Does the US Regional Greenhouse Gas Initiative Affect Green Innovation?

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Research Article

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Abstract

The U.S. Regional Greenhouse Gas Initiative (RGGI) is a regional market-based regulatory scheme for reducing greenhouse gas emissions from the electric power sector in ten northeastern states. It promotes energy efficiency, renewable energy, direct energy bill assistance to citizens, and technological innovation. Conventionally, green innovation has been one of the most effective tools for reducing greenhouse gas emissions through energy efficiency, energy transitions, and renewable energy. Thus, this study measures the impact of the implementation of RGGI on the firms' green innovation initiatives. We used 20 years of panel data from the Fortune 500 list of the United States' largest companies. Based on DID, a benchmark regression, the RGGI has a significant adverse effect on the green innovation of Fortune 500 companies, and we verified these findings with multiple robustness tests. As we investigated how energy-intensive industries were affected by RGGI, we found that it slowed down green innovation, but it was not statistically significant. This study provides a novel perspective on how the RGGI influences green innovation in firms and how different types of sectors respond to the policy. In terms of policy, we believe that a well-covered and differentiated legislation that fosters green innovation while being realistic about the policy's goal and the firm's environmental attitude, like emissions reduction through green innovation, is essential.

1.0 Introduction

Environmental regulation (E.R.) that is well-managed can help companies become more committed to green innovation. Green innovation refers to technical advances incorporated into ecological management techniques to reduce pollution, hazardous waste, and energy consumption (Chen, Y. S., 2008; Zhang, J. M. et al., 2020). Governments implement environmental regulations to lessen firms' negative externalities and increase their ecological consciousness. Scholars categorized these regulations into different dimensions. For instance, Liu et al. (2018) considered Chinese environmental regulations into three types, i.e., economic, legal, and supervised environmental regulations. Also, these ecological regulations grouped into formal and informal environmental regulations (Song, Y. et al., 2019). Others are classified based on their obligatory nature, such as mandatory, participatory, and voluntary environmental regulation.***[1]*** This study considers market-based regulation, which is economical, formal, and mandatory. The Regional Greenhouse Gas Initiative (RGGI) was established in 2009 in 10 northeastern U.S. states. It aims to cut down on GHG emissions from the power sector. By investing proceeds from the RGGI allowance auction, the RGGI participating states have more power to increase energy efficiency, low-carbon fuel switching, and green technology innovation *(ICAP, 2021)*. Also, green innovation is commonly accepted way to reduce CO2 emissions, and research suggests that market-based schemes are better at doing so.

This study aims to measure the effect of the RGGI on the green activities of U.S. Fortune 500 firms. Empirical literature documents that environmental regulation and green innovation motivate firms' environmental attitudes (Zhang, D. Y. et al., 2019). However, authors have been concluded with diverse effects. For instance, adverse effects have been found in the work of Li, L. C. et al. (2018) and Tang, K. et al. (2020), while positive and negative effects were found in the work of Fang, Bai, and Bilan (2020).

Also, Fang et al. (2020) revealed that E.R. failed to improve green innovation efficiency. Hence, the previous results are inconclusive. Meanwhile, various issues have been investigated to measure the impact of the RGGI. For instance, it significantly reduced emissions from CO_2, and SO_2 (Chan & Morrow, 2019), accelerated the coal-to-gas switching, and reduced coal-fired and increased natural gas cycle generation (Fell & Maniloff, 2018). Also, the RGGI moderately fetishes some indirect child health benefits and reduces overall infant mortality by mitigating air pollutant concentrations (Lee, J. & Park, 2019; Perera et al., 2020). Regarding CO_2 reduction from power plants, RGGI was found significant in the short-term but not long-term within regulated states (Shawhan et al., 2014). Also, the RGGI has neither had a significant effect on carbon emission from electricity production (Lee, K. & Melstrom, 2018) nor failed to improve technical efficiency (Zhou & Huang, 2016). However, previous studies look at the states/provinces level, but the firm-level effect of RGGI implementation remains unexplored.

Industrial operations are considered a primary factor for excessive CO2 emissions, and firms' environmental attitudes play a vital part in escalating toxic gases. Moreover, green innovation is one of the most acceptable ways to keep hazardous emissions and environmental regulations accountable by providing regulatory pressure for corporate innovation (Tang, H.-l. et al., 2020). The empirical literature has established that any ecological law should increase firms' environmental concerns. Therefore, we believe that a firm-level investigation is vital. To fill this gap, we collected the financial and economic data of the U.S. Fortune 500 (hereafter F500) ranked companies (headquartered in the USA) from 2000 to 2019. We empirically examine the relationship between RGGI implementation and a firm's green innovation (hereafter FGI). We contrasted energy-intensive industries (EI) and less energy-intensive (LEI). Green patents are used as proxies for GI, and green patents are defined according to the WIPO's green inventory (Cecere & Corrocher, 2016; Kesidou & Wu, 2020). FGI may be affected by RGGI and other policies, which makes the results estimation of this study biased. To determine the true impact of RGGI, we employ "Difference-in-difference" (DID) as benchmark regression to make the empirical results more robust. We also used "Difference-in-Difference-in-Difference (DDD)" to classify the energy-intensive industry's effects. Previous studies have shown that energy-intensive industries are more responsible for high CO_2 emissions, and most market-based policies are imposed to curb emissions from energy-intensive industries. For instance, RGGI was also deployed to reduce emissions from the electric power sector, the highest emitting individual sector in the last 40 years. Subsequently, we conduct a series of robustness tests to ensure the results' validity.

Our empirical investigation established a significant relationship between the green innovation of F500 companies and the RGGI implementation. The fortune 500 companies were categorized based on their business success (revenue performance). Firms' green inventions are a costly endeavor for a corporation. Practically, a strong connection between a firm's business performance and innovation activities was established in the "Derwent Innovation Index," where most of the F500 companies were included in the index as top innovating companies (Derwent-Index, 2019). We identified green patents from the firm's total patents using the WIPO's IPC green inventory. Based on DID benchmark regression, the RGGI seems to negatively influence the green innovation activities of F500 companies, which can unveil another dimension to investigate the efficacy of the RGGI. We also found similar results in the case of energy-

intensive sectors but not statistically significant. Thus, this study will indeed contribute to the growing body of knowledge in innovation by demonstrating how to use the WIPO's IPC green inventory to assess the influence of market-based programs like RGGI on firm-level green innovation. Practically, our sectoral heterogeneity analysis adds value by elucidating a sector-specific relationship between the RGGI and firms' green innovations. Additionally, this disclosed relationship assists governments' environmental agencies in identifying additional regulatory measures that will encourage and incentivize corporations to increase their green innovation engagement in addition to pre-existing restrictions. In general, this paper invites regulatory bodies to reconsider the rationale for RGGI implementation and its actual impact on firm-level green innovation, including a U.S. economic sectoral analysis.

The remainder of this section is organized as follows. Section 2 presents the related literature while Section 3 describes the hypothesis and measurement, and section 4 explains the study's variable, data, and research methods. The results of the benchmark regression, robustness tests, and discussion are evaluated in Section 5, and Section 6 stated the concluding remarks.

[1] This study considers three types of environmental regulation such "*mandatory regulation"* (i.e. 'environmental regulation', 'command and control based or fiscal and taxation or carbon tax or emission tax', 'market-based emission scheme or cap-and-trade mechanism or emission trading schemes' and so on), *"participatory regulation"* (i.e. 'R&D subsidies', 'pollution incentives'), and *"voluntary regulation"*- agreement or commitment between regulators and polluters; see details for mandatory and voluntary regulation (Ren, S. et al., 2018; Zhu, Y. et al., 2019), and *participatory regulation* (Reichardt et al., 2017; Shen et al., 2020b).

