. All in all, technology domains related to hydrogen and carbon capture applications remain close to the origin in Fig. 2. Although the number of patents in a given domain may not accurately reflect the direction of technology in that domain, the evidence presented in Fig. 2 implies that innovators in CCMT area are primarily concentrating on making progress in the relatively well-established domains of CCMT.

¹² The reason is that the within estimator applies the OLS estimator to the regression equation using transformed variables, specifically: $y_{it} - \bar{y}_i - \bar{y}_t = \alpha + \beta_1(y_{it-2} - \bar{y}_i - \bar{y}_t) + \beta_2(ext_{it-1} - \bar{ext}_i - \bar{ext}_t) + \beta_3(int_{it-1} - \bar{int}_i - \bar{int}_t) + (X_{it-1} - \bar{X}_i - \bar{X}_t)' \delta + (\epsilon_{it} - \bar{\epsilon}_i - \bar{\epsilon}_t)$. However, since $\bar{\epsilon}_i$ includes the lagged error term, the probability limit of the fixed effects estimator will differ from its population equivalent as the number of observations approaches infinity. In the first-difference transform, in contrast to the within-estimator, longer lags of the regressors remain independent of the error term and can be used as instrumental variables. Notice, however, that the first-difference transformation often leads to a significant number of missing observations in the dataset.

¹³ Panels A and B in Table 2 contains the summary statistics for the data employed in this analysis.

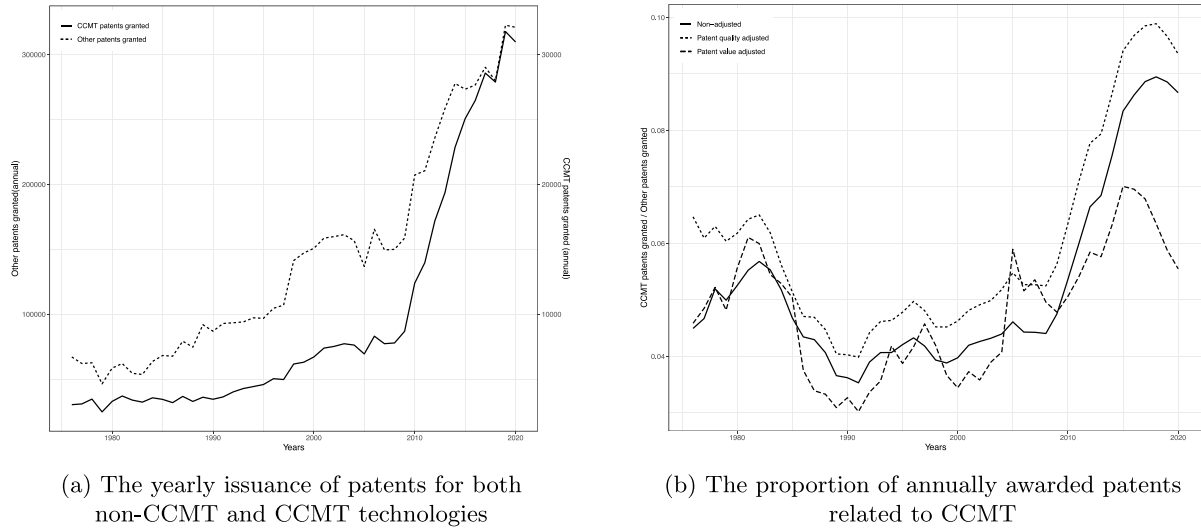


Fig. 1. The evolution of the share of CCMT patents granted by the USPTO from 1976 to 2020.

Note: In panel (b), the measurement of CCMT patents utilizes the EPO's Y02 classification system. The quality-adjusted share of CCMT patents represents the average quality of CCMT patents in a specific year, multiplied by the total number of CCMT patents, divided by the average quality of non-CCMT patents in the same year, multiplied by the total number of non-CCMT patents. Patent quality is computed using the OECD's composite quality index. Similarly, the value-adjusted share of CCMT patents indicates the average KPSS value of CCMT patents in a particular year, multiplied by the total count of CCMT patents, divided by the average KPSS value of non-CCMT patents in the same year, multiplied by the total count of non-CCMT patents.