2.0 Previous Literature

2.1 The U.S. RGGI, a Market-based GHG Emission Policy

Among all other types of environmental regulations, ETS is the fastest growing. So far, around 80 jurisdictions worldwide employ 23 market-based systems, covering approximately 9% of global emissions (Luca et al., 2020). Except for the Korean ETS, all these policies are experimental. The EU-ETS, followed by the RGGI, California and Quebec cap-and-trade, and Chinese provincial ETS pilots (CN-ETS), are prominent and similar due to floor auction reserve prices. (Flachsland et al., 2020). Only the Quebec cap-and-trade has distinct features like reshaping and merging nature with other similar policies (ICAP., 2021). Unlike other ETS programs, Korea ETS (KETS) and New Zealand ETS (NZ ETS) are unique due to national coverage. The NZ ETS has a broader sectoral range, but revenues are assigned to the general budget without allotting for specific purposes (ICAP., 2020). In contrast, RGGI and CN-ETS covered only selected states and provinces, and EU-ETS was implemented in E.U. regions.

Primarily rein in CO2 emissions from the electric power industry, the single largest cumulative source of U.S. CO2 emissions for the last 40 years. In 2009, the U.S. RGGI became the first mandatory market-based regional regulation in the U.S. that relies only on auctions to allocate emissions permits. However, the RGGI has been operational in only ten northeastern states since January 2009, namely Connecticut, Delaware,

Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, Vermont, and New Jersey. RGGI was explicitly introduced to reduce yearly CO_2 emissions from the electric power industry by 45 percent below 2005 levels by 2020 and an additional 30% by 2030 in regulated jurisdictions (C2ES, 2019; RGGI Inc., 2020). Participating states met their target for CO_2 emissions from fossil fuel consumption in the electric power sector by reducing them by more than 49% from 2005 levels in 2018 (EIA, 2021). Additionally, RGGI adjusts the cap on emissions of less than 21.9 Mt (million tons) annually across participating states. However, various factors contribute to this so-called emissions decline. It could occur due to reduced natural gas costs, decreased demand, or increased renewable capacity (Huang, L. & Zhou, 2019).[2]

The RGGI differs from the EU-ETS in that it has a fully functional auction, whereas the EU-ETS allows free grandfathering of allowances to former emitters (Borghesi & Montini, 2016; Haapala, 2017). RGGI has successfully conducted 50 auctions, selling 1.11 billion CO_2 allowances for a total of $3.78 billion (RGGI Inc., 2020). The current CO_2 emission cap was increased to 119.8 million tons from 96.2 million tons for the 11 participating states in 2021 (Virginia is participating for the first time). However, RGGI is continuously reducing the state-wise CO_2 emission budget each year to reach 86.9 million tons by 2030 (RGGI Inc., 2020). The auction proceeds are distributed to member states for energy efficiency, renewable energy, direct energy bill assistance, agriculture and home technological innovation, and other GHG reduction programs (RGGI Inc., 2020). With over ten years of deployment, RGGI provides enough data for researchers to conduct an in-depth investigation of its emissions from the electricity sector (Chan & Morrow, 2019). In addition, RGGI significantly reduces spillover CO_2 and SO_2 emissions, resulting in significant societal benefits for both RGGI member states and neighboring non-member states (Chan & Morrow, 2019). RGGI has completed its three-year compliance phase in 2020 and reimbursed billions of dollars from emission budgets to consumers, primarily to assure low-carbon power generation. Thus, we assume that RGGI impacts firms' green innovation, ensuring energy efficiency and ultimately lowering CO_2.

2.2 Green Innovation (GI)

Nearly a quarter-century has passed since Fussler and James (1996) initially defined green innovation as new goods and processes that add value to customers and businesses while having a negligible environmental impact. Some researchers have described green innovation as focused only on ecological considerations. For example, the primary objective of green innovation is not always to alleviate environmental burdens but to provide some environmental advantages (Driessen & Hillebrand, 2002). Likewise, Bernauer et al. (2007) and Dangelico and Pujari (2010) claimed that GI should comprise new or modified processes, practices, methods, and environmentally conscious products and contribute to product life-cycle sustainability.

Recently, authors added the economic success of a green innovation with an environmental benefit. For instance, GI refers to technology innovations in environmental management practices, pollution prevention, waste reduction, and energy-saving (Chen, Y. S., 2008; Zhang, J. M. et al., 2020). Lee, K. H. and Kim (2011) defined GI as integrating producer and supplier’s innovation efforts that enhance compliance

with environmental regulatory requirements and achieve target economic success. In the extended literature, many authors aligned GI with multiple dimensions. For instance, Cai and Zhou (2014) argued that sharing knowledge of green design for new product expansion or production chain promotes a corporate green attitude. Therefore, sufficient attention must be paid to the function of knowledge management concerning environmental legislation and green innovation. Likewise, green design is an initiative carried out during the design and product development phase to lessen adverse environmental effects in the whole product life cycle (Tseng et al., 2013). Every firm has combined strategies for green innovation, which will optimize the firm's revenue and environmental legitimacy (Wang et al., 2020). Practically, a business entity would not spend on activities that do not value the firm. Due to the high cost of inclusion, we feel that the firm's innovation must provide economic value for the organization. As a result, this research views GI as an activity that assists enterprises in promoting manufacturing, operating, and managing processes that result in economic gains and minimize environmental harm.

2.3 Nexus between Emissions Trading Schemes-RGGI and Firms' Green Innovation

Despite the acceptability of ETS, researchers are also keen to investigate their effects ranging on various direct and spillover (indirect) issues related to environmental and economic issues. Scholars investigate ETS's impact on ecological topics, including GHG emissions, carbon leakage, energy efficiency, and energy switching (from fossil fuel to low carbon), while R&D investment, financial performance, and market competitiveness lead to economic issues.

Several authors empirically investigated and identified reasons for reducing CO2 emissions in regulated states, especially after RGGI enactment. First, 'electricity imports' from neighboring states may result in CO2 emissions reductions within the regulated states (Lee, K. & Melstrom, 2018). Second, Kim and Kim (2016) established that the RGGI considerably accelerates coal to gas conversion. However, this reduction in emissions is primarily attributable to decreased coal inputs and emission leakage rather than 'coal-to-gas fuel switching' (Huang, L. & Zhou, 2019). Third, 'energy-efficiency improvement'- RGGI raises retail electricity prices due to increased carbon costs, which reduces electricity demand (Rocha et al., 2015). However, energy-efficiency gains, not RGGI but energy-saving technology, were responsible for declining electricity demand (Narassimhan et al., 2018; Huang, L. & Zhou, 2019). Forth, shifting operational or production activities to non-RGGI states is also known as emission or generation leakage. Fifth, during the 'economic downturn,' energy efficiency stagnated due to a lack of government spending (Huber, 2013). Permit prices in auctions recorded very low after the immediate implementation of the RGGI, but the economy also faced a global financial crisis or economic downturn (Fell & Maniloff, 2018). Thus, economic fluctuations have a cohesive impact on demand for carbon allowances, leading to carbon prices (Luca et al., 2020). Sixth, other implemented policies, i.e., Renewable Portfolio Standard (RPS), could have influenced the dented CO_2 emissions in the RGGI states (Johnson, 2014; Narassimhan et al., 2018). Finally, reducing CO_2 emissions in RGGI participating states is not exclusively for the implementation of the RGGI but cohesive to direct or indirect factors.

Theoretical literature also argued that environmental policies increase firms' innovation and bring long-term benefits (Porter & Van der Linde, 1995). Distinct E.R.s motivate firms' environmental initiatives

differently (Jaffe & Palmer, 1997; Kemp, 1997). Regulatory pressure creates innovative technological push (Lahteenmaki-Uutela et al., 2019) and market pull (Horbach et al., 2012), which forced to change the innovative activities to low-carbon technologies (Acemoglu et al., 2012). This push-pull pressure could help the firm to reduce environmental compliance costs and improve the ability to lessen ecological damages in the long run.

Recent studies show that market-based instruments influence FGI (Lyu et al., 2020; Ren, S. G. et al., 2020). The empirical literature confirms that introducing and implementing GI may bring technology innovation applied in green products or processes, persuade state-of-the-art environmental management, external knowledge adoption, energy-saving, cutting emission, and industrial output recycling (Yurdakul & Kazan, 2020; Zhang, J. M. et al., 2020). The RGGI is initiated to lessen emissions in the power sector through fuel switching high to low carbon, improve energy efficiency, promote renewable energy, and low-carbon technological development. According to WIPO's IPC green inventory, firms filling applications for a patent with these attributes can be considered green patents. We used these green patents to measure a firm's green innovation.

In this vein, proactive firms' participation in GI helps meet the regulatory burdens, improve energy efficiency, and reduce waste (Li, D. et al., 2018). Market-based instruments are found to be efficient and effective in lowering harmful emissions. Still, whether this so-called decreasing emission could be sustainable without firms' green innovation progress is yet to be explored. This sudden dented emissions trend may also happen for multiple reasons like diminished market demand, stakeholders' pressure, and even macro-economic recession (Albort-Morant et al., 2016), (Woerdman & Nentjes, 2019). Besides, the legislative enforcement economic and social pressure are also driven to pursue sustainable growth FGI (Saunila et al., 2018), which help to improve the firm's ecological performance (Guoyou et al., 2013). Besides the firm's internal and external resources, market-based mechanisms also play a vital role in promoting FGI (Cai & Li, 2018). Therefore, a theoretical foundation assuring that market-based regulation has a significant relationship between an FGI.

The theory of innovation economics acknowledges that driving motives of firm-level GI are not fully encompassed by market and technology factors, but the regulatory aspects are needed for correction. Thus, ER has a dual effect by directly addressing the environmental externalities and, indirectly, encouraging FGI (regulatory push-pull hypothesis) (Rennings, 2000). The legislative push-pull can improve the firm's resource efficiency, effectively controlling environmental hazards, encouraging FGI, and transforming the industry towards green innovation. In this point, we combined the narrow and weak version of Eco-efficiency theory with the "Porter hypothesis" framework that ER stimulates firms' innovation and stringency of ER promotes innovation (Porter, 1991). Therefore, we construct a research question: "To what extent is the U.S. RGGI promoting the firm's green innovation initiatives?" We focused on the U.S. RGGI instead of the only environmental regulations. We used FGI as a replacement for innovation initially considered in HP, extending HP and providing empirical evidence from the F500 companies like all other ETS.

[2] See more: (Ellerman & Montero, 1998)

3.0 Hypotheses And Measurements

3.1 Past Empirical Studies on Market-Based Carbon Schemes and Green Innovation

Many regulations (national or regional) have been enacted to limit the use of fossil fuels in the production process, encourage the use of renewable energy, and assure environmentally friendly technology development or adoption. In terms of E.R.s, flexible regulations provide businesses with more flexibility and effectiveness (Ramanathan et al., 2018). Along with flexibility, ETS is one of the politically viable due to cash rebates (or "carbon dividends"), which help reimburse proceeds for public benefits while meeting low GHG emission goals (Raymond, 2019). The ETS programs covered the power sector (except Tokyo and Saitama), aiming to reduce GHG emissions from fossil fuels in the power generation and transmission process. In principle, the cost of ETS allowances offers many incentives for the power industry to reduce emissions through investment in less carbon-intensive power generation, demand reduction, or transmission switching to a low-carbon power source (Luca et al., 2020). To accomplish this, all key ETS initiatives, including the RGGI, have the same objective of promoting energy efficiency, renewable energy, low-carbon innovation, direct energy bill assistance, and other greenhouse gas reduction programs (ICAP., 2020; RGGI Inc., 2020).

The success of the ETS program noticeably relies on a shift from fossil-fuel dominant technologies to low-emission technologies such as renewables or nuclear power (Rocha et al., 2015). Moreover, eco-efficiency theory (Porter Hypothesis) assumes that strict but flexible E.R.s, e.g., ETS, may offer better incentives for technological change (Cohen & Tubb, 2018; Ren, S. G. et al., 2020. All inventions related to renewable energy and others that help improve energy efficiency, switching low-carbon power production and transmission are treated as green technological innovation under the definitions WIPO’s Green Inventory IPCs classification (WIPO., 2020).

Serval authors have investigated the relationship between the impact of EU-ETS on GI focused on macro and micro level with innovations (environmentally friendly technological innovation, eco-innovation, low carbon patents). In the case of the micro(firm)-level, Calel and Dechezlepretre (2016) found a positive relation between EU-ETS and green innovation. However, green innovation also found no connection with EU-ETS (Lofgren et al., 2014). Many researchers recently attempted to examine the impact of CN-ETS on green innovation. They also found similar diverse findings as EU-ETS, for instance, positive (Zhu, J. M. et al., 2019), negative (Zhang, L. et al., 2019), mixed or inverted-U and U-shaped (Li, D. & Zeng, 2020; Song, M. L. et al., 2020; Zhuge et al., 2020), no effect or not significant (Xing et al., 2019; Shen et al., 2020a) and inhibit relationship (Lyu et al., 2020). Thus, the impact of ETSs on green innovation remains inconclusive and varies in terms of geographical and sectoral heterogeneity.

Researchers also attempt to measure the direct or indirect (spillover) impact of RGGI in the USA. For instance, Rocha et al. (2015) found CO_2 emission in the regulated states is significantly related to electricity market restructuring, e.g., the higher the allowance price, the lower the demand for electricity and

CO_2 emissions. Moreover, Kim and Kim (2016) postulated that coal to gas switching had been significantly surged due to RGGI implementation. However, electricity imports particularly replace electricity production in the regulated states, and CO_2 emissions are raised in the non-regulated states (Lee, K. & Melstrom, 2018). Followed by Huang, L. and Zhou (2019) also found reducing the CO_2 emissions trend of the RGGI implementation. Still, the reduction is primarily achieved by fewer coal inputs and emission leakage rather than fuel switching.

Counterintuitively, the RGGI has been examined regarding sulfur dioxide (SO_2) or nitrogen oxides (NOx) emissions, social benefits, carbon leakage, infant mortality, merger incentives, and political advantages. For instance, Chen, Y. H. (2009) and Chan and Morrow (2019) identified the undesirable consequences of RGGI implementation and concluded that CO_2 leakage and SO_2, NOx, is associated with carbon allowance price. Along with meeting short-term emissions targets, the ETS creates economic incentives that shift long-term production capacity toward low-CO2-intensive technologies (Chen, Y. H., 2009). Additionally, lowering the expense of regulation enables regulated enterprises to have greater discretion in doing business (Huber, 2013). As spillover of RGGI, Creti and Sanin (2017) investigated merger incentives and found a new insight for understanding many mergers in the presence of a tradable emission permits market. In addition, RGGI significantly reduces child mortality through lessening air pollutant concentrations (Lee, J. & Park, 2019). Cap-and-trade programs provide a political advantage, thus, widely accepted in the many constituents due to its ‘double dividend’ scope. It creates opportunities to redistribute the carbon revenue to citizens and enhance investment ability for low carbon technologies, helping achieve climate change or emission goals (Raymond, 2019). Therefore, we presume that RGGI must encourage green innovation of the US F500 companies located within the regulated states. Thus, based on the above analysis, the first hypothesis is stated.

Hypothesis (H_1): The U.S. Regional Greenhouse Gas Initiative (RGGI) affects firms’ Green Innovation.