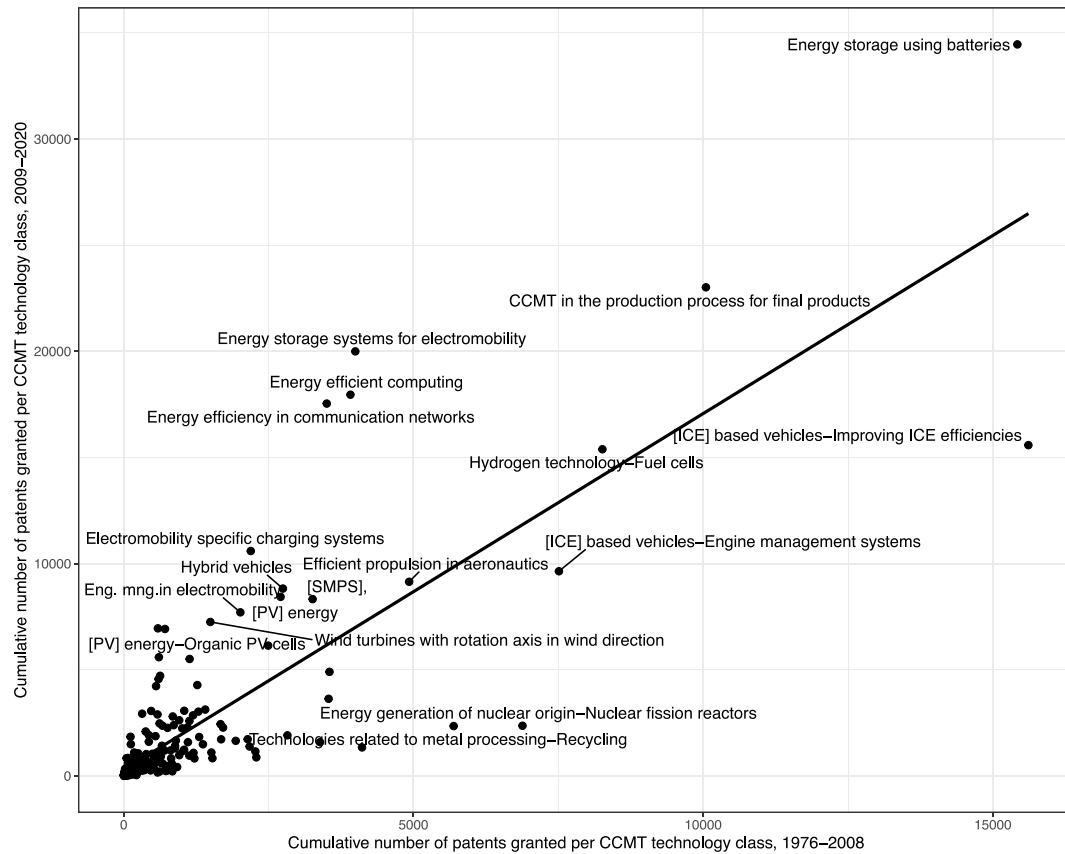


Fig. 2. Comparison of the cumulative count of patents within a specific CCMT CPC group between the periods of 1976–2008 and 2009–2020.

Note: The figure shows the cumulative count of USPTO patents in CPC groups under the Y02 class. A patent might be associated with multiple CPC classes or groups. Shortened CPC text labels are displayed exclusively for CPC groups that have amassed a cumulative count of patents surpassing 6940 between 2009 and 2020 and 5000 between 1976 and 2008.

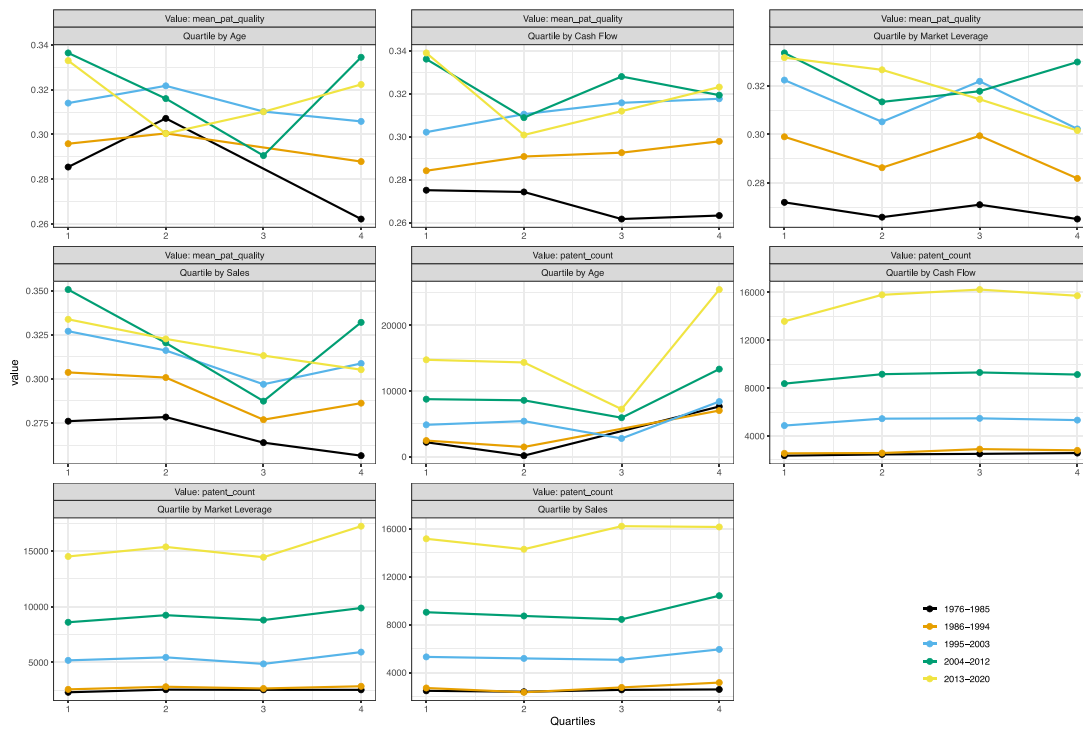


Fig. 3. Firm fundamentals, patent quality, and patent count.

Note: The figure categorizes Compustat companies that possess at least one CCMT patent granted by the USPTO into quartiles based on various financial variables. It illustrates the average quality of CCMT patents and the total number of CCMT patents per quartile within a period. Age is the number of years since initial public offering. Market leverage is long term debt (dltt) plus debt in current liabilities (dlc), divided by total assets (at) minus book equity (ceq) plus the market value of common equity (csho*prcc f). Cash flow is operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt), divided by total assets (at). Sales represents gross sales (sale). See Table 1 for a detailed description of variables.

4.3. Firm age, size, cash flow, and market leverage as drivers of high-quality CCMT growth

Since 2009, as we have seen, there has been a notable surge in the rate of CCMT innovation. The cause of the rise in CCMT innovation is the main focus of my analysis in this section, with a particular emphasis on financial factors. In what follows, I first present a descriptive analysis of the relation between firm-level variables and CCMT patent generation. Second, I employ the empirical models introduced in Section 3.2.¹⁴

In order to motivate the econometric analysis outlined above, I classify firms into quartiles based on their age, cash flow, leverage, and sales volume size during different periods between 1976 and 2020. The first four panels in Fig. 3 show the variation in CCMT patent quality across firm groups. The first panel indicates that during the period of 1976–1985, older firm quartiles typically produced CCMT patents of lower quality. However, in the most recent period, the quality of patents generally rises with the age of the firm even while the youngest firms exhibit the highest average CCMT patent quality. The second panel illustrates that during the period of 1976–1985, firms with limited internal funds were capable of generating patents of relatively high quality. However, in more recent times, the capacity to produce higher-quality patents tends to increase with the amount of available internal funds. The third panel shows that highly leveraged firms, i.e., those with greater access to external funding, tend to generate lower-quality patents. Likewise, firm size by sales volume, as the fourth panel shows, tends to be inversely related to patent quality.