3.2 ETS-Energy Intensive Industries and GI Nexus

This study considers energy-intensive industries consuming a bulk of energy in production activities and energy expenditures proportionately related to the total output. In the post-industrial era, industrial activities are the critical basis of economic prosperity, and energy is the lifeblood of industry (Michielsen, 2013). For instance, the production processes and manufacturing actions significantly consume almost 90% of the total industrial energy consumption (Salahi & Jafari, 2016). The transportation, electric power, and industrial sectors consume more than 91% of total annual energy in the USA (EIA, U., 2019). Consequently, these sectors are responsible for around 72% of total yearly GHG emissions in the U.S. (EPA, U.S., 2020). As discussed above, the RGGI was implemented to lessen GHG emissions from the electric power sector. However, fossil fuels are the most significant energy source for electricity generation, and almost two-thirds of electric generation (63%) depend on fossil fuels (EIA, U. S., 2019). Usually, the effect of large quantity production is the high-energy consumption, which leads to heavy pollution (Bai et al., 2019). Green innovation is well accepted alternative approach to solving this problem (Huang, Z. H. et al., 2019). As discussed above, the P.H. states that stringent E.R. promotes firms’ innovation. The impact of EU-ETS on technological innovation is significant in the energy-intensive industries compare to less

energy-intensive industries (Ajayi & Reiner, 2020). However, green innovation is significantly different from traditional innovation because of its double externality characteristics such as negative and positive externalities[3]. Therefore, considering the emission effects of energy intensive industries, this study considers another hypothesis which is stated below.

H_2: The U.S. RGGI does affect firms' green innovation more in the energy-intensive sectors than the less energy-intensive firms.

[3] For detail see- (Bai et al., 2019)

4.0 Variable, Data, And Research Methods

4.1 Variable Measurements and Descriptive Statistics

At the outset, the Pollution Abatement Costs and Expenditures (PACE) survey was used by many researchers to measure the environmental attitude or firms' green activities. However, PACE is insufficient to measure firms' green activities because of poor data quality (Jaffe & Palmer, 1997). Few recent studies used 'green keywords' to separate the green patents from the total patent (Li, D. Y. et al., 2019; Zhang, L. et al., 2019). However, we believe that this keyword approach has two specific limitations: first, WIPO and OECD have classified the green patent with unique International Patent Classification (IPC) in 2010 and 2015, respectively. Second, one/two words are insufficient to reveal the identity of the whole patent. To overcome this challenge, like Ghisetti and Quatraro (2017) and Yang et al. (2020), this study quantified each sample firm's year-wise green patent application as per WIPO's green inventory. Table 1 depicts all variables' measuring tools and methods and summary statistics.

Table 1 Measurement and summary statistics of the variables

VARIABLE	**Variable Calculation Method**	Unit	N	$\bar{x}$	SD	MIN	P50	MAX
Green Patent (GPAT)	IPC's Green Patent as per WIPO	Pieces	7780	2.63	11.48	0.00	0.00	224.00
Tobin's Q (TQ)	Market Cap to Book Value of Total Assets	Ratio	7780	1.82	2.31	-77.73	1.25	43.02
Firm Profile (FP)	Firm's Operating Profit Margin	(%)	7780	9.60	19.38	-829.71	9.05	270.62
Operating Ability (OA)	Net Profit Margin	(%)	7780	3.45	139.53	-1220.30	4.84	260.44
Firm Growth (FG)	Firm's sales growth	(%)	7780	78.83	4443.96	-100.00	6.08	3701.70
Business Ability (B.A.)	Firm's net income to total equity of common shares	(%)	7780	12.17	92.23	-533.55	11.67	2141.07
Age (AGE)	Year since the firm's incorporated	Year	7780	42.35	36.31	0.00	28.00	219.00
SIZE	Firm's Market Capitalization	LOG (MC)	7780	9.93	0.68	6.85	9.95	12.12
Leverage (LEV)	Total debts to total assets	(%)	7780	28.23	20.03	0.00	26.25	261.11

This study considers 7780 firm-years for 389 F500 listed firms. The results show that the mean of GPAT is 2.63 with an 11.48 standard deviation, the minimum is 0.00, and the maximum value is as high as 224, signifying a difference among the firms' green patents (see more in Table 4 and **Fig. 3** of supplementary material). Most previous studies used "total patent applications" as a proxy to measure firms' innovation. However, green patent activities are less common than patent activities by corporate entities. For instance, Zhang, D. Y. et al. (2019) measured a firm's green innovation with so-called keywords for green patents and experienced zero up to 75% (P75=0.00) of sample firms. A substantial difference in the S.D. of control variables indicates a significant performance gap among the firms though ranked in F500. We found all the control variables and dependent variables are stationary as per Levin, Lin, and Chu (LLC) and Phillips–Perron Fisher tests.

4.2 Data Description

We select the states based on the firm's headquarter location of F500 companies then classify the firms depending on the implementation of RGGI and induced year. This selection strategy provides us with three specific benefits. First, the selection of firms before states allows avoiding self-selection bias, as we are interested in comparing the treatment effect of RGGI states and others. Secondly, invention and patent applications are costly initiatives (Zhang, D. Y. et al., 2019). Hence, economic stability is positively correlated with a firm's innovation activities. Besides, F500 companies are ranked by total revenues, which helps the firms widen patent activities and green patents. Thirdly, to select the high innovative firms viz. about 35% of global top innovators are U.S. companies (Derwent-Index, 2019), most of them ranked in F500.

Initially, we found 1007 US companies that appeared in the US Fortune-500 from 2000 to 2019 and used specific criteria for finalizing our sample companies. We excluded 151 financial companies for the high scaled leverage difference and 371 'Delisted or Merged' companies for data complexity. Meanwhile, we omitted 98 companies for another three reasons: founded after 2009, changed headquarter location, or found less than three times in the F500 list. Moreover, we exclude 38 companies established before 2009 but changed headquarter location from regulated states to non-regulated states after the implementation of RGGI in 2009. Finally, we selected 389 firms that are listed and doesn't change H.Q. location and represent 38 U.S states, and 84 companies from regulated, whereas 305 companies are from non-regulated states. Besides, in terms of the 'North American Industry Classification System (NAICS)' sectoral classification, we found 40% of sectors are energy-intensive (i.e., 7 out of 15 industry) compared to 8 less energy-intensive industries (for details see in Table 3 in supplementary online documents). For the classification of energy and less energy-intensive sectors, we follow the high emitting sectors as per U.S. environmental protection agency (EPA, United States, 2017; Gerres et al., 2019).

We used multiple databases for the RGGI firm's classification and F500 companies. Firstly, the official website of RGGI, the US-EPA, and Fortune 500 used the status of RGGI, state-wise CO_2 emission data, and the rank of F500, respectively. Secondly, the European Patent Office (EPO)[4] and USPTO have gathered patent information. We classified the total patents as green (as a proxy of GI) based on IPC's green inventory defined by WIPO and 'Refinitiv Eikon and Datastream' for all control variables.

4.3 RESEARCH METHODS

4.3.1 Did Model Specification

Like all other market-based schemes, the ultimate target of the RGGI is to hold an upward trend of CO_2 emissions. Meanwhile, as RGGI is principally induced to lower CO2, green innovation is also a commonly accepted measure to help the firm improve environmental performance. Sequentially, GI helps the firms boost their ecological consciousness, leading to energy efficiency and CO_2 emission performance. Thus, the implementation of RGGI should be considered a quasi-natural experimental process. In this view, the study set 'Green Patent (GPAT)' as a random variable of FGI. Principally, RGGI (regulated) = 1 and RGGI (regulated) = 0, accordingly, indicate the firms whose headquarters are located within the covered RGGI

states (also identified as a treatment group) and those that are not covered (the control group). Here, the notion is that only treated or regulated firms are affected by RGGI, i.e., firms located within the regulated states are affected and treated as regulated firms. Therefore, the consequence of RGGI on the FGI of the treatment group is E(Green Patent|Regulated = 1) and E(Green Patent|Regulated = 0) for the control group. Hence, the study obtains the causal relationship of the RGGI on the sample firms. That is, the pure effect of RGGI on FGI of the treatment group is:

$$Y = E(GreenPatent|\, Regulated = 1) - E(GreenPatent|\, Regulated = 0)$$

1

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Based on the quasi-natural experiment of RGGI, induced in January 2009, we define 2000–2008 as a 'Pre-Treated,' 2009–2019 as a 'Post-Treated' both in the treatment and control group. Then, the study estimates the pure effects of RGGI on the GI (GPAT) of F500 companies by comparing the difference between the treatment group and the control group Pre (before) and Post (after) the implementation of RGGI based difference-in-difference concept such as

$$\boldsymbol{\delta_{DD}} = (GPAT_{Post\ Treated} - GPAT_{Pre\ Treated}) - (GPAT_{Post\ control} - GPAT_{Pre\ control}) \ldots\ldots(1a)$$