The remaining panels demonstrate the patent count for each group during a specific period. Between 2013 and 2020, there was a significant increase in the number of patents, primarily due to older or

larger companies and those with greater leverage. Moreover, the gap in patent numbers between groups of different sizes, ages, and leverage has become more pronounced recently. Overall, the descriptive analysis suggests that there appears to be a positive correlation between firm age and the availability of internal funds with patent quality and patent count. Market leverage and firm size tend to have an inverse relationship with patent quality, but a positive relationship with patent count.

One potential issue with the non-parametric analysis presented above is that companies with similar sizes, ages, and financial backgrounds may be operating in an industry that has a higher or lower likelihood of producing high-quality CCMT patents. It is also unclear whether the increase in CCMT innovation can be attributed to firms with greater leverage, internal funds, and size (i.e., between firms) or to firms reacting to changes in their size or ability to borrow or their ability to generate internal funds by innovating new CCMTs (i.e., within firms).

4.4. The role of access to debt and equity markets

To account for such industry-specific effects and to identify if firms that have a comparative advantage in CCMT innovation typically differ in size and age and in their tendency to generate internal funds or access debt or equity, first, I use the OLS estimator to estimate the parameters of the model presented in Section 3.2.1 simple cross-sectional linear regression model.¹⁵ The dependent variable is one of the measures of firm-level CCMT innovation (log total CCMT patent count or log total patent count interacted with average patent quality in a given period). The primary explanatory variables include average

¹⁴ Panel D in Table 2 provides the summary statistics for the data used in this analysis.

¹⁵ the parameters are estimated separately for firms of different sizes and for two different periods: 1976–2020 and 2013–2020.

leverage, cash flow, net equity issuance, and interest payments, while controlling for average log employment, firm age, and industry effect.

The parameter estimates are presented in Table 3. Different columns correspond to various periods, groups of firms classified by size, or different measures of CCMT innovation. Column 1 indicates a negative relationship between average leverage and total CCMT patent count from 1976 to 2020 while holding average interest payments, employment size, firm age, and other sources of funding like equity issuance and cash flows. In column 2, the relationship becomes positive between 2013 and 2020.

Columns 3 and 4 reveal that the relationship between average leverage and total CCMT patent count is positive and much more sizeable among large firms and has become even more pronounced in recent years, while the correlation is negative among small firms. For example, the quantitative magnitude in column 3 implies that one percentage point increase in the leverage ratio (i.e., total short- and long-term debt divided by assets minus book equity plus the market value of common equity) is associated with a 125-fold ($(\exp(4.843)-1)$) increase in total patent count between 1976 and 2020. Although the correlation between average leverage and total CCMT patent count for large firms is greater during the 2013–2020 period, the estimate is not very precise.

Columns 7 to 12 adjust for average patent quality. To ease the magnitude interpretation, I assume that ten CCMT patents of low quality, each with a quality index of 0.1, is equivalent to one CCMT patent of high quality with a quality index of 1. With this assumption, column 9, for example, shows that for every one percentage point increase in the average leverage ratio between 1976 and 2020, the total high-quality patent count during the same period increases by almost a factor of 5 among large firms ($(\exp(1.756)-1)$). The magnitude is economically sizeable and statistically significant at less than 10% level.

The estimated effects of the control variables are also worth noting. Regardless of the sample restriction, firm age and employment size are positively associated with the total patent count (columns 1 to 6) or the total high-quality patent count (columns 7 to 12), while average cash flow, net interest payments, and net equity issuance tend to be consistently inversely related to the total patent count or the total high-quality patent count.

It is crucial to note that most of the estimates in Table 3 are based on a small number of observations. This concern notwithstanding, the cross-sectional estimation results suggest that between 2013 and 2020 firms with a higher ability to borrow were more likely to generate high-quality CCMT patents. This relationship holds only among large firms. Table A1 provides the findings of the Poisson patent count model as an additional analysis to ensure the robustness of the results, given that the company's patent count conforms to a Poisson distribution. The outcomes are comparable. More specifically, among large firms, the average leverage ratio continues to exert a noteworthy and statistically significant influence on the quantity of high-quality patents, a key finding in Table 3. One difference lies in Table 3, where the impact of market leverage on the overall patent count is both negative and non-significant for small firms in the more recent period, contrasting with Table A1 where it is positive and significant. Much like the findings outlined in Table 3, irrespective of the restriction imposed on the sample in Table A1, there exists a positive correlation between firm age and employment size with both the overall patent count and the count of high-quality patents. Simultaneously, average cash flow, net interest payments, and net equity issuance tend to exhibit an inverse relationship with the total patent count or the count of high-quality patents.

Aggregating data at the firm level leads to an increase in sampling variation and a loss of valuable information from the variation in explanatory and outcome variables over time. The first six columns in Table 4, thus, allow outcome and explanatory variables to vary across years, without firm- and year-fixed effects. I now compare firm-year

observations as modeled in Section 3.2.2. The impact of current financial conditions on research and development and patenting strategies is typically delayed, so it is reasonable to assume that the effect of financial conditions is not immediate. To account for this potential delay, the analysis focuses on lagged explanatory variables.

Initially, my focus is on the between observations, specifically columns 1 to 6. In column 1, an increase in the lagged leverage ratio in a given combination of firm and year increases the quality-adjusted patent count during the period of 1976–2020. The effect is stronger for the period of 2013–2020 (column 2). But these estimates are not precise. Columns 3 to 5 show that the positive association between leverage and the quality-adjusted patent count is driven by large firms. Column 4 shows that the effect has significantly strengthened in more recent times. With the exception of the sample of small firms from 2013–2020, cash flow exhibits an inverse relationship with the quality-adjusted patent count across almost all subsamples. The impact of raising equity through issuing stocks is more pronounced between 2013 and 2020, primarily driven by smaller companies.

Columns 7 to 12 present the parameter estimates from the linear model with the firm- and year-fixed effects. I now investigate how changes in a firm's financial conditions over time can impact its ability to generate quality-adjusted CCMT patents. Several interesting results can be highlighted.

First, during the period of 1976–2020, firms experiencing an increase in leverage, net equity issuance, and cash flow produce more quality-adjusted CCMT patent (column 7). More recently (column 8), only net equity issuance strongly predict an increase in the quality-adjusted CCMT patent count.

Second, columns 11 and 12 suggest that an increase in a small firm's internal funds in the form of cash flow last year is associated with an increase in quality-adjusted CCMT patent applications in the following year. This shows that small firms tend to be liquidity constrained. This effect is more pronounced for the period of 2013–2020 (column 12).

Third, as column 12 shows, an increase in a small firm's ability to access external funds in the form of equity (i.e., net equity issuance) leads to an increase in quality-adjusted CCMT patent applications in the following year. Specifically, a one percentage point increase in the sales of equity ratio from the previous year leads to an increase of about 64% in quality-adjusted CCMT patents for small firms.

In order to tackle the potential problems arising from endogeneity, the outcomes of the GMM model discussed in Section 3.2.2 are presented in Table 5. The significant and positive coefficients observed for y_{it-2} confirm the enduring nature of CCMT patent production. Although the impact of leverage has become more noticeable in recent times (column 1 vs. column 4), the estimate is imprecise. The final column indicates a positive relationship between cash flow and the number of CCMT patents, although the standard error remains relatively high. Lastly, as shown in the same column, an improvement in a small firm's ability to issue equity results in a subsequent growth in CCMT patent applications.

4.5. Distribution of patent ownership concentration and its change

The evidence above establishes the rise of CCMTs, specifically in several technology domains. However, the development of CCMTs does not necessarily mean these technologies will be widely used and adopted, because obtaining access to a specific technology through patent licensing can be expensive or impossible when only a few corporations have ownership of patents in that technology domain.

To investigate the concentration of patent ownership systematically, Panel (a) of Fig. 4 displays the average Herfindahl–Hirschman Index (HHI) during the period spanning 2016 to 2020. The HHI is the total squared percentage of patents held by a particular firm within a given CCMT domain. As per conventional understanding, CCMT domains with an HHI exceeding 2500 are regarded as concentrated domains. However, only a small number of domains in the dataset meet this

Table 3
Cross sectional models of CCMT patent generation.

	Log(Total CCMT patent count)						Log(Total CCMT patent count) * Avg.CCMT patent quality					
	All		Large firms		Small firms		All		Large firms		Small firms	
	(1)(1976–2020)	(2)(2013–2020)	(3)(1976–2020)	(4)(2013–2020)	(5)(1976–2020)	(6)(2013–2020)	(7)(1976–2020)	(8)(2013–2020)	(9)(1976–2020)	(10)(2013–2020)	(11)(1976–2020)	(12)(2013–2020)
Avg. market leverage	−0.158 (0.837)	2.008 (1.298)	4.843** (2.267)	5.303 (3.274)	−2.012** (0.880)	−0.090 (1.485)	−0.127 (0.376)	0.571 (0.599)	1.756* (0.885)	2.601 (1.682)	−0.677 (0.417)	−0.097 (0.715)
Avg. cash flow	−4.096*** (0.891)	−3.525** (1.514)	0.141 (5.969)	−27.749** (10.321)	−3.240*** (0.871)	−3.487** (1.436)	−1.306*** (0.400)	−1.318* (0.699)	1.059 (2.329)	−5.055 (5.301)	−1.061** (0.413)	−1.249* (0.691)
Avg. net equity issuance	−1.939 (1.473)	−5.198** (2.338)	−15.697** (7.303)	−54.295** (17.664)	−1.107 (1.440)	−4.666** (2.322)	−0.794 (0.661)	−1.295 (1.079)	−4.851* (2.850)	−3.040 (9.073)	−0.618 (0.683)	−1.169 (1.117)
Avg. interest payments	−13.779*** (5.161)	−7.526 (9.572)	−61.469*** (18.982)	−137.981* (62.151)	−5.551 (5.198)	1.294 (9.731)	−6.228*** (2.318)	−4.205 (4.420)	−26.795*** (7.407)	−57.421 (31.925)	−3.669 (2.465)	−1.439 (4.683)
Log(Avg.employment)	0.459*** (0.050)	0.364*** (0.077)	0.496* (0.257)	0.002 (0.474)	0.441*** (0.049)	0.379*** (0.076)	0.091*** (0.022)	0.072** (0.036)	0.187* (0.100)	−0.336 (0.244)	0.087*** (0.023)	0.070* (0.037)
Max. firm age	0.020*** (0.004)	0.017*** (0.006)	0.047*** (0.008)	0.040** (0.013)	0.014*** (0.004)	0.009 (0.006)	0.006*** (0.002)	0.005* (0.003)	0.014*** (0.003)	0.017** (0.007)	0.004** (0.002)	0.002 (0.003)
Constant	3.391*** (1.024)	1.714 (1.080)	1.366 (1.331)	1.718 (1.871)	3.553*** (0.977)	2.009* (1.026)	1.479*** (0.460)	0.942* (0.499)	0.257 (0.519)	1.469 (0.961)	1.516*** (0.463)	1.043** (0.494)
Industry (SIC-4D) FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	421	187	86	33	380	167	421	187	86	33	380	167
R ²	0.570	0.660	0.830	0.945	0.517	0.640	0.439	0.576	0.793	0.888	0.404	0.595
Adjusted R ²	0.387	0.410	0.671	0.748	0.290	0.337	0.202	0.264	0.600	0.487	0.125	0.253