Therefore, the study used the DID model that is specified as follows:

$$Y_{nst} = \propto + \beta_1 RGGI_{nt} + \beta_2 YD_{nt} + \beta_3 RGGI_{nt} \times YD_t + \beta_4 X_{nt} + \gamma_n + \delta_t + \epsilon_{nt}$$

2

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Where, Y_{nst} is the firm's total green patents in state 'n' in year 't'. $RGGI_{nt}$ is a regulation dummy variable that equals 1 for RGGI states (10 northeastern states) and '0' otherwise. $\mathrm{Y.D.}_t$ is year dummy variable that equals '1' when $YD \geq 2009$ and '0' otherwise. $RGGI_{nt} \times YearDummy_t$ is the interaction term with a combination of RGGI states and the year when the policy is initiated, i.e., $RGGI_{nt} \times YearDummy_t = (RGGI \times YD)$. X_{nt} indicates specific control variables, γ_n and δ_t are the vectors of year and sector dummy variables representing year and sector fixed effects. The coefficient β_3 signifies the effect of RGGI on FGI by counting the difference before and after the implementation of RGGI between the treatment group (RGGI States) and control group (Non-RGGI States).

4.3.2 Parallel Trend Assumption and Test

DID is one of the most used methods to evaluate specific policy and make the empirical results more robust but has some causal effects like common trend assumption and other linear regression assumptions

(Angrist & Pischke, 2008, pp. 171–172). We used the parallel trend test before calculating the average treatment effects (ATE) of RGGI to confirm the common trend pre-intervention period from 2000 to 2008. Figure 1 represents the average treatment effects between the treated and control group, which estimates the coefficient of β3 in Eq. (2). We found none of the point estimates fluctuates from zero by more than two standard errors and conforms to the common trend hypothesis. Therefore, **Fig. 1** shows that GI was equivalent in both treatment and control groups before the installation of RGGI.

4.3.3 The DID-based on Propensity Score Matching (PSM)

Despite the popularity, DID suffers from endogeneity problems in a policy or treatment (Besley & Case, 2000). We calculate the DID as prescribed by Brewer et al. (2018), and Wooldridge (2021) to minimize the serial correlation and others. However, there are visible variations in the treatment and control group characteristics while conducting causal analysis through the DID method (Zhang, H. J. et al., 2019). Like CN-ETS, the RGGI is also a pilot for specific states designed within a quasi-experimental framework (Huang, L. & Zhou, 2019; Lee, J. & Park, 2019). Therefore, we are concerned about the chances of an unobserved treatment effect and reverse causal relationships during this research (Zhang, Y.-J. et al., 2020). To evade the unobserved treatment effects and change the causal relationship, we consider the Propensity Score Matching (PSM) method to estimate the propensity scores for every F500 firm and then screen out F500 companies with no systematic difference in the propensity scores (P.S.). Thus, we attain control of the self-selection bias goal (Zhang, Y.-J. et al., 2020). In line with the observable individual characteristics, self-selection bias defines as a nonrandom selection of F500 companies. It means RGGI is not a single reason but other firms' characteristics (control variables) that influence the FGI. In this vein, we used PSM to confirm the effect of RGGI on the FGI is not disturbed because of self-selection bias.

Based on PSM, this study selects the firms from the control group (non-RGGI states) that are similar in individual characteristics to firms from the treatment group (RGGI states) instead of original comparing samples. So far, this study can keep control of the self-selection bias effect, but the time and the group-specific difference remain, for instance, firm heterogeneity between the firms from RGGI states and the Non-RGGI States. Non-overlapping bias and the density weighting bias could result if such differences correlate with the dependent variables' dynamics (Abadie & Imbens, 2011). Additionally, PSM is not well-suited to take advantage of long time series, and while DID can, it relies on parallel pre-intervention trends between the treated and control groups. Panel data is a better option to minimize treatment endogeneity issues than repeated cross-sections, and PSM can better tackle endogeneity issues than DID. Like Zhang, Y.-J. et al. (2020), this study estimates the propensity score for RGGI regulated and unregulated firms. Finally, we use PSM-based DID with 20-years panel data to ensure the accurate and precise estimation of the pure effect of RGGI on an FGI, which can yield more robust results in the following sections.
[4] See details about the strength of this database in www.worldwide.espacenet.com

5.0 Results Analysis And Discussion

5.1 The effect of RGGI on firms' Green Innovation in U.S. Fortune 500

According to Equation (2), the coefficient of β_3 signifies the impact, and we run a total of 6 models with different inclusions; and Table 2 illustrates the results. Model 1 is a benchmark model that does not contain any control variables and fixed effects. In contrast, Models 2, 3, 4, and 5 either add the control variables or time/sector fixed effects in turn, while model 6 considered all control variables, year, and sector fixed effects. Column (1) represents model 1 that reveals the average impact of the RGGI on FGI by controlling for individual outcomes. The results of the benchmark regression show that the expected coefficient of the policy interaction term on a firm's green patents initiatives is -0.09241, and it is highly statistically significant, i.e., significant at a 1% level. It indicates that the implementation of RGGI does not encourage GI activities through green patents of F500 enterprises during the study period. Results remain steady in the combination of different inclusions, i.e., indicating that DID in benchmark regression is relatively robust at the primary stage. Finally, RGGI has a significant negative impact on the GI regardless of whether control variables and the fixed effects are considered.

Table 2 The effect of Regional Greenhouse Gas Initiative on firms' green innovation

	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
Variable	GPAT	GPAT	GPAT	GPAT	GPAT	GPAT
RGGI × Year Dummy	-0.09241***	-0.09281***	-0.0930***	-0.07831***	-0.07581***	-0.07429***
	(0.02532)	(0.02526)	(0.02526)	(0.02615)	(0.02603)	(0.02602)
Intercept	0.30681***	0.26041***	0.21583*	-1.6856***	-2.0087***	-2.05872***
	(0.041384)	(0.04606)	(0.12468)	(0.17617)	(0.19084)	(0.21799)
Control Variables	No	No	No	Yes	Yes	Yes
Sector Fixed Effect	No	No	Yes	No	No	Yes
Time Fixed Effect	No	Yes	Yes	No	Yes	Yes
R^2	0.0040	0.0054	0.1921	0.1512	0.1398	0.2993
Number of Firms	389	389	389	389	389	389
Observations	7780	7780	7780	7780	7780	7780

Notes: standard error in parentheses *p < 0.1, **p < 0.05, ***p < 0.01. GPAT is total firm' green patents

Our findings are not standing alone with the statistically significant negative relation, as previous results are inconclusive than only ETS program in the long run positive relation. For instance, Eiadat et al. (2008) found a statistically significant adverse impact E.R. on the adoption of environmental innovation strategy in the chemical industry of Jordan, in the European energy sector (Bel & Joseph, 2018), and in the Chinese manufacturing industry (Li, L. C. et al., 2018) and even in the heavy-polluting industries (Fang et al., 2020).

E.R. does negatively affect the FGI efficiency in the short-run (Tang, K. et al., 2020). Recently, many researchers attempted to investigate the embedding effects of CN-ETS on enterprises' GI and found inclusive findings like EU-ETS, such as no effect or not significant (Xing et al., 2019; Shen et al., 2020a). The RGGI regulated states have experienced a downward trend during each of the 3-year compliance periods since its implementation in 2009 (see **Fig. 2a** in supplementary online documents) (EIA, U. S., 2019). Nevertheless, the CO_2 emission scenario is similar in the non-RGGI regulated states (see fig. 2c in supplementary online documents). Thus, it is doubtful that the decreasing trend of energy-related CO_2 emission is a result of RGGI implementation instead found an increasing trend of electricity import from neighboring states[5].

5.2 Impact of types of Economic Sector with Difference-in-difference-in-difference (DDD)

Empirically, some firms are less energy-intensive but recorded a high level of a green patent application. Therefore, this study used the DDD method for analysis to remove sectoral interference that may cause an inconsistent green patent between the treatment and control group. At this point, we create another dichotomous variable, 1 for the energy-intensive sectors, otherwise 0. Hence, the DDD model is constructed as follows:

The outcome variable is $GPAT_{itc}$ for an individual firm *i* at year *t* in group *c* (treatment or control) and subgroup (*s*) denoting energy-intensive sector.

$$GPAT_{itc} = \beta_0 + \beta_1 RGGI_i \times Year\ Dummy_t \times sector_{ci} + \beta_2 RGGI_i \times Year\ Dummy_t + \beta_3\ Year\ Dummy_t \times sector_{ci} + \beta_4 RGGI_i \times sector_{ci} + \beta_5\ Year\ Dummy_t + \beta_6\ sector_{ci} + \beta_7 RGGI_i + \lambda X + \gamma_t + \mu_i + \epsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where the definitions of all other variables are the same as Eq. (2) and our concern in the coefficient β_1. Table 3 depicts a total of 5 models where model 1 to model 4 (represents in columns 1–4) illustrate the estimation of the average treatment effect of DDD with different inclusions. All the desired coefficients (β_1) are negative but statistically insignificant indicates that the RGGI has no significant influence in the energy-intensive sectors compared to less-energy-intensive sectors. Moreover, the co-efficient and sign of the interaction term (RGGI × Year Dummy) of DDD remain the same as benchmark models, which is also another proof of the robustness of the benchmark model. Some other similar mixed findings of sectoral analysis support our result (Stoever & Weche, 2018; Li, D. & Zeng, 2020; Song, M. L. et al., 2020; Zhuge et al., 2020).

Table 3
Impact of the U.S. RGGI and energy-intensive sector on firms' green innovation

	Model-1	Model-2	Model-3	Model-4
VARIABLES	GPAT	GPAT	GPAT	GPAT
RGGI × Year Dummy × Sector	-0.0716	-0.0718	-0.0599	-0.0614
	(0.0510)	(0.0509)	(0.0529)	(0.0527)
RGGI × Year Dummy	-0.0537	-0.0539	-0.0438	-0.0406
	(0.0378)	(0.0377)	(0.0401)	(0.0399)
Year Dummy × Sector	-0.00259	-0.00260	0.000859	0.00312
	(0.0220)	(0.0219)	(0.0234)	(0.0233)
RGGI × Sector	0.103	0.115	0.111	0.115
	(0.110)	(0.110)	(0.107)	(0.107)
Intercept	0.0617	0.0160	-1.868***	-2.145***
	(0.0645)	(0.0674)	(0.180)	(0.193)
Control Variables	No	No	Yes	Yes
Time Fixed Effect	No	Yes	No	Yes
R^2	0.0563	0.0580	0.1503	0.1608
Number of Firms	389	389	389	389
Observations	7,780	7,780	7,780	7,780
note: *** p < 0.01, ** p < 0.05, * p < 0.1 and the SEs are in parentheses, GPAT is total firm' green patents				

5.3 Robustness Test

5.3.1 Joint Support Hypothesis Test Based on PSM-DID Method

As discussed above, the DID method is not free from selection bias problems, serial correlation problems, asymptotic distribution. We used bootstrapping in the Kernel 'Probit' and 'Logit' regression to overcome the asymptotic distribution problem (Angrist & Pischke, 2008, p. 227). We preferred PSM-DID to minimize data inconsistency, serial correlation, and self-selection bias. To reduce the data error rate after matching and enhance the validity for checking the robustness of DID, we run jointly support hypothesis tests and found all the control variables are statistically insignificant in the 'Matched' condition compared to the 'Unmatched' condition. Figure 2 depicts the S.D. before and after comparing all variables (DV, CV) and shows that the joint support hypothesis test is passed. We found similar results (not reported here but available in supplementary online documents in Tables 5 and 8).

Before PSM-DID base regression analysis, we used kernel density propensity matching to check the treatment and control groups (shown in **Fig.4**). After matching both groups, the probability density of the propensity scores has mandatorily been consistent (shown in **Fig.3**), signifying that the matching effect is improved (compared to raw and matched), allowing us to apply PSM-DID as the robustness of benchmark regression.

After minimizing data error rate and improving data similarity through jointly supporting hypothesis test and Kernel Distribution of Propensity Score, we regress (both the Probit and the Logit) again based on PSM-DID, and results are shown in Table 4. These results revealed that the estimated coefficients of the interaction term (RGGI × Year Dummy), symbols, and significance levels (in Logit) of the 'Epanechnikov' kernel matching method is consistent with the benchmark DID results (Table 2). This result reinforced the benchmark DID regression, meaning that the RGGI has no remarkable impact on GI (GPAT) of F500 companies during the study period, which is also another evidence of the robustness of the benchmark regression results based on DID test revealed above.

Table 4
Propensity Score Matching based Difference-in-Difference (PSM-DID)

	Model 1	**Model 2**
Variables	Logit	Probit
	Epanechnikov	Epanechnikov
RGGI × Year Dummy	-0.3748*	-0.1624*
	(0.2055)	(0.1156)
Intercept	-25.9425***	-13.9273 ***
	(1.0224)	(0.5142)
Control Variables	Yes	Yes
Sector fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
R^2	0.3762	0.3739
Number of Firms	384	384
Observations	7010	7010
**Inference: *** p < 0.01; ** p < 0.05; * p < 0.1 and Robust Std. Err. Parentheses in bracket.		

5.4 Further Robustness Tests

Firstly, every state has legislative autonomy that may create unobservable state features and influence FGI initiatives. Hence, we introduced the "Pro-State Feature," including state fixed effects and control variables, to control the state's characteristics, and observed no significant difference (*available in* Table 4 *in*

supplementary material). Secondly, we noticed a global financial crisis within our study period. We tested the hysteresis effects and obtained similar results *(not reported here but available in* Table 4 *in supplementary material)*. Possibly, some unobservable confounders may influence the GI of RGGI-covered F500 companies. A two-step system GMM estimator is appropriate to avoid the effects of unobservable confounders in innovation studies, especially in firm-level research (Zhang, Y.-J. et al., 2020). We also examined these and found no significant difference (*see detail in Table 8 in the supplementary document*). Based on Eq. (2), we examined 15 economic sectors to estimate the impact of RGGI on FGI. We found significant sector-wise heterogeneity, i.e., the RGGI has a different effect on the FGI in their respective production line (*results available in supplementary material*). Specifically, we found only five sectors positively impacted, including the manufacturing industry. Still, two-thirds of sectors (10 out of 15) have experienced a negative trend, though insignificant. Hence, this can be evidence supporting baseline regression that the RGGI failed to encourage green innovation in F500 companies.

[5] RGGI induced to control CO_2 emission specifically from the electric power source, hence the study is expecting better clear evidence from fuel-specific CO_2 emission data depicted in **Fig. 2a, 2b, and 2c** in supplementary online documents. By analyzing CO_2 emission trends of different fuel types namely Coal, Petroleum, Natural Gas, and Electricity from 2000 to 2019, and found a similar trend both in RGGI states and the Non-RGGI States. Another recent finding by Lee, K. and Melstrom (2018) indicates that electricity imports increased after RGGI's establishment in 2009 which leads to electricity production and carbon emissions increased outside RGGI. Yet again, the study failed to establish a visible impact of RGGI, especially after the compliance period.