Note: The table displays the OLS estimates of the parameter values in the firm-level cross-sectional regression model. While the baseline sample includes 1921 Compustat firms that have been granted at least one CCMT patent by the USPTO from 1976 to 2020, in the final estimations, firms with fewer than 20 CCMT patents and negative sales are excluded. Age is the number of years since initial public offering. Market leverage is long term debt (dltt) plus debt in current liabilities (dlc), divided by total assets (at) minus book equity (ceq) plus the market value of common equity (csho*prcc f). Cash flow is operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt), divided by total assets (at). Net equity issuance is sales of equity (sstk) minus purchases of equity (prstk), divided by assets. Interest payments is interest expense (xint) divided by assets. See Table 1 for a detailed description of variables. Clustered standard errors in parentheses. Signif. Codes: ***, 0.01, **, 0.05, *, 0.1.

Table 4
Panel models of CCMT patent generation.

	Log(Patent count) * Avg.patent quality											
	Between observations over time						Within firms over time					
	All	Large firms	Small firms		All	Large firms	Small firms		All	Large firms	Small firms	
	(1)(1976–2020)	(2)(2013–2020)	(3)(1976–2020)	(4)(2013–2020)	(5)(1976–2020)	(6)(2013–2020)	(7)(1976–2020)	(8)(2013–2020)	(9)(1976–2020)	(10)(2013–2020)	(11)(1976–2020)	(12)(2013–2020)
<i>Variables</i>												
Constant	0.8309*** (0.0433)	0.8265*** (0.0591)	0.4242** (0.2123)	0.5771 (0.5404)	0.8747*** (0.0393)	0.8734*** (0.0519)						
market_leverage_t_1	0.1669 (0.2323)	0.1883 (0.4655)	0.8516** (0.3864)	1.944** (0.8473)	−0.2273 (0.1810)	−0.0560 (0.3069)	0.3408** (0.1372)	0.0118 (0.3208)	0.2536 (0.2458)	0.0939 (0.7250)	0.0785 (0.1078)	0.1300 (0.3450)
cash_flow_t_1	−0.5516*** (0.1591)	−0.1753 (0.2968)	−1.194 (0.7781)	−0.0737 (1.614)	−0.1018 (0.1229)	0.0833 (0.2747)	0.2623** (0.1159)	0.3006 (0.1930)	−0.4888 (0.5087)	0.6717 (0.7521)	0.2647** (0.1054)	0.3077* (0.1692)
net_equity_issuance_t_1	−0.0046 (0.0945)	0.2480 (0.2546)	−2.365*** (0.6637)	−2.492 (1.689)	0.0267 (0.0834)	0.3327 (0.2694)	0.1140* (0.0677)	0.3384** (0.1511)	0.0617 (0.4328)	0.0107 (0.8448)	0.0780 (0.0577)	0.4976*** (0.1299)
interest_paym_t_1	−5.080*** (1.307)	−3.356 (3.209)	−13.34*** (3.035)	−46.24*** (15.21)	−1.409 (0.9059)	−0.4137 (2.839)	0.4977 (0.7028)	−0.5632 (2.392)	2.244 (1.788)	10.58 (13.23)	0.7731 (0.6672)	−1.331 (1.985)
Log(emp)	0.0512*** (0.0118)	0.0581*** (0.0185)	0.1484*** (0.0348)	0.1454 (0.1071)	0.0182 (0.0128)	0.0172 (0.0176)	0.0804** (0.0360)	0.0909* (0.0508)	−0.0037 (0.0567)	0.1890*** (0.0659)	0.1096*** (0.0311)	0.1209* (0.0629)
<i>Clustered-SEs</i>												
At firm-level	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>Fixed-effects</i>												
Firm-FE							YES	YES	YES	YES	YES	YES
Year-FE							YES	YES	YES	YES	YES	YES
<i>Fit statistics</i>												
Observations	2844	630	904	130	1940	500	2844	630	904	130	1940	500
R ²	0.07422	0.07398	0.26736	0.19833	0.01830	0.01122	0.70091	0.85626	0.80259	0.90901	0.68006	0.82146
Within R ²							0.03489	0.02654	0.04365	0.08082	0.03694	0.04637

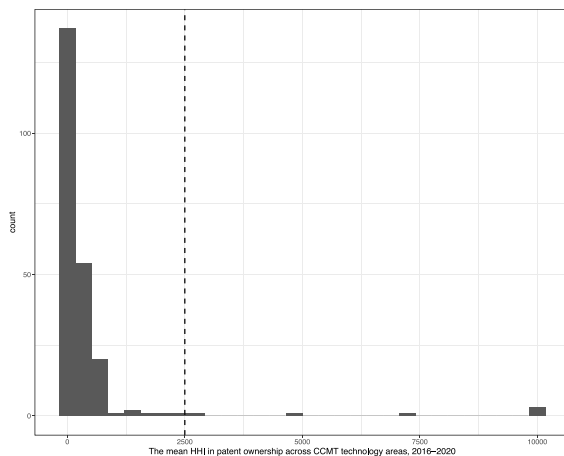
Note: The table shows the OLS estimates of the parameter values in the firm-level panel models. The sample includes Compustat firm-year observations where firms have been granted at least five CCMT patent by the USPTO from 1976 to 2020. The data is unbalanced. Market leverage is long term debt (dltt) plus debt in current liabilities (dlc), divided by total assets (at) minus book equity (ceq) plus the market value of common equity (csho*prcc f). Cash flow is operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt), divided by total assets (at). Net equity issuance is sales of equity (sstk) minus purchases of equity (prstk), divided by assets. Interest payments is interest expense (xint) divided by assets. See Table 1 for a detailed description of variables. Clustered standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 5

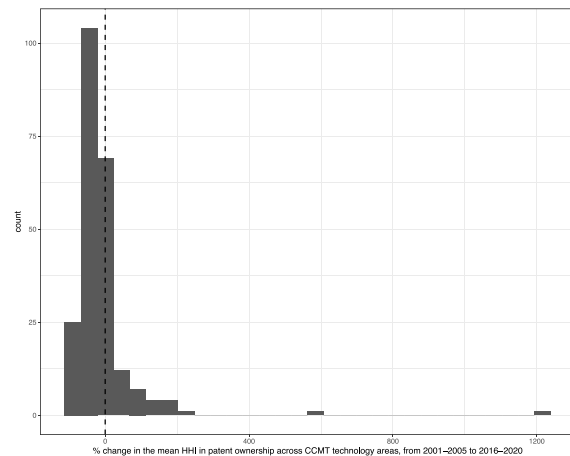
Dynamic panel models for the quality adjusted CCMT patent count, estimated with the system GMM.

	1976–2020			2013–2020		
	All	Large	Small	All	Large	Small
y_{t-2}	0.535*** (13.36)	0.584*** (3.53)	0.478*** (12.18)	0.725*** (7.70)	0.738*** (3.32)	0.663*** (8.47)
Market leverage $_{t-1}$	0.125 (1.02)	−0.255 (−0.31)	0.0769 (0.48)	0.279 (0.86)	−0.358 (−0.22)	0.0794 (0.26)
Cash flow $_{t-1}$	−0.174 (−1.30)	0.268 (0.15)	−0.0652 (−0.56)	0.324 (1.20)	0.986 (0.69)	0.211 (0.82)
Net equity issuance $_{t-1}$	0.0491 (0.51)	−0.248 (−0.12)	0.0884 (0.97)	0.614** (2.18)	−1.299 (−0.76)	0.523** (2.35)
Interest payments $_{t-1}$	−1.741** (−1.97)	3.843 (0.47)	−0.925 (−1.00)	0.576 (0.16)	13.20 (0.35)	1.136 (0.36)
Log(employment)	0.0222*** (2.92)	0.0711** (2.42)	0.00497 (0.61)	−0.00639 (−0.47)	0.0649 (0.56)	−0.00946 (−0.70)
_cons	0.482*** (12.19)	−0.00701 (−0.02)	0.556*** (14.26)	0.308*** (4.00)	−0.182 (−0.71)	0.391*** (4.79)
<i>N</i>	2684	850	1834	622	128	494
Hansen χ^2 test	261.27	27.29	218.38	135	10.69	123.38
Year dummies	YES	YES	YES	YES	YES	YES

Note: The table shows the system GMM estimates of the parameter values in the firm-level dynamic panel models. The sample includes Compustat firm-year observations where firms have been granted at least five CCMT patent by the USPTO from 1976 to 2020. The data is unbalanced. Market leverage is long term debt (dltt) plus debt in current liabilities (dlc), divided by total assets (at) minus book equity (ceq) plus the market value of common equity (csho*prcc f). Cash flow is operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt), divided by total assets (at). Net equity issuance is sales of equity (sstk) minus purchases of equity (prstk), divided by assets. Interest payments is interest expense (xint) divided by assets. See Table 1 for a detailed description of variables. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



(a) The average patent ownership HHI in CCMT domains, 2016–2020



(b) The change in the average patent ownership HHI in CCMT domains, from 2001–2005 to 2016–2020

Fig. 4. Patent ownership concentration in CCMT domains.

Note: The patent ownership HHI (Herfindahl–Hirschman Index) is computed by summing the squared ownership shares of each unique patent assignee (as disambiguated by the USPTO) within a specific CCMT domain, considering the entire population of patents granted by the USPTO.

criterion. Panel (b) depicts the changes in average HHI across CCMT domains from 2001–2005 to 2016–2020. While some domains have seen a sharp rise of up to 1150% in HHI, most CCMT domains have experienced a decrease in patent ownership concentration.

Fig. 5 presents the thirty CCMT domains with the most substantial rise and fall in HHI, along with the average HHI in these domains between 2016 and 2020. Several technology domains, including wind turbines, alternative fuels in internal combustion engines, hydrogen technology in transportation, and various areas within aeronautics or air transport, experienced a significant increase in patent ownership

concentration. It is important to emphasize that the increase in HHI is not limited to domains presented in Fig. 5. For instance, patents related to hybrid vehicles experienced about a 53% increase in the average patent ownership concentration between 2001–2005 and 2016–2020. Although the mean concentration remained low in all of these domains, it is noteworthy that technology domains considered to have low accessibility in Gallagher (2014)'s field research, for example, appear to have an increase in patent ownership concentration. Meanwhile, in technology areas such as energy storage utilizing capacitors, hydro energy, photovoltaic energy, non-fossil energy in aviation, computing systems,