6.0 Conclusion

This research analyzed the effect of the RGGI on the green innovation of F500 companies from 2000 to 2019. We used DID regression as a benchmark model and performed multiple robustness tests to investigate this. We found that the RGGI influences FGI by approximately − 0.09241, and the relationship is statistically significant at the 1% level. Indicating that the RGGI has a detrimental effect on firms' green innovation in the RGGI regulated states compared to other U.S. states, and examination of robustness tests confirm this statement. RGGI's influence on different industrial levels, such as the EI and LEI sectors, was further examined using DDD and heterogeneity analysis to demonstrate the individual relationship between RGGI and specific sectors. Second, we have identified a small window of opportunity regarding the RGGI's independent effect on the EI and LEI sectors. Additionally, the coefficient of the key interaction term (in DDD) of treatment, time, and industry (RGGI Year Dummy Sector) is negative (-0.0716), showing that the RGGI has no statistically significant impact on the EI sectors. However, we discovered a positive, statistically significant relationship in five economic sectors: manufacturing from energy- and carbon-intensive sectors; and another four sectors from less-energy- and carbon-intensive sectors (results available in supplementary online documents); implying that the RGGI failed to reduce CO2 emissions through firms' green innovation.

Based on the analysis of the results, we believe that increasing the RGGI's coverage in all sectors will lead to better outcomes for firms' green innovation. For instance, the RGGI has a significant positive impact on

several high-emitting industries, such as manufacturing; therefore, total sectoral coverage would improve the GI trend of F500 firms. Thus, the U.S. government may consider including manufacturing and other important sectors in RGGI to encourage the firm's green growth. Second, since RGGI is now triggered in the lower-emitting states (see **Figs. 2 and 3** in the supplemental online materials), full coverage of this scheme over the entire U.S. is sure to provide significant results. Third, a reciprocal approach, such as a mix of subsidies or special fund allocations and market-based rules, can significantly impact enterprises' green actions (Bai et al., 2019; D. Li & Zeng, 2020). Thus, when combined with present policies, subsidies for FGI and special funds will improve firms' green efforts.

However, some limitations are inevitable in this study; we keep these for future researchers. First, the RGGI is induced in ten specific states only, and each state has legislative autonomy. Thus, we were conscientious that any state's features might influence FGI. In this context, we introduced and regressed with a "Pro-State Feature" and found no significant difference with benchmark regression. Nonetheless, specific state-level differences (e.g., incentives, voluntary initiatives) might have influenced FGI and kept it for future researchers. Second, some subsidiaries of a large company may have been involved in the innovation process or patent application (Capaldo & Petruzzelli, 2014). We settled this issue by limiting the USA to an 'innovator's address.' Then, we chose the listed companies in the U.S. stock markets to confirm business activities but could not consider the proportion of industrial activities within regulated states and left this issue for future researchers.

Third, as R & D is the prime input of firms' innovation, the disclosure trend of green R & D is still not enough to conduct good academic research. Thus, the gradual development of firm-level green information will carry out much research in this field. Forth, in-depth industry-wise analysis with no limits to listed and non-listed or comparative impact on private and public or 'large firm' and 'small and medium firm' or 'state-owned' and 'listed' can also enrich the empirical understanding of the relationship between this policy and firms' green behavior.

Declarations

Ethical Approval: This is our original research, and this manuscript is not submitted to more than one journal for simultaneous consideration.

Consent to Publish: All authors are agreed to publish this research as per journal's policy.

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Figures

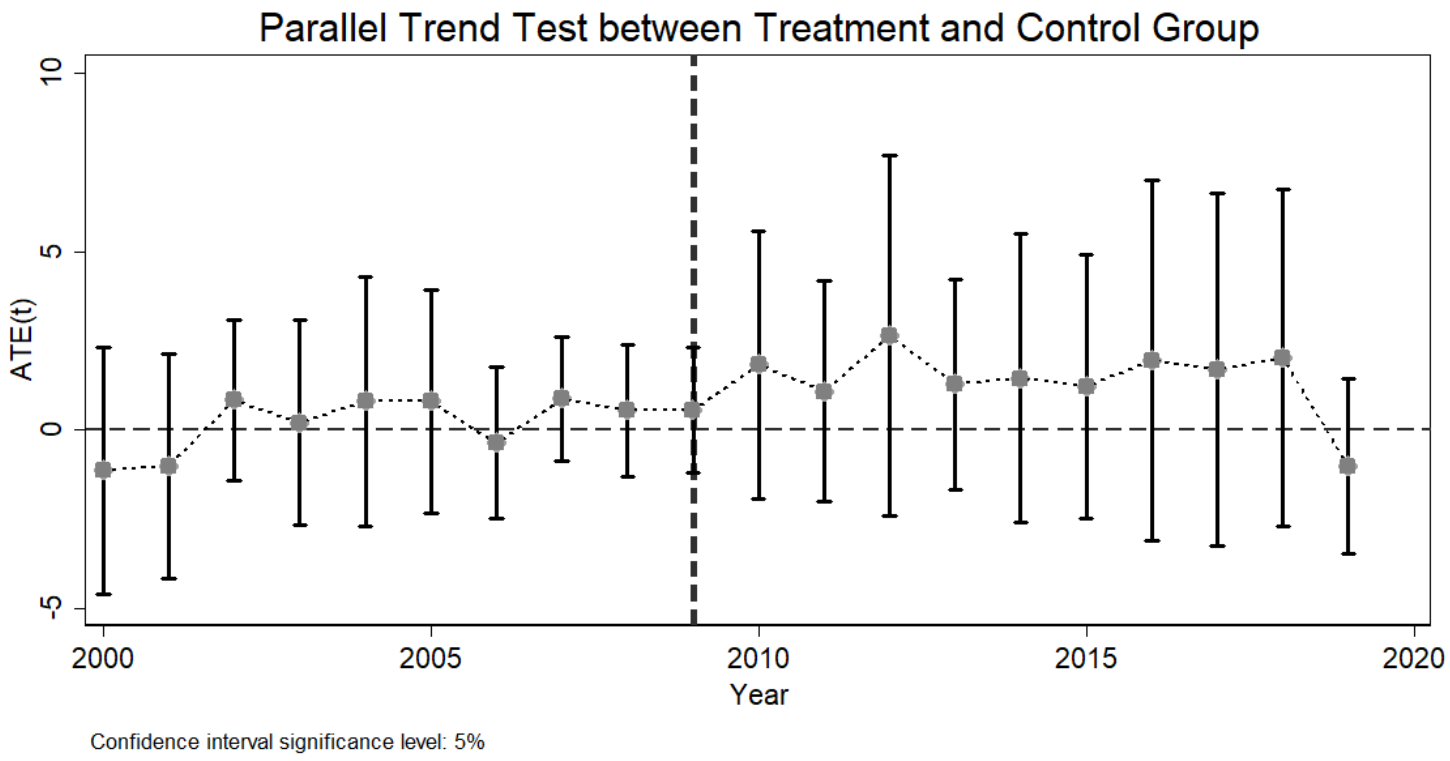

Figure 1

Parallel Trend Test

Note: *Data are for 2000–2019 of 389 fortune 500 firms. Point estimates by year are of β3 in Eq. (2), illustrating average treatment effects (ATE) of on firm GPAT difference between regulated and non-regulated states compared to the base year of 2009. Vertical segments capture two standard-error confidence intervals.*