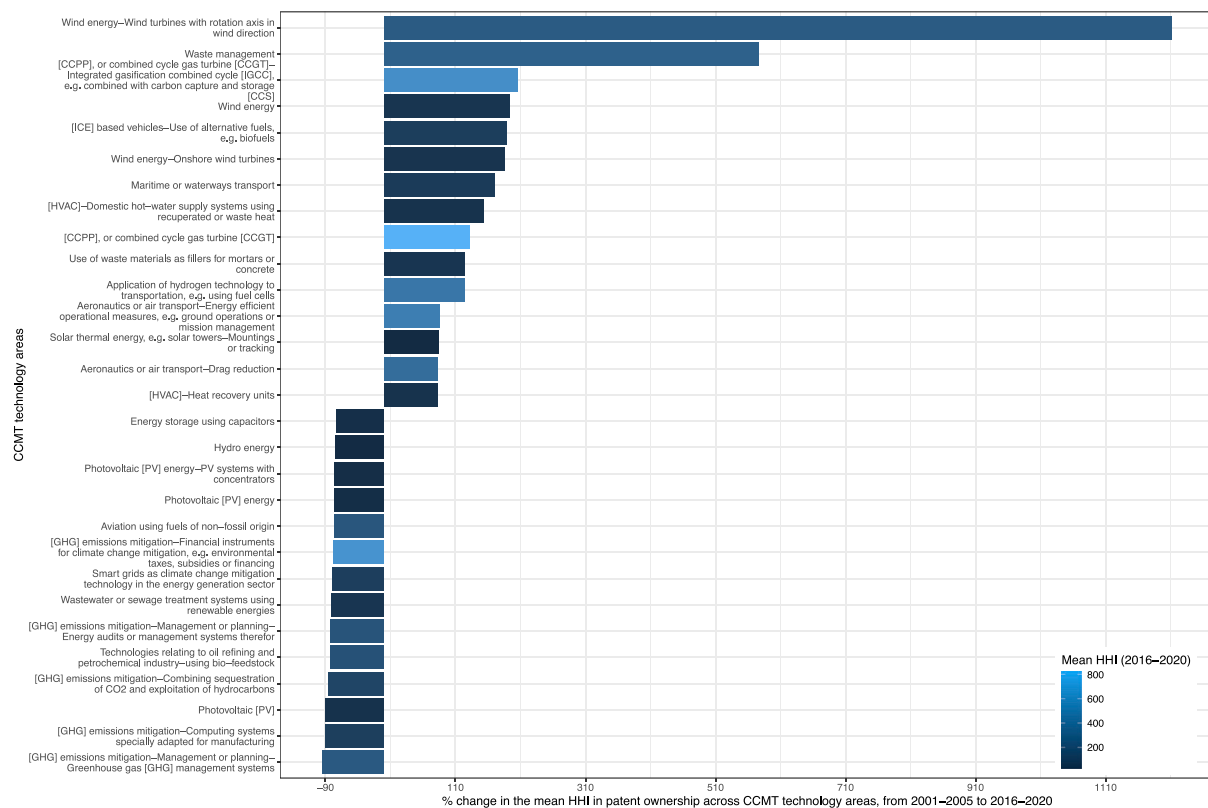


Fig. 5. The thirty CCMT domains with the most substantial rise and fall in HHI, along with the average HHI in these domains between 2016 and 2020.

and CO₂ sequestration through the utilization of hydrocarbons, the concentration of patent ownership has decreased and remained widely dispersed.

4.6. Discussion

I emphasize three key findings related to CCMT innovation and two noteworthy results concerning CCMT diffusion.

Regarding CCMT innovation, first, the results shared in this analysis show a consistent increase in both the quality-adjusted total and proportional count of CCMT-related patents in the United States from 2009 onwards, while recent studies that examine global patent patterns have discovered a decline in the production of high-quality CCMT inventions since 2013. This decrease has been attributed to either the drop in oil prices and technological maturity in certain fields, (Probst et al., 2021), or the shale gas boom since 2010 (Acemoglu et al., 2019). Nevertheless, the findings in this paper indicate that the quality-adjusted share of CCMT patents is still growing within the US, the world's technological frontier.¹⁶ Second, through the classification of

publicly traded companies holding at least one CCMT patent based on their financial characteristics and the examination of variations over time within each group regarding the quantity and quality of CCMT patents, it becomes evident that during the period spanning from 2013 to 2020, companies that are older, larger in scale, or possess greater capacity to leverage and generate internal funds tend to produce a greater quantity of CCMT patents. I also have employed a cross-sectional linear regression model and revealed a noteworthy correlation between the total patent count and the average leverage, while controlling for other firm characteristics and industry-specific effects.

Third, to identify whether larger and more leveraged firms or firms reacting to changes in their size, borrowing ability, or internal

¹⁶ The method employed in this paper can be argued to offer specific benefits in capturing patterns in CCMT innovation and at least three factors can be identified as contributors to the different findings presented in this study. One of the contributing factors is the varying definition of CCMTs utilized across studies. For instance, Acemoglu et al. (2019) exclude patents that pertain to enhancing the efficiency of the grid (Y02E40), improving electricity storage (Y02E60), or reducing pollution from fossil fuel electricity generation (Y02E20), while I follow the EPO's Y02 classification system for CCMTs as given since the Y02 classification aims to categorize all technologies that manage, mitigate, or avoid greenhouse gas emissions that originate from human activities. The second contributing factor is the different data sources used across studies. While I employ the USPTO's PatentsView database, which comprises patents granted in the United States, both Probst et al. (2021) and Acemoglu et al. (2019), for instance, rely on the PATSTAT database,

a world patent database containing data on roughly more than 100 million patent applications to patent offices in about 80 countries. Although PATSTAT offers global coverage and data on priority and continuing applications, its changing data exchange conventions with national authorities make it more focused on Europe, as noted by Kang and Tarasconi (2016) (p.59). Choosing to concentrate on patents granted within the US presents several benefits. Concentrating on the USPTO can prevent discrepancies in evaluation criteria among various patent systems. Also, since the US is considered a leading technology hub in numerous fields and has been ranked as the second-best country in terms of international intellectual property protection and the US owns a substantial technology market, high-quality patent holders have compelling reasons to pursue patents through the USPTO. The definition of high-quality patents varies and is a third factor that contributes to the different findings. Probst et al. (2021), for instance, employ the size of the patent family – that is, the number of countries where the same patent is registered – to identify high-quality patents. The underlying assumption is that companies will seek patent protection in many different countries if they consider their innovation more valuable. The OECD patent quality indicator used in this study not only measures the diversity in the size of patent families but also assesses other commonly-used indicators of patent quality such as scope, and citations (backward and forward), among others (see Methods).

funds are responsible for the increase in CCMT innovation, I have employed several panel models. According to the pooled OLS estimates, the lagged leverage ratio is positively associated with quality-adjusted patent count between 1976–2020, with a stronger effect observed during 2013–2020, primarily driven by large firms. Increasing leverage within a firm also result in more CCMT patents. Small firms that experience an increase in access to external equity funding and have more internal funds observe an increase in CCMT patent applications. For example, a percentage point increase in the sales of equity ratio from the previous year leads to an increase of about 64% in quality-adjusted CCMT patents for small firms. However, this effect is only observed during the 2013–2020 period. Even after considering the potential endogeneity of the predictors, this evidence remains valid. In short, small firms producing CCMT tend to be liquidity constrained and a change in ability to access equity increases patenting performance.

An important policy takeaway from these results concerning CCMT innovation is that the decline in corporate credit risk and the decrease in yields on corporate bonds resulting from the expansionary monetary policies initiated after 2008 could have favored large corporations. At the same time, smaller enterprises could have also enjoyed advantages stemming from the rise in stock market values driven by these monetary policies, potentially making equity financing more viable.

When it comes to diffusion of CCMTs, there is no universal outcome that applies to all technology domains. Domains like energy storage using capacitors, hydro energy, photovoltaic energy, non-fossil energy in aviation, computing systems, and CO₂ sequestration through hydrocarbons have seen a decline in patent ownership concentration, remaining widely dispersed. However, several technology sectors, such as wind turbines, alternative fuels for internal combustion engines, hydrogen technology in transportation, and various aspects of aeronautics and air transport, witnessed a notable uptick in patent ownership concentration. For example, patents related to hybrid vehicles experienced an approximately 53% increase in average patent ownership concentration between 2001–2005 and 2016–2020. While the average concentration remained relatively low in all these domains, it is worth noting that technology areas traditionally regarded as having limited accessibility, as observed in Gallagher (2014)'s field research, also exhibit an increase in patent ownership concentration.

One valuable insight for industrial policymakers from the findings on CCMT diffusion is the potential necessity of industrial policies aimed at fostering innovation within these vital CCMT domains. Such policies could serve to enhance competition and facilitate broader accessibility to these technologies.

5. Concluding remarks

In conclusion, the goal of net-zero emissions presents a dual challenge. This challenge revolves around the innovation and diffusion of climate change mitigation technologies (CCMTs). Examining a wide range of data sources and employing various analytical techniques, this study offers insights into both facets of the CCMT landscape.

On the innovation front, it is evident that CCMT patents are on the rise within the United States. The surge in CCMT invention took place simultaneously with a series of events. In the course of the 2008 US presidential campaign, both primary candidates from the major political parties, namely Barack Obama and John McCain, advocated for the implementation of a cap on carbon emissions. After Barack Obama won the election, the House of Representatives passed one of the most significant cap-and-trade regulations, which was viewed as a landmark accomplishment by many, even though the bill was unable to pass the Senate in 2010.¹⁷ Therefore, the election of President

Obama and the realistic prospect of cap-and-trade regulation may have incentivized many firms to accelerate their efforts to innovate in the area of CCMT.

This study, nevertheless, points to the impact of unconventional monetary policy adopted after the 2008 financial crisis. This is because the pace of CCMT innovation continued to be rapid even while regressive environmental policies were on the political agenda during President Donald Trump's term. According to the evidence presented in the paper, the rise in CCMT has been propelled by large firms that have access to debt markets and smaller firms that are capable of borrowing from equity markets. Expansionary monetary policies during this period increased commercial bank lending (Rodnyansky and Darmouni, 2017), reduced corporate credit risk and yields on corporate bonds (Krishnamurthy and Vissing-Jorgensen, 2011), and rose stock prices (Bhattarai and Neely, 2022). The reduction in corporate credit risk and lower yields on corporate bonds may thus have provided an advantage to big companies, while small businesses could have benefited from the upward trend in stock market prices, which may have made equity financing more accessible. The implications for policy are significant, with monetary policies post-2008 favoring large corporations and boosting equity financing, which can be leveraged to support CCMT innovation. This demonstrates the interconnected nature of financial markets, corporate funding, and technological advancement.

On the diffusion front, the concentration of patent ownership within various CCMT domains varies significantly. While some domains exhibit a decline in concentration, others experience an increase. For example, within distinct technology domains like wind turbines, alternative fuels for internal combustion engines, hydrogen technology in transportation, and various domains of aeronautics and air transport, limited access and high costs may be associated with a handful of companies owning and licensing CCMT patents. To encourage competition and facilitate broader access to these technologies, it may be essential to implement focused industrial policies designed to promote innovation in these vital CCMT domains.

It is important to highlight some limitations of the study. The paper defines CCMT using the EPO's Y02 classification scheme. Not all CCMTs, as defined by the EPO, are equivalent, however. In several sustainable development scenarios, the weight of CCMTs aiming to improve the efficiency of internal combustion engines, for instance, differs from the weight of CCMTs designed to enhance the efficiency of renewable energy sources. It would be feasible in future research to weigh CCMTs based on their usage intensity in several sustainable development scenarios before delving into the analysis of their determinants at the firm level. Also, despite the extensive efforts made to eliminate endogeneity concerns, it is important to note that the findings in this study primarily remain correlational in nature. To enhance and supplement the results presented in this paper, studies that leverage causal inference can provide valuable insights into CCMT innovation and diffusion.

CRediT authorship contribution statement

Enes Işık: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

¹⁷ The drive to establish the regulation was initiated by an unconventional alliance of powerful environmental organizations and polluting firms, which was referred to as the US Climate Action Partnership (USCAP). The formation of the USCAP coalition suggests that many major corporations started recognizing the inevitability of climate regulation.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jclepro.2024.141090>.

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