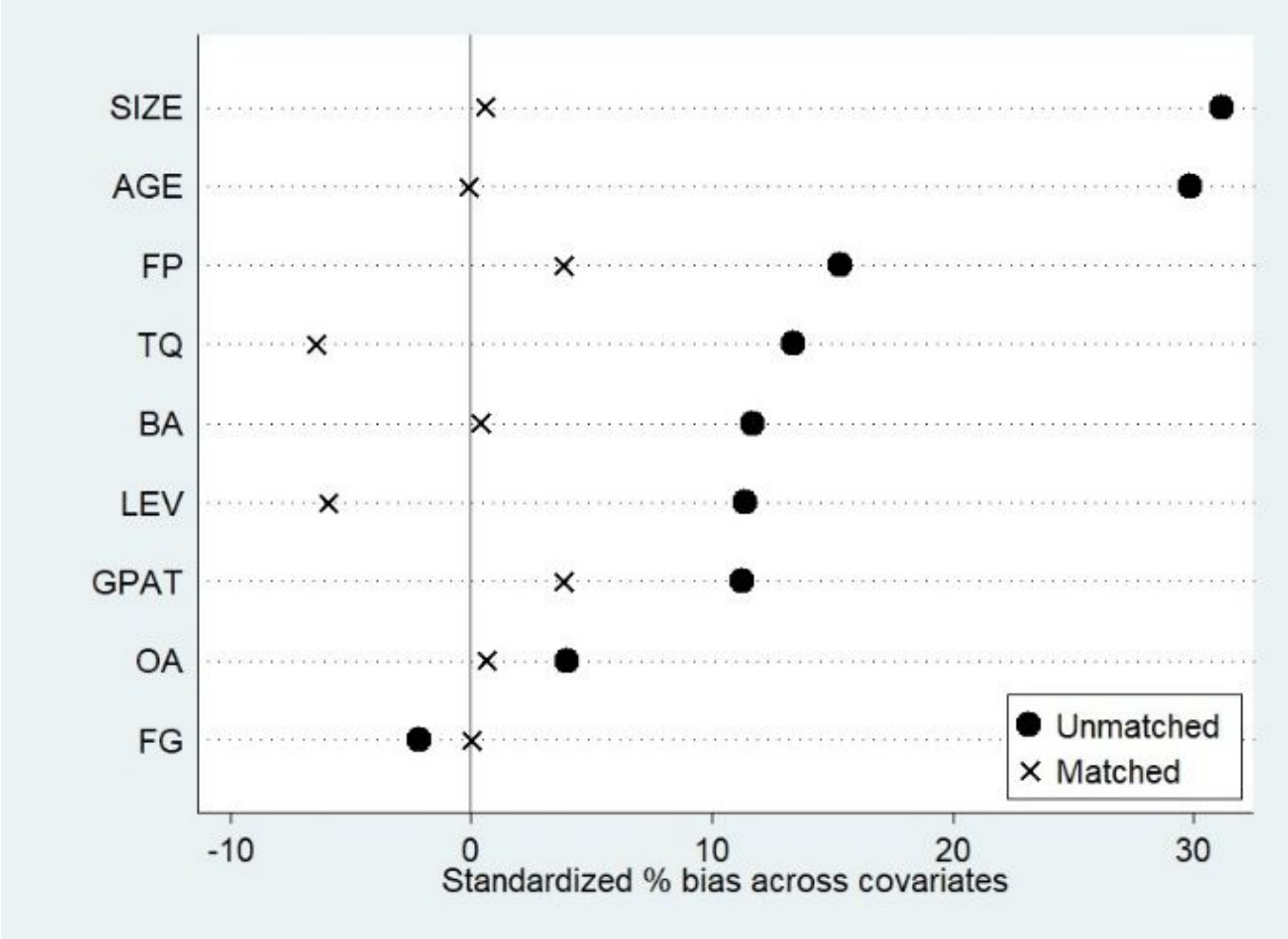

Figure 2

The standard deviation (S.D.) before and after the matching of variables. Source: Graphical Output of Balance Test

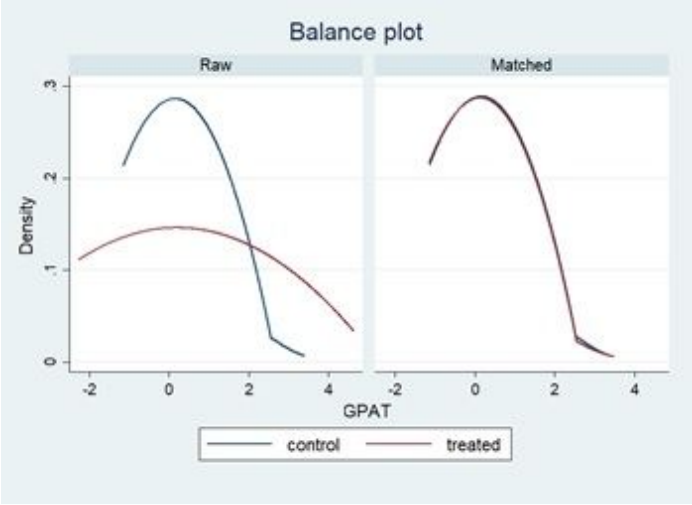

Figure 3

Kdensity Balance Plot. Source: Graphical Output of Balance plot

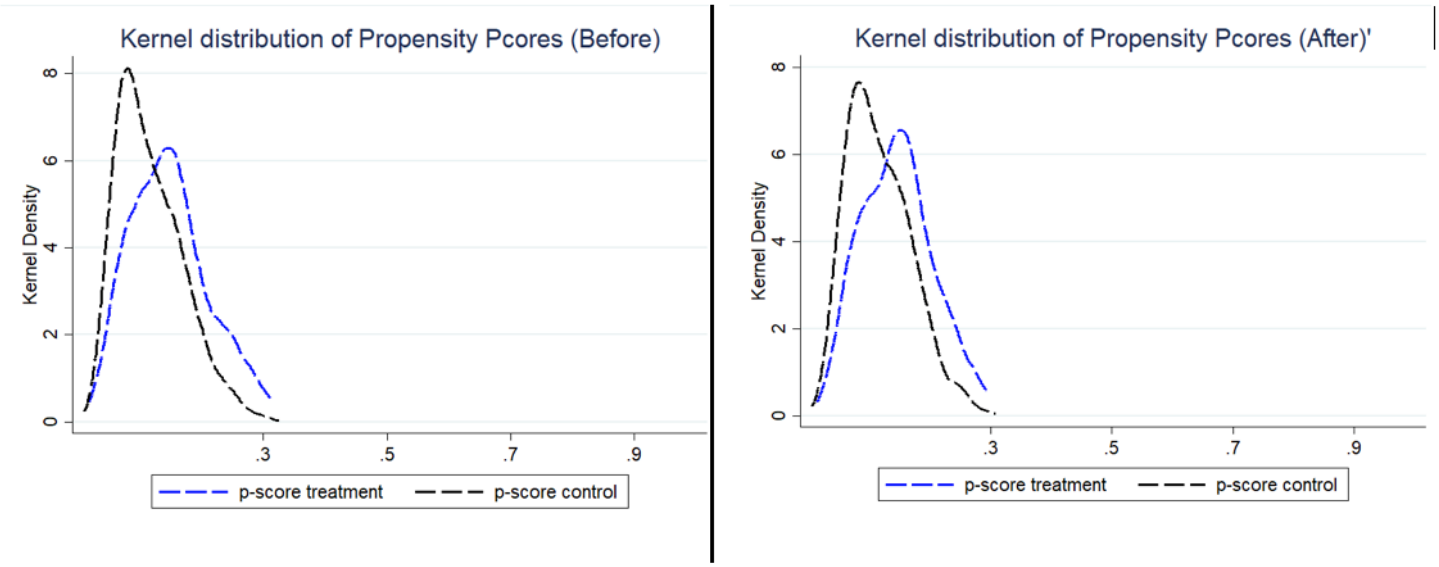

Figure 4

The probability density of the propensity scores. Source: Graphical Output of Kernel Density Test

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